Examining Social Reinforcement Learning Biases in Social Anxiety

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The start of graduate school was harder than I expected. I think I underestimated how challenging it would be to go from a place that I knew well, and where I had a strong network of friends, to a totally new environment where I knew almost no one. That I'm leaving Charlottesville with the same feeling of community that I had in Cambridge is a true testament to the incredibly warm, supportive, and brilliant people I was lucky to meet at UVa, who have shaped my personal and professional worlds for the last six years.

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General Introduction

Although social connectedness is critical to health and wellbeing, the 12% of Americans who experience social anxiety disorder in their lifetime often avoid social situations, which can lead to pervasive impairments. Aberrant social reinforcement learning, or differences in learning from positive and negative social feedback, may underlie many of the cognitive, emotional, and behavioral difficulties in social anxiety disorder. While reinforcement learning is well studied in other mental disorders and in the non-social domain, only a few studies have begun to probe aspects of social reinforcement learning. This dissertation serves as a more comprehensive, direct examination of this critical, understudied learning process. In it, I take a computational approach to investigate how biases in social reinforcement learning may contribute to social anxiety and whether these learning processes can be changed with a targeted, online intervention.

The three studies that comprise this dissertation are drawn from a larger data collection that included two laboratory sessions separated by five weeks, with half of the sample randomly assigned to an intervention between them. Studies 1 and 2 assess the extent to which socially anxiety is characterized by biased learning from social feedback in two domains relevant to social anxiety disorder: social interactions and social performance. Study 1 uses a social probabilistic learning task to assess how people use positive and negative social feedback to adjust their expectations of others. Study 2 examines the extent to which people use positive and negative social feedback to adjust their expectations of their own performance on a speech. Study 3 tests the degree to which the social reinforcement learning biases measured in Studies 1 and 2 are malleable through a brief online cognitive bias modification intervention. Each study is written as a standalone paper to facilitate submission for publication. This dissertation seeks to advance knowledge about social anxiety disorder by pinpointing specific biases in social reinforcement learning (Studies 1 and 2), which may improve our ability to develop targeted treatments (Study 3).

Study 1: Examining Social Reinforcement Learning in Social Anxiety

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Abstract

Reinforcement learning biases have been empirically linked to anhedonia in depression and theoretically linked to social anhedonia in social anxiety disorder, but little work has directly assessed how socially anxious individuals learn from social reward and punishment. In this study, *N*=157 individuals high and low in social anxiety symptoms completed a social probabilistic selection task that involved selecting between pairs of neutral faces with varying probabilities of changing to a happy or angry face. Computational modeling was performed to estimate learning rates, and accuracy in choosing the more rewarding face was also analyzed. No significant group differences were found for learning rates. Contrary to hypotheses, participants high in social anxiety showed impaired punishment learning; they were more successful at choosing the most rewarding face than they were at avoiding the most punishing face, and their punishment learning accuracy was lower than that of participants low in social anxiety. Exploratory analyses found that high (vs. low) social anxiety participants were less successful at selecting the more rewarding face on more (vs. less) punishing pairs of faces. Potential explanations for these results are considered.

Keywords: social anxiety, reinforcement learning, probabilistic learning, avoidance, punishment, reward

Examining Social Reinforcement Learning in Social Anxiety

Social anxiety disorder is common, with a lifetime prevalence of 12% in the United States (Kessler, Berglund, et al., 2005), and highly impairing. Socially anxious individuals tend to have negatively biased thoughts about social situations, such as expectations that others will reject them, and they tend to dread and/or avoid social situations, accordingly (Hirsch & Clark, 2004). Concerns about rejection and behavioral avoidance may be partially explained by a tendency to base your expectations of how others will respond to you more on experiences of rejection than experiences of approval. This study uses computational modeling to investigate social anxiety-based differences in social reinforcement learning; that is, how high vs. low socially anxious individuals learn from positive and negative social outcomes in different ways.

Computational Modeling of Social Reinforcement Learning in Social Anxiety

Computational psychiatry is a relatively new field that aims to develop a more fine-grained understanding of mental illnesses by algorithmically modeling neural and cognitive processes, thus pinpointing mechanistically where dysfunctions occur (Montague et al., 2012). Researchers have argued that computational studies, like the present study, are well suited to test how sensitivity to positive and negative feedback and responses to uncertainty may lead to the generalized aversive learning, avoidance behavior, enhanced threat detection, and state anxiety that characterize anxiety disorders (Raymond et al., 2017).

Here, we examine biased social reinforcement learning, a potential treatment target that remains understudied in social anxiety disorder. Reinforcement learning (RL) describes the process by which people learn to predict outcomes and optimize behavior in an environment where taking actions leads to *rewards* (positive outcomes) and *punishments* (negative outcomes; Sutton & Barto, 1998). RL differences between healthy and clinical populations have been documented across many disorders (Whitton et al., 2016), including anhedonia in major depressive disorder (Pizzagalli, 2014), which is highly comorbid with social anxiety disorder (Kessler, Chiu, et al., 2005). Among the anxiety disorders, social anxiety disorder is uniquely related to diminished positive affect, and relates to lower positive affect at similar levels as major depression (Brown et al., 1998). Further, the diminished positive affect that socially anxious individuals experience in daily life extends beyond what can be accounted for by depression alone (Kashdan, 2007; Kashdan & Collins, 2010). This suggests that, like depression, social anxiety may be associated with aberrant RL given both have unique relations with diminished positive affect.

Another reason to think that social anxiety might be characterized by aberrant RL in the social domain comes from evidence that the processing of social reward appears to be disrupted in socially anxious individuals. They fear not only negative, but also positive, social evaluation (Weeks & Howell, 2012). Several neuroimaging studies have demonstrated that socially anxious adults (relative to control participants) show reduced activation in regions that are part of the brain’s reward network when anticipating (Cremers et al., 2015; Richey et al., 2014, 2017) and receiving social reward (Becker et al., 2017), as well as increased amygdala activation when receiving social punishment (for a review, see Freitas-Ferrari et al., 2010). These findings suggest that the relative motivational preference for social reward is disrupted in social anxiety (Cremers et al., 2015; Richey et al., 2019). Individuals with social anxiety disorder (vs. control participants) also show less striatal response to cooperative partners in a trust game, suggesting aberrant learning about how rewarding other people are (Sripada et al., 2013). These neural findings suggest that aberrant social RL may be a cognitive difference that characterizes social anxiety. Computationally modeling this process may help us pinpoint where in the learning process disruptions occur (i.e., are socially anxious individuals quick to update their beliefs about others after negative interactions, but slow after positive interactions?). This level of precision may eventually lead to the development of more targeted interventions.

Anxiety-Related Differences in Learning Rate

One RL parameter that is useful for understanding how people use information to update their beliefs is the learning rate, or the degree to which you weight recent information relative to more distal information. Anxiety researchers are beginning to find evidence of learning rate differences in volatile environments and when learning about threats, but much remains unknown about learning in stable environments and about rewards. In a volatile environment, where the probabilities of your actions leading to reward versus punishment are changing, it is often adaptive to update your expectancies quickly, relying more on outcomes of your recent decisions, as the recent past is likely more informative than the distal past. In an aversive environment, where decisions can lead to either negative or neutral outcomes, individuals higher in anxiety symptoms modulate their learning rates less in response to environmental volatility—that is, they show less of a difference in how much they rely on new information in volatile versus stable environments than less anxious individuals (Browning et al., 2015). Other work suggests that anxious individuals may update their expectancies too much from negative outcomes in volatile environments, leading to suboptimal behavior (Aylward et al., 2019; Huang et al., 2017). However, more research is needed to provide insight into anxiety-related learning biases in the social domain, which may differ from general RL, and in stable environments. For example, a recent study found that anxious participants were slower than healthy control participants at learning to stop investing in exploitative social partners, which the researchers attributed to reduced learning from negative social events and less of an increase in learning as uncertainty increased (Lamba et al., 2020). While these studies all provide evidence of suboptimal decision-making under uncertainty tied to learning rate differences in anxious individuals, discrepancies in their results suggest that more research is needed to understand how social RL may differ from RL more broadly, and how learning occurs in a stable environment, rather than a volatile one.

Regarding social RL specifically, two earlier studies have assessed whether social anxiety affects learning rate for updating mental representations of other people (Beltzer et al., 2019; Piray et al., 2019), with largely consistent results. Congruent with findings that anxious individuals have difficulty dynamically adapting their learning rate to environmental volatility in aversive environments (Browning et al., 2015), socially anxious individuals also appear to have difficulty making use of information about environmental stability and volatility in aversive social environments (Beltzer et al., 2019; Piray et al., 2019). In an online ball-catching game with computerized avatars with volatile probabilities of reward and punishment, participants higher in social anxiety symptoms were less likely to choose to throw the ball to avatars who had previously been the most punishing avatar, regardless of their current probability (Beltzer et al., 2019). Further, more (vs. less) socially anxious individuals may have remained hypervigilant even when environmental volatility decreased; they adapted their learning rate less to increasing stability in the environment. In another study, Piray and colleagues (2019) found theoretically consistent results: more socially anxious participants' decision-making did not benefit as much from periods of stability (compared to periods of volatility), whereas control participants performed much better when the environment was more stable than volatile. When taken together (Beltzer et al., 2019; Piray et al., 2019), these two studies provide accumulating evidence of disrupted dynamic adaptation of learning rate to environmental stability in threatening environments for socially anxious individuals. To our knowledge, though, learning rate has only been studied in a socially anxious population in volatile environments, with comparisons performed between more stable and more volatile epochs. As such, less is known about whether socially anxious individuals exhibit aberrant learning rates in a stable environment (as might occur frequently in daily life during periods without major changes in one's social environment), which is a contribution made by the present study.

Anxiety-Related Differences in Accurately Choosing Rewarding and Avoiding Punishing Stimuli

In addition to social anxiety-based differences in learning rates for social reward and punishment, social anxiety may also be characterized by differences in how individuals apply those learned expectations of reward and punishment when faced with a choice. For instance, a socially anxious person who has learned that a particular colleague tends to reject their ideas might consistently avoid sharing their thoughts with that colleague, showing good accuracy at avoiding social punishment from a nasty colleague. Here, being accurate means that, when you are faced with a decision, you choose the action more likely to lead to reward and less likely to lead to punishment. Thus, we can examine both how readily a person learns from recent information that the colleague is rejecting (i.e., learning rate) and the person's accuracy in effectively choosing reward and avoiding punishment when they have an opportunity to apply that learning with the colleague (by analyzing how frequently the person successfully chooses rewarding and avoids punishing stimuli).

Research on anxiety-related biases in reward and punishment learning accuracy has found mixed results. One study found that within a depressed sample, higher anxiety symptoms predicted greater accuracy, as well as faster reaction times, for avoiding punishing stimuli (Cavanagh et al., 2019), but not for choosing rewarding stimuli. This suggests that anxiety is related specifically to enhanced decision-making for avoiding punishment. However, another study found that people with generalized anxiety disorder were *less* successful at learning to choose rewarding social outcomes and avoid punishing social outcomes than control participants (LaFreniere & Newman, 2019). Note that these studies used different populations, behavioral tasks, and modeling approaches. Anxiety may be related to altered decision-making related to choosing rewards and avoiding punishments, but more research is needed to clarify.

Looking at social anxiety specifically (rather than more generalized anxiety), more socially anxious individuals appear to be more likely to avoid socially punishing stimuli compared to control participants. In one study (Abraham & Hermann, 2015), participants completed a version of a popular probabilistic selection task (Frank, Seeberger, & Reilly, 2004) that was adapted to include social stimuli and social feedback (the classic, non-social version was also used in the study discussed above that found greater accuracy in avoiding punishment among depressed participants with higher anxiety; Cavanagh et al., 2018). In the first phase of the social probabilistic selection task (which is very similar to the version used in the current study), called the *training phase*, participants were presented with pairs of neutral faces with varying probabilities of providing social reward (a happy face) or punishment (an angry face) when chosen. Participants learned these probabilities through trial and error. By analyzing the frequency with which participants chose each face in each pair, the researchers found that, on the pair with the most similar probabilities, more socially anxious participants were less likely than healthy control participants to choose the more rewarding face. This suggests there may have been some learning disruptions for the socially anxious participants, although we cannot deduce whether it was aberrant reward or punishment learning without computational modeling of this task. Following the training phase was a *testing phase*, during which the most rewarding and most punishing faces were presented in combination with each of the other faces, and no feedback was given. In the testing phase, more socially anxious participants were more accurate than control participants at avoiding the most punishing face. On the non-social version of the task above, Voegler and colleagues (2019) similarly observed that socially anxious participants were more accurate at avoiding punishment than choosing reward when they were not being observed, and social observation elicited a similar bias for greater punishment versus reward learning accuracy in healthy control participants. Together, these results suggest that social anxiety may be characterized by a tendency to be more accurate at learning to avoid social punishment than choose social reward.

Overview of the Present Study

The current study assessed the extent to which social anxiety is characterized by differences in learning how likely other people are to be socially rewarding or punishing. We analyzed how learning rates for social reward and punishment differ as a function of social anxiety by applying an RL model to the training phase of the social probabilistic selection task. We also analyzed how social anxiety affects their learned accuracy at choosing social stimuli predictive of reward and avoiding social stimuli predictive of punishment during the testing phase.

To do this, we built upon and extended Abraham and Hermann's (2015) methodology by using a very similar task and adding computational modeling to provide more insight into potential social RL biases in social anxiety. We attempted to replicate Abraham and Hermann's (2015) finding of socially anxious participants' greater accuracy in avoiding punishment in the test phase with a new sample. Additionally, this study applied an RL model to the training phase to test whether learning rates for social reward and/or punishment differ in social anxiety. This study contributes to the literature in a number of ways: a) assessing whether social anxiety is characterized by differences in learning rates for social reward and social punishment when learning about other people in a stable environment; b) attempting to replicate findings of social anxiety-related avoidance of punishing stimuli; c) extending this evaluation of reward and punishment learning accuracy to understand how social anxiety affects making more fine-grained distinctions between social stimuli (described more fully below); and d) incorporating novel methodological features, including having stimuli and feedback that are both social.

Hypotheses

Given previous findings of higher anxiety being related to greater accuracy in learning to avoid punishing stimuli (Cavanagh et al., 2019), and specifically, higher social anxiety symptoms being related to greater avoidance of punishing social stimuli (Abraham & Hermann, 2015), we hypothesized that more socially anxious participants would show higher accuracy in learning to avoid punishing social stimuli relative to accuracy in learning to choose rewarding social stimuli, as compared to participants lower in social anxiety symptoms.

In order to more deeply understand reward and punishment learning accuracy, a secondary analysis was performed on accuracy of learning to discriminate between stimulus pairs of varying difficulty (more difficult pairs being those whose reward probabilities were more similar) and varying average reward probabilities. Previous research has found that people tend to be slower and less accurate when making difficult decisions, whereas they are faster (but not less accurate) when making decisions between highly rewarding pairs (Fontanesi et al., 2019).

We hypothesized that more socially anxious participants would show higher accuracy (selecting the more rewarding face) on difficult pairs that were relatively more punishing, whereas participants lower in social anxiety would show higher accuracy on difficult pairs that were relatively more rewarding. This effect would be consistent with better punishment learning accuracy (relative to reward learning accuracy) in participants with higher social anxiety, as compared to lower social anxiety.

We hypothesized that social anxiety-related differences in learning rates may have smaller effect sizes than the accuracy effects discussed above and therefore might not be detected in the present study for two reasons. First, compared to other computational parameters (e.g., Pavlovian bias, temperature), prior research has found less consistent evidence of altered learning rates in anhedonia (Robinson & Chase, 2017) and we see anhedonia as relevant to understanding the diminished positive affect in social anxiety. Second, anxiety-related differences in learning rates may be related to poor adaptation to environmental volatility (i.e., when the reward and punishment values are changing over time: Beltzer et al., 2019; Browning et al., 2015; Huang et al., 2017; Piray et al., 2019), whereas the present study investigated learning in a stable environment. While we were less confident that learning rate differences would be large enough to be reliable, we did have a directional hypothesis based on theoretically related findings of enhanced negative affect, positivity deficits, and disrupted social reward processing in social anxiety. Specifically, we hypothesized that more socially anxious participants would show a more negative bias in learning rates, which might be expressed as higher punishment learning rates and/or lower reward learning rates, as compared to less socially anxious participants. Plans for analyses and hypotheses were preregistered at https://osf.io/q7h9x.

Method

Participants

N=157 adults (18-45 years old) were recruited from the University of Virginia undergraduate participant pool and the Charlottesville community. Community participants were recruited through advertisements sent to university email lists for undergraduate and graduate students and flyers posted in public areas. Prospective participants were screened for social anxiety symptoms with the Social Interaction Anxiety Scale (SIAS; Mattick & Clarke, 1998). The sample included *n*=114 participants with moderate to severe social anxiety (scoring 29 or greater out of a possible 80 points on the SIAS, approximately ¼ of a standard deviation below the mean in a sample diagnosed with social phobia; Mattick & Clarke, 1998) and *n*=43 participants with low social anxiety (scoring 10 or lower, which is ¾ of a standard deviation or lower below the mean of a previous community sample; Mattick & Clarke, 1998)[1]. Because the mobile app used for the ecological momentary assessment component of the parent study (not analyzed in this study) only ran on certain versions of iOS and Android OS, participants who did not have a compatible smartphone were excluded.

From the social probabilistic selection task, data from the training phase were available for *n*=42 low social anxiety and all *n*=114 high social anxiety participants. Data from the testing block were available for *n*=41 low social anxiety and *n*=113 high social anxiety participants. In the low social anxiety group, data from the social probabilistic selection task did not save correctly for one participant, and there was a technical issue during the testing block for another. In the high social anxiety group, one participant's testing block was discontinued early due to experimenter error. For demographics for the *N*=156 participants from whom we have at least some data from the social probabilistic selection task, see Table 1.

Measures

Social Interaction Anxiety Scale

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[1] The high social anxiety group was part of a larger study that included a subsequent randomization to an intervention, which is why *n* for this group is larger than for the low social anxiety group.

The Social Interaction Anxiety Scale (SIAS; Mattick & Clarke, 1998) is a commonly used 20-item self-report scale measuring social anxiety in dyads and groups (e.g., “I find myself worrying that I won’t know what to say in social situations.”). Participants rate their endorsement of each item on a 5-point Likert scale ranging from “not at all” to “extremely.” Rodebaugh, Woods, and Heimberg (2007) have demonstrated that the three reverse scored items do not load onto the same factor as the straightforwardly worded items, and seem to reflect extraversion more than neuroticism. Removing these reverse scored items generally improves the psychometric properties of the scale. All items were used in recruiting participants into high and low socially anxiety groups (for comparison to a previous sample), but following Rodebaugh et al.’s recommendations, only ratings on the straightforwardly worded items were used in dimensional analyses within the high social anxiety group.

Social Probabilistic Selection Task

The social probabilistic selection task (Abraham & Hermann, 2015) is a widely used probabilistic category-learning paradigm (Frank et al., 2004) that was adapted to include socially relevant information as stimuli (neutral faces) and socially evaluative reinforcement as feedback (positive: happy faces, negative: angry faces). This task consisted of two phases: training and testing (see Figure 1). In the training phase, participants were shown two neutral faces at a time, and told that one face would become happy if chosen, while the other would become angry. They were instructed to select the face they thought was more likely to become happy. The pairs had different reward contingencies, but these were never explicitly told to participants; instead, they learned through trial and error. In one pair, one face became happy 80% of the times it was chosen and angry 20% of the times it was chosen, whereas the other face became happy 20% of the time and angry 80% of the time. This contingency is referred to as 80/20, and we refer to the stimuli by their reward probabilities 80 and 20, respectively. The other pairs had 70/30 and 60/40 contingencies. Participants completed at least two practice blocks. They advanced to the testing phase once they reached accuracy criteria of 64% correct identifications (i.e., selecting the more rewarding face) for the 80/20 pair, 59% for the 70/30 pair, and 49% for the 60/40 pair, or once they completed 6 practice blocks (based on Frank et al., 2004). In the testing phase, participants were shown all faces from the training phase, but this time the faces were recombined in all possible stimulus pairs, including those not shown during the training phase, and no feedback was given (i.e., no happy or angry faces follow the selection). They were instructed to choose the more rewarding face from each pair based on the probabilities learned during training.

Based on previous research finding different effects of the task's facial stimuli sex (Abraham & Hermann, 2015; Olsson et al., 2013) and race (Lindstrom et al., 2014) on social RL, opposite-sex White faces were used as stimuli for this first test to reduce variance due to this heterogeneity, though we recognize this was a tradeoff. Because this task was administered to high social anxiety participants twice (at baseline and at a follow-up session), two sets of faces were used as stimuli (the NimStim and FACES sets; Ebner, Riediger, & Lindenberger, 2010; Tottenham et al., 2009), with their order counterbalanced for both low and high social anxiety participants. Both sets of faces included more models than were needed for this study, so we selected from each set six models whose expressions of happiness, anger, and neutral emotion were well identified by previous samples (Ebner et al., 2010; Tottenham et al., 2009). From the NimStim set, which includes open- and closed-mouth emotional expressions, open-mouthed happy and angry faces were selected because previous samples identified their emotions more accurately (Tottenham et al., 2009). The social probabilistic selection task was presented in MATLAB.

From this task, we gathered several measures of social RL. We applied a Q-learning algorithm to each participant's choices during the training phase to estimate how heavily each participant weighted new information about social reward and punishment when predicting the value of each face, also known as learning rates for social reward and punishment (described more fully in the computational modeling section in the Plan for Analyses section below). From the testing block, we calculated how frequently they the most rewarding face ("reward learning accuracy"), and avoided the most punishing face ("punishment learning accuracy"), when paired with all other faces. For a secondary analysis assessing learning of more difficult probabilities of reward and punishment (i.e., discriminating between stimuli whose probabilities of reward and punishment were more similar to each other, rather than focusing more specifically on the most rewarding and most punishing stimuli), we analyzed accuracy in choosing the more rewarding face of all pairs presented in the testing block.

Procedure

After obtaining informed consent, all participants completed the social probabilistic selection task and questionnaires. This study was part of a larger data collection that included other behavioral tasks, ecological momentary assessment, and an intervention, which are outside the scope of the current research question and are analyzed elsewhere. The intervention and ecological momentary assessment portions of the study occurred after the baseline lab session at which this study's data were collected.

Plan for Analyses

We applied an RL model to the social probabilistic selection task to assess learning about static probabilities that others will be socially rewarding or punishing. The parameters analyzed include learning rates for positive and negative social feedback, and accuracy of learning to choose rewarding faces and avoid punishing faces. We compared these parameters across social anxiety groups, as well as within the high social anxiety group. We also performed several secondary and exploratory analyses to better understand social anxiety-related differences in social RL and some of our unexpected findings (see Exploratory Analyses in the Results section).

Computational Model Selection and Performance

The social probabilistic selection task was computationally modeled using the hBayesDM package (Ahn et al., 2017) in R. This package offers hierarchical Bayesian modeling of the probabilistic selection task using the Q-learning estimation procedure implemented in Frank et al. (2007). Hierarchical Bayesian modeling simultaneously estimates individual- and group-level parameters with a Markov chain Monte Carlo (MCMC) sampling scheme. Assuming that participants within each social anxiety group share some similarity while still estimating model parameters for each participant increases reliability over models fitted separately to each individual's data (without consideration of group-level similarities) because data are often noisy for this task. Because the hBayesDM package implements Bayesian models, parameter estimates are provided as posterior distributions, rather than point estimates.

We compared two candidate Q-learning models. One Q-learning model fitted trial-by-trial behavioral data from the training phase of the task with separate learning rate parameters for positive and negative feedback (given neural models suggesting separate mechanisms for these types of learning, and findings that models with separate positive and negative learning rates tend to fit the data better; Gershman, 2015). A *Q* value was computed for each stimulus *i* at trial *t*, and these *Q* values were updated by multiplying each prediction error by a learning rate α following the algorithm:

$$Q_i(t+1) = Q_i(t) + \alpha_R[r(t) - Q_i(t)]_+ + \alpha_P[r(t) - Q_i(t)]_-$$

where *r(t)* = 1 for positive (happy) and 0 for negative (angry) feedback. The reward learning rate α_R was applied for positive prediction errors, when the outcome was better than expected, and the punishment learning rate α_P was applied for negative prediction errors, when the outcome was worse than expected. Another, simpler candidate model was also tested with a single learning rate α:

$$Q_i(t+1) = Q_i(t) + \alpha[r(t) - Q_i(t)]$$

Q values were entered into the following softmax equation with inverse temperature β to determine the probability of a participant selecting a given stimulus in each stimulus pair (e.g., A over B in the example below, but the same applies for CD and EF):

$$P_A(t) = \frac{e^{Q_A/\beta}}{e^{Q_A/\beta} + e^{Q_B/\beta}}$$

To ensure that MCMC chains were well mixed and converged to stationary distributions for stable parameter estimates, we checked whether $\hat{R}$ values for parameters were approximately 1, produced and examined trace plots of the group-level parameters, and plotted and visually examined posterior distributions of the group- and individual-level parameters.

Primary Analyses

Learning Rates Between Social Anxiety Groups. To assess whether learning rates for reward and punishment differed between social anxiety groups, a mixed effects model was performed predicting learning rate from fixed effects of social anxiety group and valence (reward vs. punishment), their interaction, and a random intercept for participant.

Reward and Punishment Learning Accuracy Between Social Anxiety Groups. Participants who learn more (vs. less) from rewarding feedback should more reliably choose the most rewarding stimulus during the testing phase of the task, and participants who learn more from punishing feedback should more reliably avoid the most punishing stimulus during the testing phase. An index of reward learning accuracy (how well participants learn from positive feedback) was calculated as the proportion of times the most rewarding stimulus (80) was chosen when paired with all other stimuli (70, 60, 40, and 30) during the testing phase of the social probabilistic selection task. Similarly, an index of punishment learning accuracy (how well participants learn from negative feedback) was calculated as the proportion of times the most punishing stimulus (20) was avoided (not chosen) when paired with all other stimuli (70, 60, 40, and 30) during the testing phase. Because accuracy follows a binomial distribution, a generalized linear mixed model with a logit link function was performed predicting accuracy from fixed effects of social anxiety group and choice type (pairs including 80 vs pairs including 20), their interaction, and a random intercept for participant.

Secondary Analyses

Discriminability Between Social Anxiety Groups. In addition to examining learning accuracy for the most rewarding and most punishing stimuli, we performed a secondary analysis using data from the testing phase to determine whether social anxiety is characterized by differences in discriminating between more difficult stimulus pairs. Specifically, this analysis tested whether decision difficulty and average reward/punishment magnitude affect decision accuracy differently for people high vs. low in social anxiety symptoms. Here, we define *difficulty* as the absolute value of the difference in the probability of reward and punishment between the two stimuli in the pair (e.g. the 80/20 stimulus pair has difficulty 60 and is less difficult to discriminate than the 80/70 pair, which has difficulty 10). Note that lower scores on this variable reflect pairs that are more difficult to discriminate. *Magnitude* refers to the average reward probability of the stimulus pair (e.g., the 80/70 pair has magnitude 75, which is more rewarding than the 80/20 pair, which has magnitude 50). This model was performed as a generalized linear mixed model with a logit link function predicting accuracy from fixed effects of social anxiety group, difficulty (centered), magnitude (centered), and all two- and three-way interactions, with a random intercept for participant. This secondary analysis had the benefit of using all of the data from the testing phase (120 trials), whereas the reward and punishment learning accuracy analysis described above only used some of the data (64 trials).

Dimensional Analyses Within the High Social Anxiety Group. Research suggests symptoms of social anxiety exist along a continuum (McNeil, 2001), so there may be meaningful variation not just between the high and low social anxiety groups, but also within groups—particularly within the high social anxiety group, whose SIAS scores ranged from 29 to 73 (whereas the low social anxiety group's scores only ranged from 0 to 10). Similar RL studies have found effects of anxiety measured continuously in clinical groups, even in the absence of effects between groups (e.g., Cavanagh et al., 2018). So, as a follow-up, all analyses were performed with social anxiety assessed dimensionally within the high social anxiety group (rather than categorically, between groups). These models followed the same form as the between-groups models, except with SIAS score (centered) replacing the social anxiety group variable.

Results

Descriptive Statistics

Social Anxiety

As expected, social anxiety symptoms, as measured by the sum of the straightforwardly worded items of the SIAS, were significantly lower in the low social anxiety group (M = 4.98) than in the high social anxiety group (M = 38.45), $t(146.89) = 34.44$, $p < 0.001$.

Computational Model Selection and Performance

Two candidate Q-learning models were fitted to the training phase data from the social probabilistic selection task, separately for groups low and high in social anxiety. We compared prediction accuracy of each model for each group's data using LOOIC (leave-one-out information criterion) given our relatively small sample size (Vehtari et al., 2017). Because the more complex model had a lower LOOIC, it was selected for further analysis (see Table 2 for LOOIC values). From the more complex model, we visually inspected trace plots of the parameters for both groups, which indicated that MCMC samples were well mixed and converged to stationary values, consistent with $\hat{R}$ values around one for all participants in both groups. The group-level parameters in both groups had unimodal posterior distributions. Visual inspection of the individual-level parameters in both groups showed relatively wide posterior distributions, indicating some uncertainty in the estimates at an individual level.

Primary Analyses

Learning Rates Between Social Anxiety Groups

A mixed effects linear regression was performed predicting individual-level learning rate estimates from fixed effects of social anxiety group, prediction error valence, and their interaction, with a random intercept for participant. This model found no significant main effects or interactions. See Table 3.

Reward and Punishment Learning Accuracy Between Social Anxiety Groups

A generalized linear mixed model with a logit link function was performed predicting accuracy in the testing phase from fixed effects of social anxiety group, choice type, and their interaction, with a random intercept for participant. Significant main effects were found for both social anxiety group and choice type, but they are not interpreted here because they were subsumed within a significant interaction (Figure 2). See Table 4. Post-hoc pairwise comparisons of the estimated marginal means (with a Tukey adjustment) indicated that, contrary to hypotheses, the high social anxiety group's punishment learning accuracy (M = 0.78, SE = 0.02) was significantly lower than their reward learning accuracy (M = 0.87, SE = 0.01, OR = 0.50, p < .001), the low social anxiety group's punishment learning accuracy (M = 0.88, SE = 0.02, OR = 0.47, p = .003), and the low social anxiety group's reward learning accuracy (M = 0.89, SE = 0.02, OR = 0.44, p = 0.001). No other pairwise comparisons were statistically significant. This result suggests that the low social anxiety group was similarly likely to choose the more rewarding face from pairs that included the most rewarding and most punishing faces. However, contrary to hypotheses, the high social anxiety group was less likely to avoid the most punishing face than they were to choose the most rewarding face from pairs that included the most rewarding and most punishing faces. In other words, the high, but not low, social anxiety group showed impairments in learning to avoid punishing faces.

Secondary Analyses

Beyond the primary results reported above investigating the social probabilistic selection task in ways consistent with prior research, secondary analyses were performed examining the testing phase data in new ways that incorporated more trials and address questions of accuracy at varying degrees of difficulty.

Discriminability Between Social Anxiety Groups

A generalized linear mixed model with a logit link function was performed predicting accuracy in the testing phase from fixed effects of social anxiety group, difficulty, magnitude, and all two- and three-way interactions, with a random intercept for participant. There were significant main effects of social anxiety group, difficulty, and magnitude, but these are not interpreted because they were subsumed within two significant interactions: social anxiety group X difficulty (Figure 3), and social anxiety group X magnitude (Figure 4). Post-hoc comparisons of the estimated linear trends for each social anxiety group indicated that the effect of difficulty on accuracy was significant and positive for each group, but this trend was stronger for the low social anxiety group. In other words, both groups were more likely to select the more rewarding face on less difficult pairs, and this effect was more pronounced for the low (b = 0.06, SE = 0.003) versus high social anxiety group (b = 0.04, SE = 0.002, p < .001). The effect of magnitude on accuracy was significant and positive within the high social anxiety group (b = 0.02, SE = 0.003), but non-significant in the low social anxiety group (b = - 0.004, SE = 0.006), and the effects in each of these groups were significantly different from each other (p < .001). In other words, the high social anxiety group was more likely to select the more rewarding face on more rewarding (vs. more punishing) pairs, but the relative magnitude of the pair did not affect accuracy for the low social anxiety group. See Table 5.

Dimensional Analyses Within the High Social Anxiety Group

All between-group analyses were also performed within the high social anxiety group, with social anxiety assessed dimensionally (SIAS score). SIAS score was not involved in any statistically significant effects; these results are presented in Supplementary Materials.

Exploratory Analyses

To probe our surprising results more deeply, we performed several exploratory analyses assessing possible explanations for the null learning rate effect. The possible explanations examined included that the high social anxiety group needed more training to learn the probabilities in the training phase and that they learned some pairs' probabilities more accurately than others (described more fully in Supplemental Results). Based on our exploratory analyses, these factors likely do not explain the observed effects. We also explored whether participants might have grouped several faces together based on reward/punishment thresholds, as described below.

Threshold Model for Reward and Punishment Learning Accuracy

We considered the possibility that participants might have learned which faces were generally rewarding (60, 70, or 80% probability of reward) or generally punishing (60, 70, or 80% probability of punishment) during the training phase, but might have less success discriminating varying probabilities of reward or punishment within those subsets of faces. We thought that participants might be learning broad categories of reward and punishment but view, for instance, any face that becomes angry more than it becomes happy as so aversive that they do not differentiate within the punishment category (akin to the dichotomous good/bad and absolutist thinking exhibited by people with anxiety and mood disturbances; Al-Mosaiwi & Johnstone, 2018). Accordingly, we compared testing phase accuracy across different types of face pairs: (1) pairs containing two relatively punishing faces (termed “lose/lose pairs;” specifically, both faces’ reward probabilities are ≤40%), (2) pairs containing two relatively rewarding faces (termed “win/win pairs;” both faces’ reward probabilities are ≥60%), and (3) pairs containing one relatively punishing and one relatively rewarding face (termed “hybrid pairs;” one face’s reward probability is ≤40% and the other’s is ≥60%). While both the discriminability analysis described earlier and this threshold analysis modeled accuracy as a function of variables related to magnitude and difficulty, they differed in important ways. The discriminability analysis modeled magnitude and difficulty dimensionally as two separate variables, whereas the threshold analysis grouped face pairs into three categories based on the reward probabilities of each face.

A generalized linear mixed model with a logit link function was performed predicting accuracy in the testing phase from fixed effects of social anxiety group and pair type, with a random intercept for participant. We found significant main effects of social anxiety group and pair type, subsumed within a significant interaction. Post-hoc comparisons of estimated marginal means found that accuracy was lower for the high (vs. low) social anxiety group on lose/lose (high: M = 0.60, SE = 0.02; low: M = 0.71, SE = 0.02; OR = 0.60, p = 0.02) and hybrid pairs (high: M = 0.86, SE = 0.01; low: M = 0.92, SE = 0.01; OR = 0.58, p = 0.01), but did not differ for win/win pairs (high: M = 0.74, SE = 0.02; low: M = 0.72, SE = 0.03; OR = 1.12, p = 0.98). For both high and low social anxiety groups, accuracy was greater on hybrid pairs than on lose/lose (high: OR = 0.24, p < .001; low: OR = 0.23, p < .001) or win/win pairs (high: OR = 2.24, p < .001; low: OR = 4.31, p < .001). For the high social anxiety group, accuracy on lose/lose pairs was lower than on win/win pairs (OR = 0.53, p < .001), a difference not observed in the low social anxiety group (OR = 0.98, p = 1.00). This suggests that the high social anxiety group did not discriminate as well among relatively punishing faces as they did among relatively rewarding faces. See Table 6 and Figure 5.

Discussion

This study used a social probabilistic selection task to assess how individuals high vs. low in social anxiety symptoms learn from social reward and punishment. We found no significant differences in reward and punishment learning rates based on social anxiety group. This null result was consistent with prior work suggesting that anxiety-related differences in learning rate might be more related to differences adapting to environmental volatility rather than learning differences in a stable environment. Contrary to hypotheses, participants high (vs. low) in social anxiety were less successful at learning to avoid socially punishing stimuli than learning to choose socially rewarding stimuli. This result was evidenced in several ways. The high social anxiety group had lower accuracy at avoiding the most punishing face than at choosing the most rewarding face. Their accuracy at choosing the more rewarding face from a pair increased as the average reward value (i.e., magnitude) of the pair increased. And, the exploratory threshold model analyses indicated they were less accurate at selecting the more rewarding face from lose/lose vs. win/win pairs, suggesting greater discriminability among rewarding vs. punishing faces. None of these effects were observed in the low social anxiety group.

Impaired Punishment Learning Accuracy in Socially Anxious Individuals

The finding that people with high social anxiety show impaired punishment learning accuracy runs counter to past studies finding greater accuracy in learning from punishment vs. reward in participants with elevated social anxiety (Abraham & Hermann, 2015) and generalized anxiety (Cavanagh et al., 2019; LaFreniere & Newman, 2019). However, this result is theoretically consistent with a study by Lamba and colleagues (2020), which found that participants high (vs. low) in generalized anxiety symptoms tended to learn less from negative social outcomes, and consequently, overinvested in exploitative social partners. Given the mixed results for accuracy across studies using slightly different populations and behavioral tasks (e.g. learning from social vs. non-social stimuli, learning in static vs. volatile environments), the current finding bears replication, but the present results add to a literature that suggests that anxious individuals might actually show impaired learning from social punishment.

There are several intriguing potential explanations for this surprising effect. We examined whether the high (vs. low) social anxiety group might have needed more training to learn the probabilities, or whether they learned some pairs' probabilities more accurately than others, but found that these factors were unlikely to explain their impaired punishment learning accuracy. Next, we considered whether more socially anxious individuals might show something of a threshold effect specific to social punishment: that they respond to all faces that are more likely to become angry than happy (i.e., all faces above a certain punishment threshold) as "bad," while still discriminating among the more rewarding faces by degree. This account was supported by our finding that high social anxiety participants were less accurate at selecting the more rewarding face on lose/lose vs. win/win trials, a difference not observed in low social anxiety participants. However, two other pieces of evidence argued against this explanation.

Compared to the low social anxiety group, the high social anxiety group had poorer accuracy not just on lose/lose trials, but also on hybrid trials. If socially anxious participants grouped “bad” faces together and learned to avoid them, we would expect to see impaired accuracy on lose/lose trials, but intact accuracy on hybrid trials. Additionally, we found that accuracy increased linearly with the average reward value of the face pair for the high social anxiety group, suggesting that this may be more of a continuous versus a threshold effect.

Another potential explanation for this finding of impaired social punishment learning is that the high social anxiety group might have perceived the neutral face stimuli as more aversive than the low social anxiety group did, in line with prior research finding facilitated avoidance learning for neutral faces among people in high in social anxiety (Stevens et al., 2014). If so, the affective value of the neutral face might be closer to the angry versus happy face for the high (vs. low) social anxiety group, and the appearance of an angry face would represent less of a deviation from neutral than the appearance of a happy face. Consequently, in this task, the perceived magnitude of social punishment might be less than that of social reward for the high (vs. low) social anxiety participants, which might explain their impaired social punishment learning observed here. This potential explanation was not tested here, but could be examined empirically in a future study.

Intact Social Reward Learning in Socially Anxious Individuals

Interestingly, we found evidence of intact social reward learning in our high social anxiety group, which is surprising given prior work on social anhedonia in social anxiety (e.g., Blay et al., 2021; Richey et al., 2019). It is possible that we did not find evidence of a bias towards learning more from social punishment than reward in our high social anxiety group because we used an analogue, rather than clinically diagnosed, sample. However, it is not obvious why this would be the case (and there was no evidence of social anxiety severity effects based on the secondary dimensional analyses within the high social anxiety group).

It is also worth considering that social reward might be quite motivating for socially anxious individuals, especially earlier in development or in novel social contexts. Richey and colleagues' sensitivity shift theory (2019) proposes that behaviorally inhibited children, who are more sensitive to both reward and punishment, go on to develop social anhedonia later in development if they experience adverse social contexts in late childhood and early adolescence (e.g., peer victimization, low parental warmth). It is possible that our sample, comprised mostly of undergraduates in late adolescence and early adulthood, are still developmentally characterized by a high degree of social reward-seeking, especially in a novel social context (i.e., college) that has many opportunities to meet new people and experience different social situations and outcomes.

Clinical Implications

The results of this study suggest that, although learning rates were similar across social anxiety groups, participants high (vs. low) in social anxiety were less successful at learning to avoid social punishment. While we hypothesized that more socially anxious participants would be biased *towards* learning from social punishment, rather than *away* from it, we speculate how this surprising effect could possibly underlie the social avoidance behavior that is characteristic of social anxiety. This study found that socially anxious individuals were worse at modulating their behavior to avoid social rejection (operationalized by lower accuracy at avoiding the most punishing face in the testing phase). Considering how this process may unfold in their daily lives, it is possible that they may experience more negative social interactions than do less socially anxious individuals. Given socially anxious individuals are particularly concerned about negative social evaluation, they might take more extreme steps to avoid these social situations in which they tend to experience more rejection (e.g., not going to a party, self-disclosing very little with acquaintances, avoiding eye contact). However, these actions taken to avoid potential rejection situations may, counterproductively, elicit negative reactions from others, serving effectively as a self-fulfilling prophecy for poorer quality social interactions. This account is similar to the stress generation hypothesis described in depression (Hammen, 1991), in which depressed individuals engage in interpersonal patterns that increase the likelihood of stressful life events, which in turn increase symptoms and reinforce the maladaptive beliefs and expectancies that contributed to those negative interpersonal patterns. This pattern may similarly occur for socially anxious individuals (Farmer & Kashdan, 2015; Goodman et al., in prep.; Siegel et al., 2018); negative expectancies of other people may lead to behavior that elicits negative reactions from others, further reinforcing those negative beliefs. As such, clinicians may intervene on maladaptive social behaviors and/or cognitions to break this negative cycle. When selecting negative automatic thoughts to challenge, though, clinicians should consider that some negative expectancies of others may not be wholly unsupported, given socially anxious individuals' potential difficulty learning to avoid negative social interactions.

Limitations

This study has a number of limitations to consider, related to the stimuli used in the social probabilistic selection task and our modeling approach. A strength of this task is both the stimuli and outcomes are social (as compared to other social RL tasks that employ monetary outcomes). However, while this behavioral task allows us to cleanly measure social RL, its simplicity limits its ecological validity and affective salience. First, the stimuli were static images of faces, which lack other social features important to real social interactions (e.g., movement, sound). Future studies might consider adding more dynamic stimuli, like short videos of the neutral face becoming a happy or angry face, coupled with vocal expressions. Prior studies have shown that dynamic, versus static, social cues elicit higher arousal ratings (Sato & Yoshikawa, 2007) and reactivity in the amygdala and other brain regions involved in emotion processing (Pelphrey et al., 2007; Trautmann et al., 2009). Similar video clips have been successfully used in social fear conditioning paradigms in the past (Pejic et al., 2013; Wiggert et al., 2017).

Additionally, our sample was largely comprised of non-Hispanic, White, undergraduate students, whose social context and developmental stage may differentiate them in important ways from other socially anxious populations. For instance, individuals holding marginalized racial and ethnic identities may learn differently from social reward and punishment coming from in-group vs. out-group members given prior experiences of discrimination, whereas this pattern might look different for non-Hispanic White individuals. Further, given prior research finding sex- and race-related effects on social RL, we opted to use opposite-sex White faces for our stimuli. Yet, we recognize that our sample and this design decision limit generalizability of our findings.

Conclusion and Future Directions

This study found, contrary to hypotheses, that individuals high in social anxiety symptoms showed impaired, rather than enhanced, social punishment learning, and relatively intact social reward learning. Future studies that use more ecologically valid stimuli (e.g., video clips), and socially anxious samples at different developmental stages (e.g., older adults), and diagnosed samples who have more severe social avoidance, may provide additional insight into how social reinforcement learning may relate to social anxiety and social avoidance.

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Table 1

Demographics by Social Anxiety Group

Variable	Low Social Anxiety	High Social Anxiety
n	42	114
Sex		
Females (%)	29 (69.05%)	85 (74.56%)
Males (%)	13 (30.95%)	29 (25.44%)
Non-binary identity (%)	0 (0%)	0 (0%)
M_{age} in years (SD_{age})	19.31 (1.87)	20.37 (2.94)
Undergraduates (%)	39 (92.86%)	90 (78.95%)
Ethnicity		
Latinx/Hispanic (%)	2 (4.76%)	3 (2.63%)
Not Latinx/Hispanic (%)	40 (95.24%)	111 (97.37%)
Prefer Not to Answer (%)	0 (0%)	0 (0%)
Race		
White (%)	31 (73.81%)	84 (73.68%)
Asian (%)	9 (21.43%)	22 (19.30%)
African American/Black (%)	0 (0%)	10 (8.77%)
Middle Eastern (%)	2 (4.76%)	3 (2.63%)
American Indian/Alaska Native (%)	0 (0%)	0 (0%)
Native Hawaiian/Pacific Islander (%)	0 (0%)	3 (2.63%)

Table 2

LOOIC of Candidate Models

	Low Social Anxiety	High Social Anxiety
Two Learning Rates	7,595.75	24,068.17
Single Learning Rate	7,601.66	24,130.49

Table 3

Model Estimates Predicting Learning Rate by Social Anxiety Group

	Learning Rate			
Predictors	*Estimates*	*CI*	*t*	*p*
(Intercept)	0.23	0.21 – 0.25	20.95	**<0.001**
SA Group	0.00	-0.02 – 0.03	0.45	0.652
PE Valence	-0.01	-0.03 – 0.00	-1.41	0.158
SA Group X PE Valence	0.00	-0.02 – 0.02	0.01	0.994
Random Effects				
σ^2	0.02			
$\tau_{00\ \text{subjID}}$	0.01			
ICC	0.22			
N_{subjID}	156			
Observations	312			
Marginal R^2 / Conditional R^2	0.007 / 0.228			

Note: SA Group = social anxiety group (high vs. low). PE Valence = prediction error valence (positive vs. negative).

Table 4

Model Estimates Predicting Testing Phase Accuracy by Social Anxiety Group

	Accuracy			
Predictors	*Odds Ratios*	*CI*	*t*	*p*
(Intercept)	6.07	4.93 – 7.46	17.04	**<0.001**
SA Group	0.80	0.65 – 0.98	-2.12	**0.034**
Choice Type	1.21	1.13 – 1.28	5.76	**<0.001**
SA Group * Choice Type	1.17	1.10 – 1.25	4.88	**<0.001**
Random Effects				
σ^2	3.29			
$\tau_{00\ id}$	1.14			
ICC	0.26			
N_{id}	154			
Observations	9780			
Marginal R^2 / Conditional R^2	0.028 / 0.279			

Note: SA Group = social anxiety group (high vs. low). Choice Type = trials including the most rewarding face (reward learning accuracy) vs. the most punishing face (punishment learning accuracy).

Table 5

Discriminability Model Estimates Predicting Testing Phase Accuracy by Social Anxiety Group

	Accuracy			
Predictors	*Odds Ratios*	*CI*	*t*	*p*
(Intercept)	5.26	4.54 – 6.10	21.97	**<0.001**
SA Group	0.79	0.68 – 0.92	-3.05	**0.002**
Difficulty	1.05	1.05 – 1.06	29.10	**<0.001**
Magnitude	1.01	1.00 – 1.01	2.28	**0.023**
SA Group X Difficulty	0.99	0.99 – 1.00	-4.74	**<0.001**
SA Group X Magnitude	1.01	1.00 – 1.02	3.37	**0.001**
Difficulty X Magnitude	1.00	1.00 – 1.00	-0.44	0.661
SA Group X Difficulty X Magnitude	1.00	1.00 – 1.00	1.14	0.255
Random Effects				
σ^2	3.29			
$\tau_{00\ id}$	0.59			
ICC	0.15			
N_{id}	154			
Observations	18316			
Marginal R^2 / Conditional R^2	0.146 / 0.277			

Note: SA Group = social anxiety group (high vs. low). Difficulty = difference between reward probabilities of the two faces in a pair. Magnitude = mean reward probability of the two faces in a pair.

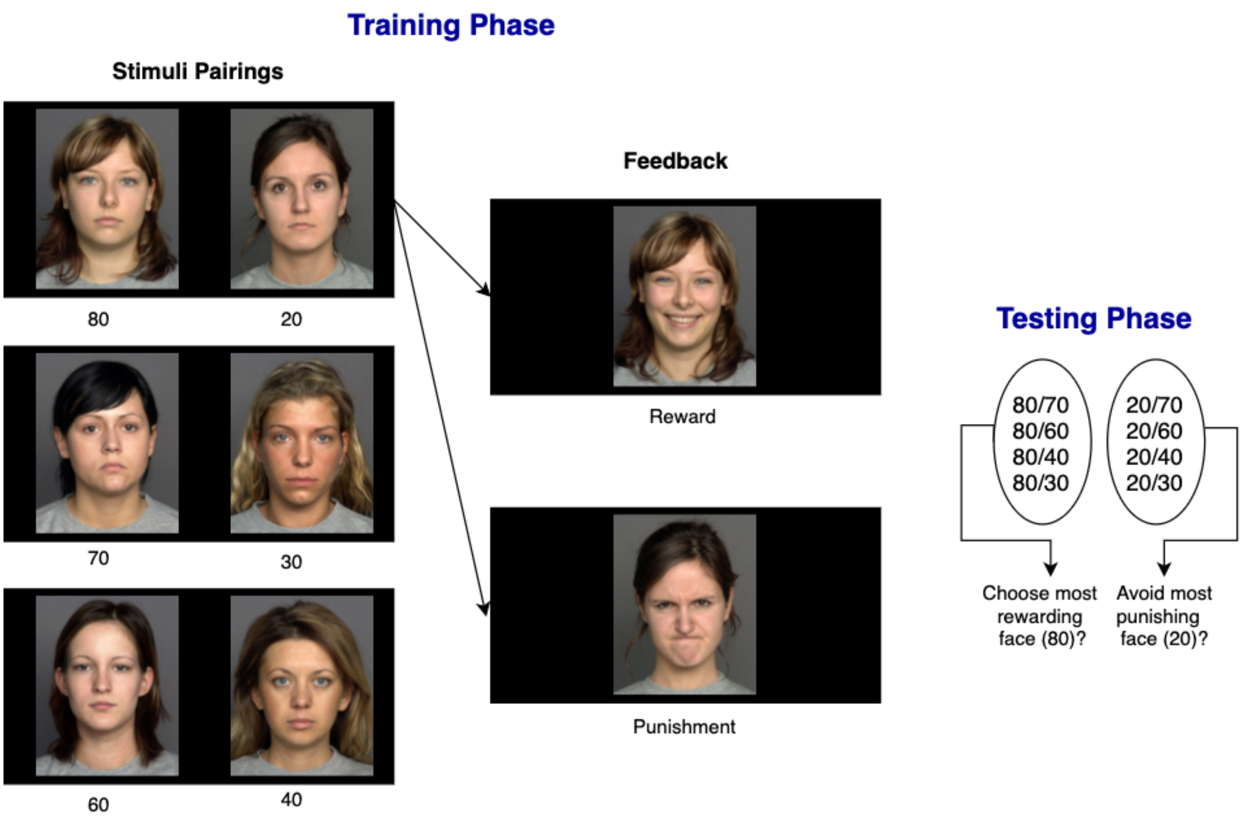
Table 6

Threshold Model Estimates Predicting Testing Phase Accuracy by Social Anxiety Group

	Accuracy			
Predictors	*Odds Ratios*	*CI*	*Statistic*	*p*
(Intercept)	3.47	3.00 – 4.00	17.00	**<0.001**
SA Group	0.86	0.74 – 0.99	-2.14	**0.032**
Win/win vs. Hybrid	0.76	0.71 – 0.82	-7.94	**<0.001**
Lose/lose vs. Hybrid	0.55	0.52 – 0.59	-17.58	**<0.001**
SA Group X Win/win vs. Hybrid	1.24	1.16 – 1.32	6.21	**<0.001**
SA Group X Lose/lose vs. Hybrid	0.91	0.85 – 0.97	-2.85	**0.004**
Random Effects				
σ^2	3.29			
$\tau_{00\ id}$	0.57			
ICC	0.15			
N_{id}	154			
Observations	18316			
Marginal R^2 / Conditional R^2	0.098 / 0.232			

Figure 1

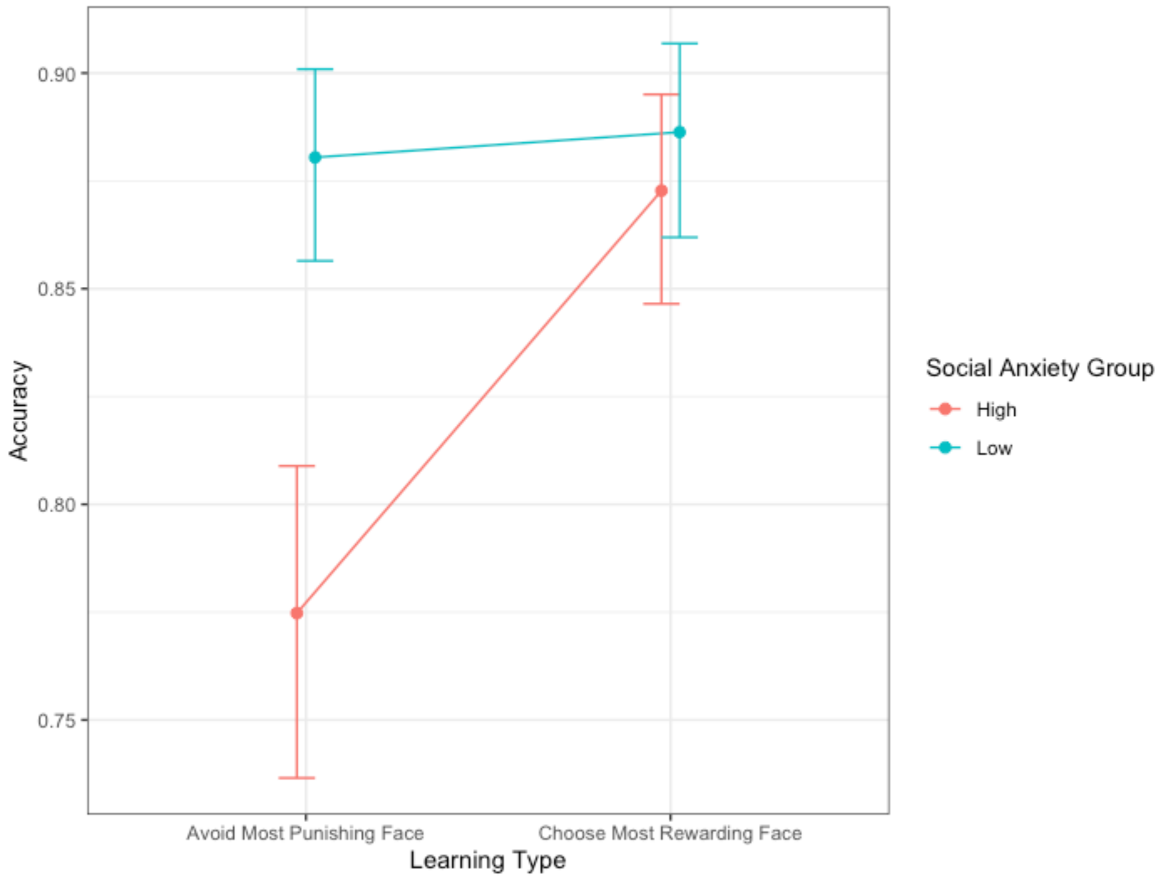
Social Probabilistic Selection Task



Note. The Social Probabilistic Selection Task consisted of two phases: training and testing. In the training phase, neutral face stimuli were presented in pairs with varying probabilities of reward (becoming a happy face) or punishment (becoming an angry face) when chosen. In the example above, stimuli are referred to by their reward probabilities, and their punishment probabilities are 100-p(reward) (e.g., stimulus 80 would reward the participant 80% of the times chosen and punish the participant 20% of the times chosen). The instructions for the training phase explained, "Two faces will appear simultaneously on the computer screen. One person will become HAPPY when you choose them and the other will become ANGRY. At first you will not know which is which. You will learn through trial and error. Try to guess the HAPPY person as quickly and accurately as possible. In this task, no person is ALWAYS happy when you choose them, but some people have a higher chance of being happy than others. Try to pick the person you find to have the highest chance of becoming happy when you choose them." During the testing phase, neutral faces were recombined into all the possible pairs, and participants were told to decide between them based on what they had learned in the training phase. No feedback was given during the testing phase. Instructions explained, "It is time to test what you have learned! During this set of trials you will NOT receive feedback (happy or angry) to your responses. If you see new combinations of faces in the test, please choose the person that seems more likely to become happy based on what you learned during the training sessions. If you are not sure which one to pick, just go with your gut instinct!"

Figure 2

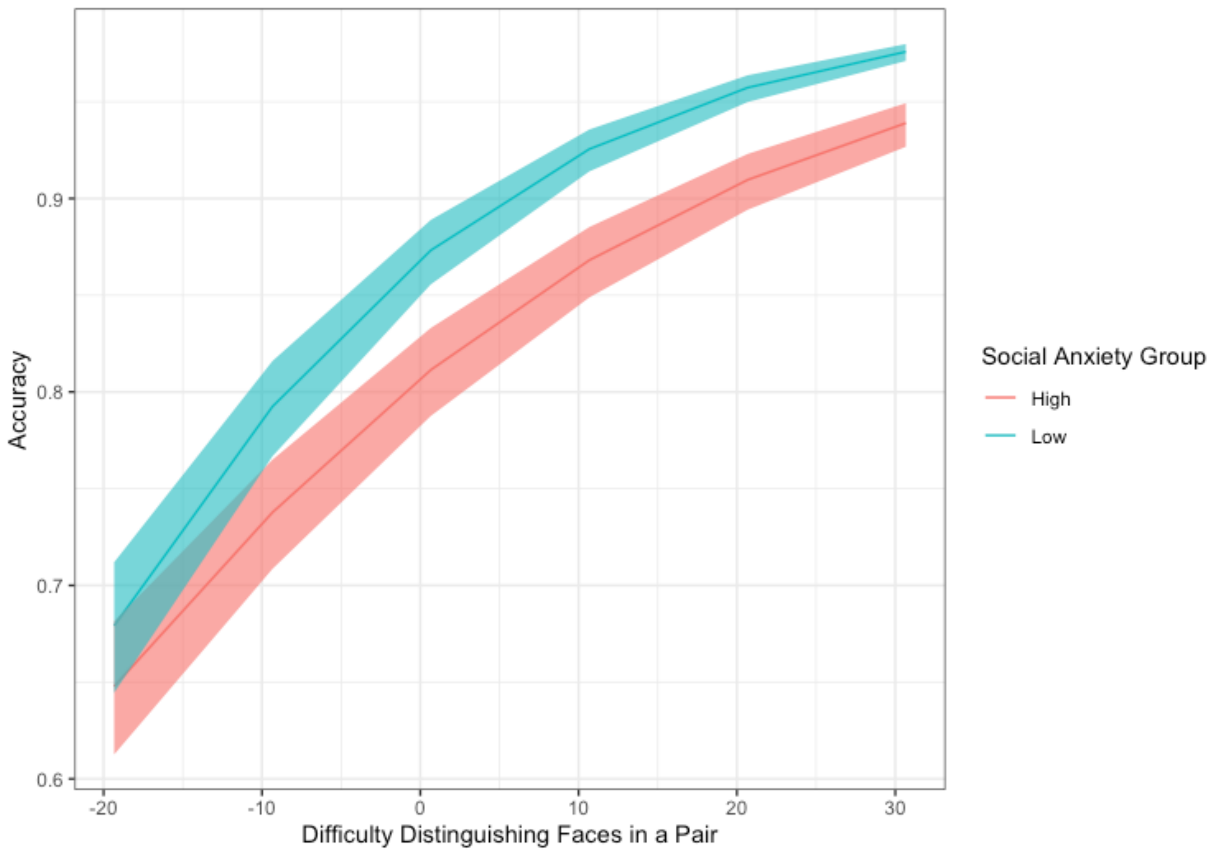
Reward and Punishment Learning Accuracy by Social Anxiety Group



Note: Avoid Most Punishing Face = rate of choosing the more rewarding face on pairs that included the most punishing face. Choose Most Rewarding Face = rate of choosing the more rewarding face on pairs that included the most rewarding face.

Figure 3

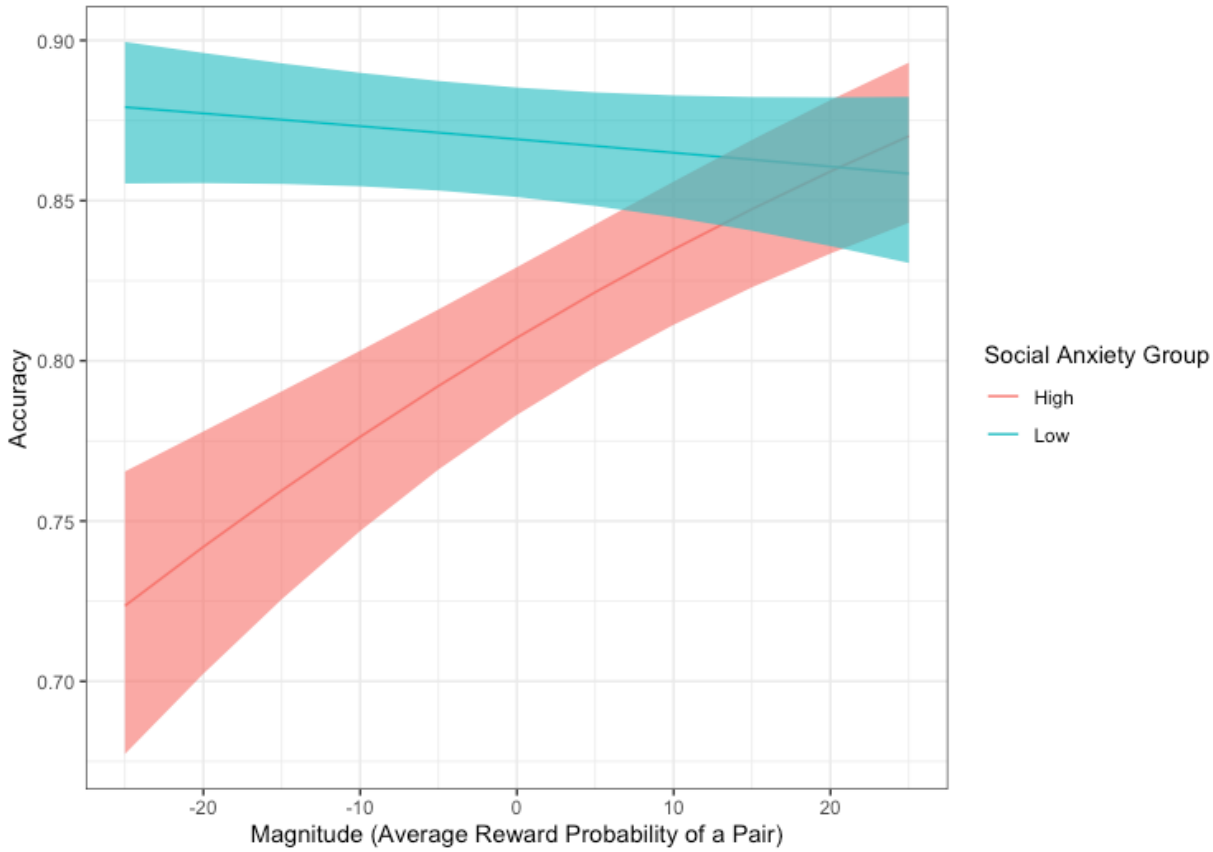
Accuracy as a Function of Difficulty by Social Anxiety Group



Note: Difficulty = difference between reward probabilities of faces in a pair, such that higher scores reflect easier pairs (note that this variable is centered). Accuracy = rate of choosing the more rewarding face.

Figure 4

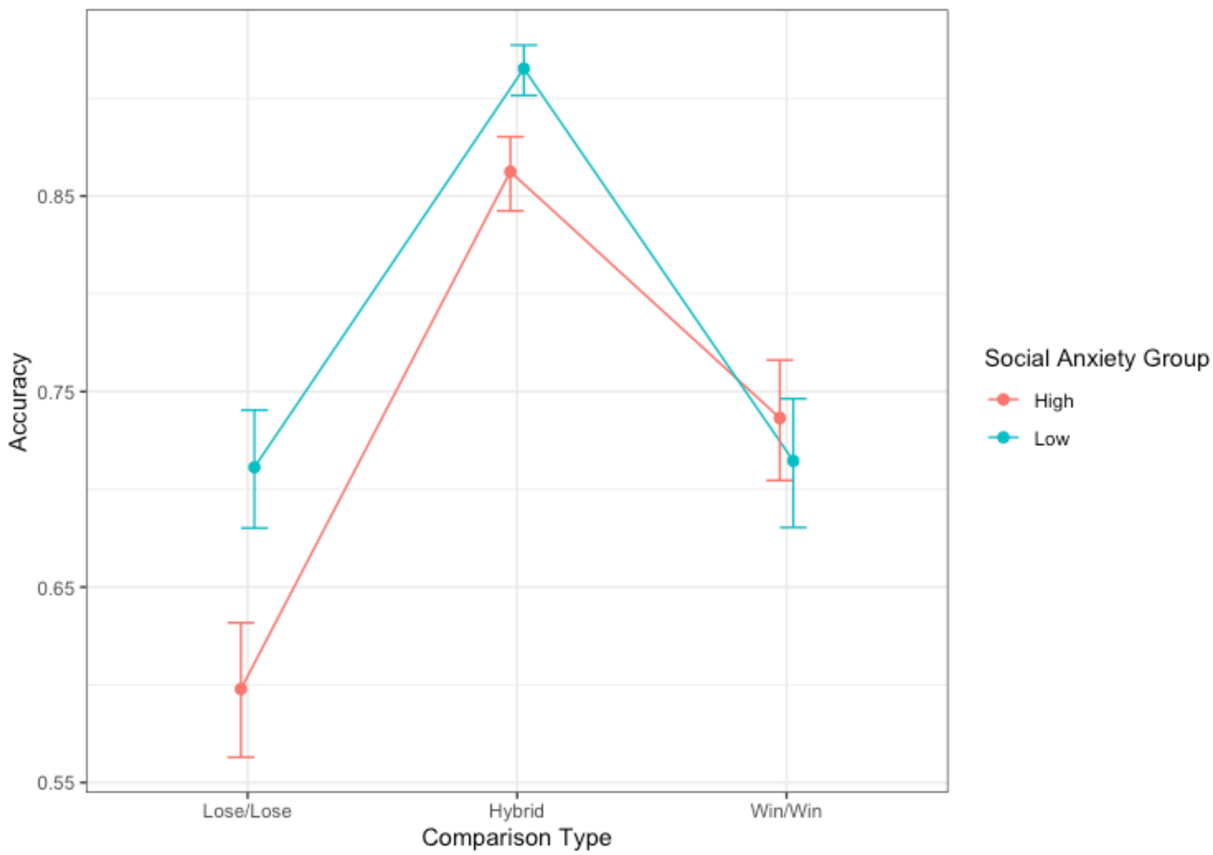
Accuracy as a Function of Magnitude by Social Anxiety Group



Note: Magnitude = mean reward probability of faces in a pair, such that higher scores reflect more rewarding pairs (note that this variable is centered). Accuracy = rate of choosing the more rewarding face.

Figure 5

Accuracy as a Function of Comparison Type by Social Anxiety Group



Note: Lose/Lose = pairs containing two relatively punishing faces (both faces' reward probabilities are ≤40%). Hybrid = pairs containing one relatively punishing and one relatively rewarding face (one face's reward probability is ≤40% and the other's is ≥60%). Win/Win = pairs containing two relatively rewarding faces (both faces' reward probabilities are ≥60%). Accuracy = rate of choosing the more rewarding face.

Supplemental Results

Dimensional Analyses Performed Within the High Social Anxiety Group

Learning Rate

A mixed effects linear regression was performed within the high social anxiety group, predicting individual-level learning rate estimates from social anxiety symptoms (the sum of straightforwardly worded items on the SIAS), prediction error valence, and their interaction, with a random intercept for participant. Similar to the between-groups model, this model also found no significant main effects or interactions. See Supplementary Table 1.

Reward and Punishment Learning Accuracy

A generalized linear mixed model with a logit link function was performed within the high social anxiety group, predicting accuracy in the testing phase from fixed effects of social anxiety symptoms, choice type, and their interaction, with a random intercept for participant. Similar to the between-groups model, a main effect of choice type was found, such that reward learning accuracy (P(correct) = 0.87, *SE* = =0.01) was higher than punishment learning accuracy (P(correct) = 0.77, *SE* = =0.02) within the high social anxiety group. See Supplementary Table 2.

Secondary Analyses Performed Dimensionally Within the High Social Anxiety Group

Discriminability

A generalized linear mixed model with a logit link function was performed within the high social anxiety group, predicting accuracy in the testing phase from fixed effects of social anxiety symptoms, easiness, magnitude, and all 2- and 3-way interactions, with a random intercept for participant. There were significant main effects of both easiness and magnitude. Participants in the high social anxiety group had higher accuracy on easier (vs. more difficult) pairs, and they had higher accuracy on more rewarding (vs. more punishing) pairs. See Supplementary Table 3.

Exploratory Analyses

Comparing Number of Training Blocks Needed Across Social Anxiety Groups

A t-test was performed to assess whether the high social anxiety group needed more blocks during the training phase before moving to the testing phase. Although the high social anxiety group tended to have more training blocks (*M* = 3.22, *SD* = 1.63), than the low social anxiety group (*M* = 2.81, *SE* = 1.45), the difference was not statistically significant ($t(81.69) = 1.51$, $p = 0.13$).

Comparing Training Phase Accuracy Across Social Anxiety Groups

To assess whether social anxiety groups differed in their rates of choosing the more rewarding face from different pairs during the training phase, a generalized linear mixed model was performed predicting accuracy from fixed effects of social anxiety group and pair type (AB, CD, or EF), with a random intercept for participant. The contrasts comparing CD and EF to AB were both significant, and there were significant interactions between social anxiety group and each of these contrasts. See Supplementary Table 4. Post-hoc tests found that for the high social anxiety group, accuracy on AB pairs was significantly higher than CD (*OR* = 1.32, $p < .001$) and EF pairs (*OR* = 1.76, $p < .001$), and CD accuracy was significantly higher than EF accuracy (*OR* = 1.34, $p < .001$). For the low social anxiety group, accuracy was significantly higher on AB than EF pairs (*OR* = 1.89, $p < .001$), and accuracy on CD pairs was significantly higher than on EF pairs (*OR* = 1.68, $p < .001$), but there was no significant difference between AB and CD accuracy (*OR* = 1.13, $p = 0.47$). These results suggest that overall, both groups successfully learned to select the more rewarding face on all pairs, and the groups did not significantly differ in their accuracy on any of the pairs presented in the training phase. See Supplementary Table 5 for estimated marginal means and standard errors for each pair.

Bayesian Analyses of Learning Rates

Given uncertainty in the individual-level learning rate estimates, we performed a set of four exploratory Bayesian analyses comparing the group-level posterior distributions of learning rates. We compared positive and negative learning rates within each social anxiety group, and we compared each learning rate between groups. We performed these analyses by computing the 95% highest density interval of the difference between the two posterior distributions. All four of these intervals crossed zero, suggesting no pairwise differences between groups.

Supplementary Table 1

Model Estimates Predicting Learning Rate Within High Social Anxiety Group

	Learning Rate			
Predictors	*Estimates*	*CI*	*t*	*p*
(Intercept)	0.19	0.09 – 0.29	3.69	**<0.001**
SIAS	0.00	-0.00 – 0.00	0.91	0.364
PE Valence	-0.03	-0.11 – 0.05	-0.63	0.528
SIAS X PE Valence	0.00	-0.00 – 0.00	0.34	0.736
Random Effects				
σ^2	0.02			
$\tau_{00\ subjID}$	0.01			
ICC	0.23			
N_{subjID}	114			
Observations	228			
Marginal R^2 / Conditional R^2	0.010 / 0.240			

Note: SIAS = Social Interaction Anxiety Scale straightforwardly worded items. PE Valence = prediction error valence (positive vs. negative).

Supplementary Table 2

Model Estimates Predicting Testing Phase Accuracy Within High Social Anxiety Group

	Accuracy			
Predictors	*Odds Ratios*	*CI*	*t*	*p*
(Intercept)	4.84	3.94 – 5.95	14.93	**<0.001**
SIAS	1.00	0.97 – 1.02	-0.33	0.742
Trial Type	1.41	1.33 – 1.50	11.09	**<0.001**
SIAS X Trial Type	1.00	1.00 – 1.01	0.84	0.402
Random Effects				
σ^2	3.29			
$\tau_{00\ id}$	1.10			
ICC	0.25			
N_{id}	113			
Observations	7186			
Marginal R^2 / Conditional R^2	0.027 / 0.270			

Note: SIAS = Social Interaction Anxiety Scale straightforwardly worded items. Trial Type = trials including the most rewarding face (choose A accuracy) vs. the most punishing face (avoid B accuracy).

Supplementary Table 3

Discriminability Model Estimates Predicting Testing Phase Accuracy Within High Social Anxiety Group

	Accuracy			
Predictors	*Odds Ratios*	*CI*	*t*	*p*
(Intercept)	4.19	3.60 – 4.87	18.62	**<0.001**
SIAS	1.00	0.99 – 1.02	0.16	0.875
Easiness	1.04	1.04 – 1.05	27.57	**<0.001**
Magnitude	1.02	1.01 – 1.02	6.25	**<0.001**
SIAS X Easiness	1.00	1.00 – 1.00	0.66	0.508
SIAS X Magnitude	1.00	1.00 – 1.00	-0.53	0.599
Easiness X Magnitude	1.00	1.00 – 1.00	0.76	0.448
SIAS X Easiness X Magnitude	1.00	1.00 – 1.00	-0.58	0.560
Random Effects				
σ^2	3.29			
$\tau_{00\ id}$	0.60			
ICC	0.15			
N_{id}	113			
Observations	13451			
Marginal R^2 / Conditional R^2	0.118 / 0.254			

Note: SIAS = Social Interaction Anxiety Scale straightforwardly worded items. Easiness = difference between reward probabilities of the two faces in a pair. Magnitude = mean reward probability of the two faces in a pair.

Supplementary Table 4

Threshold Model Estimates Predicting Training Phase Accuracy by Social Anxiety Group

	Accuracy			
Predictors	*Odds Ratios*	*CI*	*Statistic*	*p*
(Intercept)	2.88	2.53 – 3.29	15.84	**<0.001**
SA Group	0.96	0.84 – 1.09	-0.66	0.511
CD vs AB	1.07	1.03 – 1.12	3.08	**0.002**
EF vs AB	0.72	0.69 – 0.75	-15.69	**<0.001**
SA Group X CD vs AB	0.94	0.90 – 0.98	-2.88	**0.004**
SA Group X EF vs AB	1.05	1.01 – 1.10	2.31	**0.021**
Random Effects				
σ^2	3.29			
$\tau_{00\ subjID}$	0.51			
ICC	0.13			
N_{subjID}	156			
Observations	28871			
Marginal R^2 / Conditional R^2	0.016 / 0.147			

Note: SA Group = social anxiety group (high vs. low). AB = trials including faces A (80% reward, 20% punishment and B (20% reward, 80% punishment); CD = trials including faces C (70% reward, 30% punishment) and D (30% reward, 70% punishment; EF = trials including faces E (60% reward, 40% punishment) and F (40% reward, 60% punishment).

Supplementary Table 5

Probability of Choosing the More Rewarding Face on Training Phase Pairs

	M (SE)	
Face Pair	*Low SA*	*High SA*
AB	0.80 (0.02)	0.79 (0.01)
CD	0.77 (0.02)	0.74 (0.01)
EF	0.67 (0.03)	0.68 (0.02)

Study 2: Social Anxiety and Biased Social Feedback Learning

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Abstract

Background and Objectives: Socially anxious individuals expect others to judge their performance in evaluative social situations more harshly than others actually do, suggesting a negative social feedback learning bias. This study investigates social anxiety-related biases in learning from social feedback using a paradigm that delivers false but individually anchored speech performance feedback to increase its importance to participants.

Methods: Participants high (*n*=42) and low (*n*=32) in social anxiety symptoms rated how they expected to perform, and then performed, a stressful speech for two judges. Post-speech, participants were given false feedback anchored around their own pre-speech self-expectancies. Participants then reported how they expected they would perform on a similar speech in the future. Their future expectancies were modeled as a function of their pre-speech expectancies and the difference between their pre-speech expectancies and the feedback received.

Results: Planned analyses did not find any social anxiety-linked biases in learning from positive or negative feedback. However, exploratory analyses found that participants, regardless of social anxiety, learned more from positive than negative feedback, and that participants high (vs. low) in social anxiety symptoms learned more from feedback on items related to poor (vs. good) speech performance.

Limitations: The feedback paradigm allowed us to computationally model social feedback learning, but lacked the emotional ambiguity of real-world social feedback.

Conclusions: Socially anxious individuals may have a bias towards learning from feedback about feared aspects of poor performance. If replicated, this may help explain why socially anxious individuals' negative expectancy biases persist despite disconfirmatory feedback.

Keywords: social anxiety, reinforcement learning, feedback learning, public speaking, social performance, expectancy updating

Social Anxiety and Biased Social Feedback Learning

The 12% of Americans who will meet lifetime criteria for social anxiety disorder (SAD) regularly avoid socially evaluative situations or endure them with great distress (Kessler, Berglund, et al., 2005). This avoidance likely stems in part from underestimating previous social performances: for example, individuals with SAD tend to rate their own public speaking performance as worse than others rate them to a greater extent than do non-anxious individuals (Ronald M. Rapee & Lim, 1992). These underestimations might result from biased learning (from positive and negative feedback about their performance) and/or biased memory (of their performance and the feedback they received). Over time, biased learning and memories may lead to biased expectations about how future social situations will unfold. To advance our understanding of how these expectancy biases persist, this study used a public speaking task to examine how learning biases about social performance operate in more (vs. less) socially anxious individuals. Following Radomsky and Rachman's (2004) advice on "the importance of importance of…research," the selected paradigm used individually anchored speech performance feedback to increase the personal relevance of the task and feedback for participants.

Memory Biases for Social Feedback

Although this study focused on learning biases (how feedback is used to update beliefs about *future* performance), the literature on memory biases (beliefs about *past* performance) may inform how socially anxious individuals incorporate social performance feedback. Research on memory biases in social anxiety finds somewhat mixed results (see Coles & Heimberg, 2002; Hirsch & Clark, 2004 for review). However, several studies suggest that socially anxious individuals remember more negative than positive feedback about their social performance (e.g., Edwards et al., 2003) and lack a protective self-enhancing positive memory bias for aspects of poor social performance (Cody & Teachman, 2010). These differences may become more pronounced over time through ruminative post-event processing (Cody & Teachman, 2010, 2011; Glazier & Alden, 2017, 2019).[2] The memory bias work highlights social anxiety-linked differences in the perceived effectiveness of past social performance but does not address how that perceived difference might guide expectations of future performance.

Biases in Learning from Feedback

Learning biases occur when individuals in one group (e.g., more socially anxious individuals) learn from positive and negative feedback differently from those in another group (e.g., less socially anxious individuals) and therefore update their future performance expectancies in different ways. Self-perceptions of social performance can be thought of as a product of social reinforcement learning: a person updates how they expect to perform by combining how they already think of their performance with new feedback they receive from others, possibly weighting positive and negative feedback differently. Reinforcement learning describes how people learn to predict outcomes and optimize behavior when taking actions that lead to *rewards* and *punishments* (Sutton & Barto, 1998).

Aberrant reinforcement learning—or learning from rewards and punishments in a way that is ultimately unhelpful—has been documented across many disorders (Whitton et al., 2016), but has only recently been examined in SAD. For example, a recent study used reinforcement learning models to assess how groups varying in social anxiety symptoms learn from positive and negative feedback when under social-evaluative threat versus alone; more (vs. less) socially anxious participants updated their beliefs about future performance on a non-social task more strongly from negative (vs. positive) feedback, specifically when an audience was present to judge their initial performance (Müller-Pinzler et al., 2019). This study supports a negative learning bias in socially anxious individuals when social-evaluative threat is salient.

To examine reinforcement learning from social performance feedback, Koban et al. (2017) fitted simple reinforcement learning models to understand how individuals varying in

[2] Note mixed findings for immediate memory biases (Glazier & Alden, 2019) and for memory biases changing from immediate recall to after a delay (Edwards et al., 2003).

social anxiety weighted positive and negative speech feedback. In reinforcement learning, the degree to which a person weights recent information relative to more distal information is parameterized as the learning rate. In this study, the researchers examined learning rates for how participants used feedback to update their feelings about themselves and evaluations of their performance. They found that participants with SAD (vs. healthy control participants) tended to more heavily weight negative feedback when rating how they felt about themselves (Koban et al., 2017). In other words, criticism made socially anxious participants feel worse about themselves than it did for control participants. Further, after a delay, healthy control participants adjusted their self-evaluations of how they had performed more from positive than negative feedback, whereas participants with SAD adjusted their self-evaluations more from negative than positive feedback. This study was an important first step in computationally modeling how social feedback is used to update beliefs about one's *past* social performance. The present study uses similar methods and extends the work by computationally modeling how social feedback is used to update beliefs about one's *future* social performance. We focused on expected future performance because it likely plays a role in whether someone elects to avoid an upcoming situation–a major source of impairment in social anxiety.

Overview and Hypotheses

Participants high and low in social anxiety symptoms predicted how they would perform on an upcoming speech for a panel of judges, rating ten items related to good performance and ten related to poor performance. After the speech, they received individually-anchored false[3] feedback from the judges on each item and were asked to rate how they expected they would perform on a similar speech in the future. Using reinforcement learning, we assessed the weights participants gave to feedback that was more positive and more negative, respectively, than their own pre-speech performance expectancies, when updating how they expected to

[3] This study concerns how people learn from false social feedback about their own social performance. Actual judge ratings were not used.

perform. We refer to these values as positive and negative update weights, respectively. These update weights are conceptually similar to learning rates (albeit with slight calculation differences given different task designs).

Hypotheses were preregistered at https://osf.io/7r3gc/. We hypothesized that participants high (vs. low) in social anxiety symptoms would exhibit a more negative social feedback learning bias. We thought this might be evidenced in higher update weights for negative social feedback and/or lower update weights for positive social feedback, either of which would reflect that more socially anxious participants learned more from negative versus positive social feedback, relative to less socially anxious participants. Importantly, computationally modeling separate update weights for positive and negative feedback clarifies whether processing of criticisms, compliments, or both are altered in social anxiety.

Given past findings that social anxiety-related negative memory biases for speech feedback only occurred for items related to poor performance (Cody & Teachman, 2011), all analyses included an interaction term for item valence. Note that we use two terms that include the word "valence" to refer to two separate variables: *item valence* refers to items measuring good versus poor performance, and *prediction error valence* refers to feedback that was more positive versus negative than participants' pre-speech expectancies.

The current study advances our understanding of how socially anxious individuals use positive and negative social feedback to update their expectancies about their social performance, and whether this social feedback learning differs from less anxious individuals. As such, this work sheds light on a potential mechanism for the maintenance of negative expectancy biases.

Method

Participants

N=98 adults (18-45 years old) were recruited from the University of Virginia undergraduate participant pool and the Charlottesville community. Community participants were recruited through advertisements sent to university listservs for undergraduate and graduate students and flyers posted in public areas. Prospective participants were screened for social anxiety symptoms with the Social Interaction Anxiety Scale (SIAS; Mattick & Clarke, 1998). The sample included n=55 participants with moderate to severe social anxiety (scoring ≥29 on the SIAS, approximately ¼ of a standard deviation below the mean in a sample diagnosed with SAD; Mattick & Clarke, 1998) and n=43 participants with low social anxiety (scoring ≤ 10, ¾ of a standard deviation below the mean of a previous community sample; Mattick & Clarke, 1998).

Procedure

All participants completed a baseline lab session that included questionnaires and behavioral tasks, including the speech expectancies task. This baseline session constituted the full study for participants low in social anxiety symptoms, whereas those high in social anxiety symptoms also completed five weeks of ecological momentary assessment (not analyzed here) and a follow-up lab session five weeks later that included a second administration of the speech expectancies task. For the speech expectancies task, high social anxiety participants completed the pre-speech ratings and speech at both sessions, but received false feedback and completed post-feedback ratings only at their final session. We made this design decision to be able to immediately debrief participants about the false feedback deception without influencing subsequent measures. As such, analyses use data from the baseline session for low social anxiety participants and the follow-up session for high social anxiety participants. This study was part of a larger data collection; for details about the other components, see supplementary materials.

Measures

Social Interaction Anxiety Scale

The SIAS (Mattick & Clarke, 1998) is a 20-item self-report scale measuring social anxiety in dyads and groups (e.g., “I find myself worrying that I won’t know what to say in social situations.”). Participants rated each item on a 5-point Likert scale ranging from “not at all” to “extremely.” All items were used in recruiting participants into high and low social anxiety groups (for comparison to a previous sample), but following Rodebaugh et al.’s (2007) recommendation for improving psychometric properties, only ratings on the straightforwardly worded items were used in analyses. The SIAS was administered at recruitment and follow-up for high social anxiety participants; because we analyzed behavioral data from the follow-up session for high social anxiety participants, we used their SIAS data from this session for consistency. Due to an administrative error, item 18 of the SIAS was not presented to the high social anxiety group, so we used the mean (rather than sum) score as our measure of social anxiety symptoms.

Speech Expectancies Task

Similar to Koban et al. (2017), participants completed a modified version of the Trier Social Stress Test (Kirschbaum et al., 1993), a widely used social evaluative stressor. Participants were given two minutes to mentally prepare a four-minute speech. Because this task was administered at baseline and follow-up, the order of two speech topics (their perfect job and why they are well suited for it, or what they like or dislike about their hometown) was counterbalanced. Before the speech, participants rated from 0 (“disagree”) to 100 (“agree”) how well they expected to perform on ten items related to good social performance (e.g., “I will appear calm”) and ten related to poor performance (e.g., “I will appear to be sweating”), in randomized order (see Appendix A; adapted from Cody & Teachman, 2010). Two confederate judges witnessed and video-recorded the speech. The judges were instructed not to communicate signs of approval, feedback, or intense facial expressions, maintaining as neutral an expression as possible.

After the speech, participants received what was ostensibly judge feedback on their performance (see Figure 1). This feedback was false but designed to be believable, as it was anchored around the participant’s own pre-speech self-ratings, similar to Koban et al. (2017). Feedback on each item was calculated as the participant’s self-rating on that item plus a random integer between -50 and 50, bounded by the 0-100 rating scale. For each item, participants were shown their own pre-speech self-rating, then the false feedback rating, and then were asked to rate how they expected they would perform on a future speech on that same item and 0-100 scale. The speech ratings and feedback were presented in PsychoPy2 (Peirce et al., 2019).

We checked for suspicion using a funnel debriefing at the end of the study. Participants were asked open-ended questions that progressed from more general feedback about the study to queries for suspicion about the speech task. The last, most specific, question was "Did you believe the judges' feedback on your speech?"

Analytic Approach

All analyses were performed in R 4.0.2 (R Core Team, 2020). First, we estimated two update weights for each participant—one for feedback that was more positive than their pre-speech self-ratings (i.e., a positive prediction error where feedback - pre-rating > 0) and another for feedback that was more negative than their pre-speech self-ratings (i.e., a negative prediction error where feedback - pre-rating < 0)—according to:

$$\text{post-rating} \sim \text{pre-rating} + b_{valence}(\text{feedback} - \text{pre-rating})$$

where pre-rating is the participant's rating of how they expected to perform on an item before giving a speech, feedback is the false judges' rating that they were shown on that item after their speech, and post-rating is the participant's rating for how they expected they would perform on that item during a similar speech in the future. As such, b_{pos} represents the update weight given to positive prediction errors (i.e., "positive update weight"), and b_{neg} represents the weight given to negative prediction errors (i.e., "negative update weight").

Social Feedback Learning as a Function of Social Anxiety Group

To compare expectancy updating between social anxiety groups, we conducted a linear mixed effects model that predicted update weights from fixed effects of social anxiety group (high/low social anxiety), prediction error valence (positive/negative prediction errors), item valence (items measuring good/poor social performance), and all two- and three-way interactions. We included a random intercept for participant.

Results

Data Reduction

Of the *N*=98 participants (43 low social anxiety, 55 high social anxiety) who consented to participate, one low social anxiety participant did not complete the pre-speech ratings and one did not complete the post-speech ratings due to experimenter error, four high social anxiety participants dropped out of the study between the baseline and follow-up sessions, two declined to complete the speech at the follow-up session, and one was unable to come into the lab for the follow-up session, yielding complete speech expectancy task data for 89 participants (41 low social anxiety, 48 high social anxiety). Of those with complete speech task data, nine low social anxiety and six high social anxiety participants indicated that they did not believe the judges' feedback during funnel debriefing and were thus excluded from analyses, resulting in a final sample of *N*=74 participants (32 low social anxiety, 42 high social anxiety). See Table 1 for demographic characteristics.

Descriptive Statistics

Descriptive analyses of participants' pre-speech and post-feedback ratings found that participants high in social anxiety symptoms expected to perform worse than did those low in social anxiety symptoms, but both groups' self-ratings improved after giving the speech and receiving feedback. Descriptive analyses of speech feedback found that the feedback-generating procedure worked as it was designed to. See supplementary materials for more detail.

Social Anxiety

As expected, social anxiety symptoms were significantly lower in the low social anxiety group (M = 0.25) than in the high social anxiety group (M = 1.73), $t(42.87) = 13.59$, $p < 0.001$.

Planned Primary Analyses

Social Feedback Learning as a Function of Social Anxiety Group

Due to singular model fit, we dropped the random intercept from the planned mixed effects model and instead tested a linear model. Four observations (1.5% of the data) were identified as influential outliers (Cook's distance > four divided by the number of observations), and were therefore removed (Cook, 1977). No main effects or interactions were significant (see Table 2), suggesting that expectancy updating on this task did not differ as a function of social anxiety group, item valence, or prediction error valence.

Another planned analysis that modeled social anxiety symptoms dimensionally found no significant effects; see supplementary materials.

Exploratory Analyses

State Anxiety

In light of these planned tests finding no evidence of a social anxiety-linked learning bias, we performed several exploratory analyses to better understand whether *state* anxiety around the speech might be related to learning biases, potentially moderated by trait social anxiety symptoms. These analyses found no statistically significant findings; see supplementary materials.

Update Weights Estimated Over More Trials

We considered the possibility that the update weights used in our main analyses might not be sufficiently reliable as they were estimated over approximately five trials each (because separate update weights were estimated for positive and negative prediction errors on good vs. poor performance items; see Austin & Steyerberg, 2015). To address this concern, we performed exploratory analyses on update weights calculated over more trials—specifically, over all 20 items, over positive and negative prediction error trials (~10 trials each), and over items related to good and poor performance (~10 trials each).

When one update weight was estimated per participant over the whole task, there was no significant difference in update weights between high (M = 0.45) and low social anxiety groups (*M* = 0.44), *t*(70.48) = -0.06, *p* = 0.95. For update weights estimated for positive and negative feedback, we conducted a mixed effects model predicting update weights from social anxiety group, prediction error valence, and their interaction, with a random intercept for participant. We dropped the random intercept due to singular fit. Nine outliers (6.1%) were identified and removed. A significant main effect was found for prediction error valence, such that update weights were higher for positive versus negative prediction errors, suggesting that across the whole sample, participants updated their beliefs more when they received feedback that was more positive (vs. more negative) than their pre-speech ratings. There were no other significant effects (see Table 4).

For update weights estimated for items related to good versus poor performance, we conducted a mixed effects model predicting update weights from social anxiety group, item valence, and their interaction, with a random intercept for participant. Nine outliers (6.1%) were identified and removed. A significant main effect of item valence was found, but is not interpreted because it was subsumed within a significant interaction with social anxiety group (see Table 5). Visual inspection of this interaction revealed that low social anxiety participants tended to update their beliefs similarly on items related to good performance, whereas high social anxiety participants tended to update their beliefs more on items related to poor performance (see Figure 2).

Discussion

This study assessed how individuals high and low in social anxiety symptoms updated their expectancies of how they would perform on a future speech based on false feedback from people judging their prior speech, with the aim of better understanding how negative expectancy biases persist in socially anxious individuals. In our planned analyses, we did not find support for our hypothesized effects; specifically, we did not find evidence that relative to less socially anxious individuals, more socially anxious individuals updated their expectancies more based on negative versus positive feedback. However, we did find interesting results in exploratory analyses, which, if replicated, suggest that socially anxiety may be characterized by biased learning from feedback about aspects of poor social performance.

Null Results for Planned Analyses of Social Anxiety-Linked Learning Rate Biases

Our planned analyses did not find the hypothesized bias towards learning from negative feedback in individuals high in social anxiety symptoms. In fact, we did not find any significant differences in expectancy updating as a function of social anxiety symptoms when conceptualized either categorically (i.e., high vs. low social anxiety groups) or continuously (within the high social anxiety group), item valence, or prediction error valence.

Differences from Koban et al. (2017)

While these results differed from hypotheses based on Koban and colleagues' (2017) finding of a social anxiety-linked bias towards learning from negative feedback, our social feedback and learning paradigm differed from their design in several ways. First, Koban's study included 58 items related to speech performance, and their analyses did not separate these items by valence (good/poor social performance). The present study used 20 items, which were separated by valence in analyses. We made this design decision both to reduce burden on participants who were completing several other tasks during a long lab session and to assess differences in learning from feedback about good and poor performance (given its relevance in studies of memory biases). However, an unintended consequence of this design decision was that we estimated update weights over many fewer trials per participant than in Koban and colleagues' study, which may have reduced our ability to reliably model these update weights for the specific conditions we wished to assess.

There were also notable differences in the types of learning each study assessed. The present study assessed how social feedback is used in updating beliefs about *future* social performance, whereas Koban et al.'s study assessed how social feedback was used in updating feelings and beliefs about *past* social performance. Also, Koban et al. measured belief updating from feedback after a 20-minute delay, whereas we measured belief updating immediately after feedback. Given prior findings of social anxiety-linked negative memory biases worsening with time from post-event processing (Cody & Teachman, 2010; Glazier & Alden, 2017, 2019), our null finding for a negative learning bias immediately post-feedback may not conflict with Koban et al.'s finding of a negative learning bias after a delay.

Lastly, there are potentially important differences between the two studies in how the tasks were presented. In our study, participants saw their pre-speech rating and the false feedback on the same screen where they entered their post-feedback rating for each item, effectively removing any chance for participants to misremember their prior beliefs or the feedback. In Koban et al., participants rated their performance 20 minutes after feedback without being reminded of their original self-ratings or the judges' feedback, thus allowing more opportunity for memory biases to color their updated ratings. As such, several differences between the two studies' paradigms may explain our discrepant findings.

Ambiguity of Social Feedback

Although we were surprised not to find evidence of a social anxiety-linked learning bias related to prediction error valence, it is possible that negative expectancy biases persist in the face of feedback for reasons other than a learning bias, like negative biases in interpreting ambiguous social feedback (see Hirsch & Clark, 2004). Real-life social performance feedback tends to be ambiguous: if given direct feedback at all, it might be vague and brief (e.g., "That was interesting."), and nonverbal signals might be unclear (e.g., head nodding may indicate approval but also may be used to reduce social discomfort). However, our paradigm was specifically designed to disentangle the effects of interpretation versus learning biases by removing this ambiguity: giving feedback as a specific number on a scale for each speech performance dimension. As such, it remains possible that socially anxious individuals interpret ambiguous feedback in negatively biased ways and incorporate that into their beliefs, but when feedback is unambiguous, as it was in our paradigm, social anxiety may not be particularly linked to biased feedback learning.

Exploratory Results: Learning from Positive Feedback and Poor Performance Indicators

We conducted a number of exploratory analyses to probe possible reasons for the lack of significant findings, including whether our null findings might have resulted from update weights being estimated over too few trials to form reliable estimates, which led to some intriguing findings. First, across the sample, participants learned more from positive than negative feedback. This was somewhat surprising, as studies tend to find that both anxious and non-anxious samples learn either equally from positive and negative feedback or more from negative feedback (Müller-Pinzler et al., 2019; Voegler et al., 2019). Further, Koban et al. (2017) found that socially anxious individuals' feelings about themselves and beliefs about a past speech were updated more from negative than positive feedback. However, note that participants in our study were asked to update their expectancies shortly after a stressful speech, and the pattern observed in our exploratory analyses does resemble results typically seen in healthy control participants during recovery from a stressor, who show a bias towards learning to choose rewarding stimuli (Lighthall et al., 2013). It remains possible that a bias towards learning from positive social feedback might facilitate recovery from stress, regardless of social anxiety symptoms. However, given the dearth of research on social feedback learning immediately after a stressor, this result bears replication.

Another possible explanation for this exploratory finding is that participants may have been more surprised by positive (vs. negative) feedback on the speech, and thus updated their beliefs more from it (Behrens et al., 2007). Positive feedback was not mathematically more surprising than negative feedback in terms of prediction error, as feedback was specifically generated to be similarly more positive and more negative than pre-speech self-ratings. However, participants might have expected to receive negative feedback from the judges because of the judges' neutral expressions and lack of positive feedback during the speech, which might be interpreted as disapproving either because of a participant's social anxiety-linked negative interpretation bias for neutral faces (Yoon & Zinbarg, 2008), or because of a culturally-based expectation of smiling. If participants expected negative feedback from the judges, then their positive feedback might have been more surprising than their negative feedback, which may have led participants to update their beliefs more from positive than negative feedback.

Our second exploratory finding is that relative low social anxiety participants, those high in social anxiety updated their expectancies more based on poor (vs. good) social performance feedback. While our main hypotheses focused on learning biases related to prediction error valence, this finding suggests that *item* valence actually may be more relevant to learning biases in social anxiety, similar to the memory bias literature. Memory bias studies usually define positive and negative feedback as high ratings on items related to good and poor performance, respectively, which accords more with our definition of *item* than *prediction error* valence. In fact, this finding is consistent with prior memory bias findings that, relative to healthy control participants, socially anxious individuals remember more feedback on items related to poor performance, and their memories of this negative feedback endure with greater fidelity than their memories of feedback on items related to good performance (Cody & Teachman, 2011; Edwards et al., 2003). Socially anxious individuals might be more concerned about avoiding poor performance than achieving good social performance (e.g., being very worried about having long pauses, but less worried about speaking fluently), and therefore learn more from feedback on items about poor performance. This could be conceptualized as a prevention regulatory focus (e.g., viewing goals in terms of promoting safety and avoiding loss; Higgins, 1997), which is consistent with cognitive behavioral models of social anxiety that emphasize the desire to avoid negative social evaluation. This bias towards learning more from feedback on items related to poor performance could also be conceptualized as a learning bias for information that is important, significant, and threatening--consistent with models of memory bias in obsessive-compulsive disorder (Radomsky & Rachman, 2004).

Clinical Implications

This study found that immediately after a socially evaluative performance situation, socially anxious individuals learned more from feedback on items related to poor (vs. good) performance, but we did not find evidence of a social anxiety-linked bias for learning more from negative than positive feedback. This provides support for many techniques used in cognitive behavioral therapy that aim to challenge cognitive biases by encouraging socially anxious individuals to consider a wide base of objective evidence when forming beliefs. Similarly, interventions that focus on giving clear feedback about aspects of a person's feared poor social performance may be more effective in changing negative performance expectancies if, as our results found, socially anxious individuals update their beliefs more from feedback about these negative qualities. In line with this suggestion, studies have found beneficial outcomes for adding unambiguous peer or audience feedback to video feedback on speeches given by socially anxious individuals (Chen et al., 2010, 2015, 2018).

Limitations and Conclusion

While this study design has several strengths (e.g., ability to separately model positive and negative feedback, and items related to good vs. poor performance), it also has limitations. Although the paradigm used permits computational modeling of belief updating and has many ecologically valid qualities, it might nonetheless limit generalizability to many real-life social performance situations. Also, while this paradigm provided feedback on more dimensions than likely occurs in real life, there still might have been too few items in each cell to reliably model learning at the level of both feedback and item valence (thus motivating our exploratory analyses). Further, our sample was comprised mostly of undergraduates, whose experiences with public speaking may differ from the general population's, and our high social anxiety group was not clinically diagnosed with SAD. Potential comorbidities and medication use were not assessed. Finally, our sample largely identified as not Latinx/Hispanic White and female, and these identities may affect how people learn from feedback.

Many interesting and worthwhile questions could be pursued as follow-ups to this study. First, researchers might assess which qualities of performance are most relevant to a given individual's social anxiety (Moscovitch, 2009; Moscovitch & Huyder, 2011) to further increase personal relevance of the task (see Rachman & Radomsky, 2004). Second, future studies might consider how socially anxious people update their global (e.g., "How well do you think you will do overall?") versus specific (e.g., "How well do you think you will keep eye contact?") expectancies from feedback, given previous studies have found global beliefs to show particularly negative biases (Cody & Teachman, 2011). Third, to bridge the literatures on learning and memory biases, researchers might measure both updating from and recall of feedback after different delays (e.g., 20 minutes and 3 days later). This design could examine both the relationships between learning and memory, and the durability of different responses to feedback. Lastly, future studies might take into account how judges would actually evaluate participants' social performance (e.g., by coding videos of the speeches).

While this study did not find evidence of a social anxiety-linked bias towards learning more from negative than positive social feedback, it did find preliminary evidence of a bias towards learning more from feedback on items related to poor (vs. good) social performance. These analyses need to be replicated but raise interesting questions about what aspects of social performance feedback are particularly impactful in developing and maintaining expectancies for future social performance and social avoidance.

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Table 1

Demographics by social anxiety group.

Variable	Low SA	High SA
n	32	42
<u>*Sex*</u>		
Females (%)	23 (71.89%)	29 (69.05%)
Males (%)	9 (28.13%)	13 (30.95%)
Non-binary identity (%)	0 (0%)	0 (0%)
M_{age} in years (SD_{age})	19.22 (1.34)	20.14 (2.67)
Undergraduates (%)	31 (96.88%)	35 (83.33%)
<u>*Ethnicity*</u>		
Latinx/Hispanic (%)	2 (6.25%)	2 (4.76%)
Not Latinx/Hispanic (%)	30 (93.75%)	39 (83.33%)
Prefer Not to Answer (%)	0 (0%)	1 (2.38%)
<u>*Race*</u>		
White (%)	22 (68.75%)	31 (73.81%)
Asian (%)	6 (18.75%)	9 (21.43%)
African American/Black (%)	1 (3.13%)	5 (11.90%)
Middle Eastern (%)	1 (3.13%)	0 (0%)
American Indian/Alaska Native (%)	0 (0%)	0 (0%)
Native Hawaiian/Pacific Islander (%)	0 (0%)	2 (4.76%)

Note: SA = Social Anxiety.

Table 2

Estimates for Linear Model Predicting Update Weights Between Social Anxiety Groups

	Update Weight			
Predictors	*Estimates*	*CI*	*Statistic*	*p*
(Intercept)	0.45	0.34 – 0.56	8.11	**<0.001*** **
Social anxiety (SA) group	0.08	-0.03 – 0.19	1.43	0.155
Prediction error (PE) valence	0.09	-0.02 – 0.20	1.55	0.121
Item valence	-0.01	-0.12 – 0.10	-0.20	0.839
SA group X PE valence	-0.03	-0.14 – 0.08	-0.62	0.537
SA group X Item valence	-0.02	-0.13 – 0.09	-0.36	0.719
PE valence X Item valence	0.05	-0.06 – 0.16	0.92	0.357
SA group X PE valence X Item valence	0.06	-0.05 – 0.17	1.02	0.309
Observations	271			
R^2 / R^2 adjusted	0.026 / 0.000			

Note: Contrasts were set as follows: for social anxiety group, high social anxiety participants were coded 1 (vs. low social anxiety participants were coded -1); for prediction error valence, positive update weights were coded 1 (vs. negative update weights were coded -1); for item valence, items related to good social performance were coded 1 (vs. items related to poor social performance were coded -1). ****p*<.001.

Table 3

Estimates for Linear Mixed Effects Model Predicting Update Weights with SIAS Considered Dimensionally Within the High Social Anxiety Group

	Update Weight			
Predictors	*Estimates*	*CI*	*Statistic*	*p*
(Intercept)	0.37	-0.41 – 1.15	0.93	0.352
SIAS	0.01	-0.41 – 0.43	0.03	0.974
Prediction error (PE) valence	0.29	-0.49 – 1.07	0.74	0.461
Item valence	-0.25	-1.03 – 0.53	-0.62	0.533
SIAS X PE valence	-0.19	-0.61 – 0.23	-0.89	0.372
SIAS X Item valence	0.21	-0.21 – 0.63	0.97	0.333
PE valence X Item valence	-0.03	-0.81 – 0.75	-0.08	0.934
SIAS X PE valence X Item valence	0.14	-0.28 – 0.56	0.64	0.519
Random Effects				
σ^2	2.99			
$\tau_{00\ participant}$	0.00			
ICC	0.00			
$N_{participant}$	40			
Observations	151			
Marginal R^2 / Conditional R^2	0.033 / 0.034			

Note: Contrasts were set as follows: for prediction error valence, positive update weights were coded 1 (vs. negative update weights were coded -1); for item valence, items related to good social performance were coded 1 (vs. items related to poor social performance were coded -1).

Table 4

Estimates for Exploratory Linear Mixed Effects Model Predicting Update Weights Estimated Separately Over Positive and Negative Feedback, Collapsed Across Item Valence

	Update Weight			
Predictors	*Estimates*	*CI*	*Statistic*	*p*
(Intercept)	0.50	0.46 – 0.55	20.35	<0.001***
Prediction error (PE) valence	0.13	0.08 – 0.18	5.55	<0.001***
SA	0.03	-0.02 – 0.07	1.05	0.295
SA X PE valence	-0.04	-0.08 – 0.01	-1.64	0.101
Random Effects				
σ^2	0.08			
$\tau_{00\ participant}$	0.00			
ICC	0.05			
$N_{participant}$	73			
Observations	139			
Marginal R^2 / Conditional R^2	0.183 / 0.227			

Note: Contrasts were set as follows: for social anxiety group, high social anxiety participants were coded 1 (vs. low social anxiety participants were coded -1); for prediction error valence, positive update weights were coded 1 (vs. negative update weights were coded -1). ****p*<.001.

Table 5

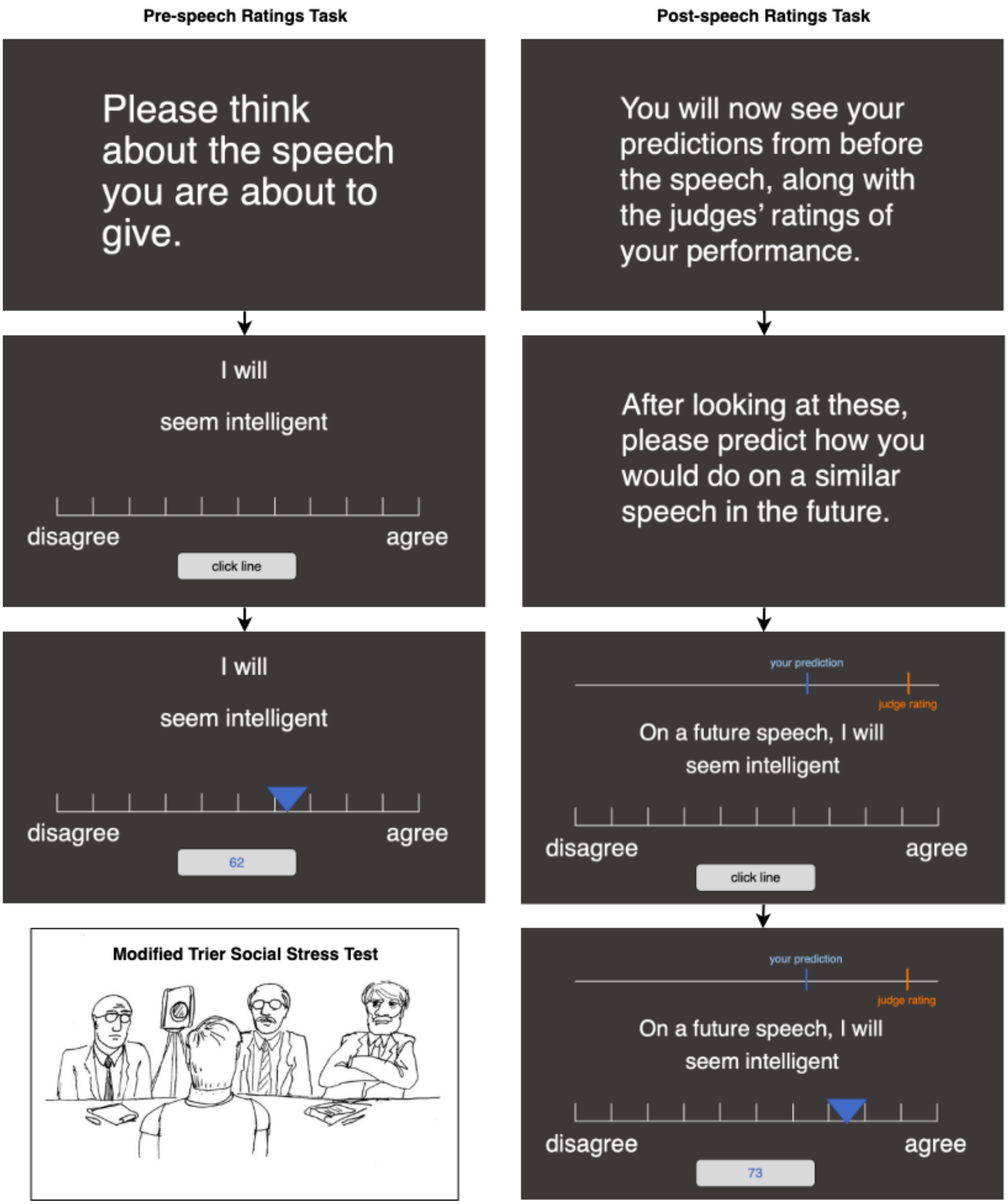
Estimates for Exploratory Linear Mixed Effects Model Predicting Update Weights Estimated Separately Over Items Related to Good vs. Poor Social Performance, Collapsed Across Feedback Valence

	LR			
Predictors	*Estimates*	*CI*	*Statistic*	*p*
(Intercept)	0.47	0.41 – 0.52	17.16	**<0.001*** **
Item valence	-0.04	-0.06 – -0.01	-3.36	**0.001** **
SA	0.00	-0.05 – 0.06	0.09	0.925
Item valence X SA	-0.03	-0.05 – -0.01	-2.62	**0.009** **
Random Effects				
σ^2	0.01			
$\tau_{00\ participant}$	0.04			
ICC	0.75			
$N_{participant}$	71			
Observations	139			
Marginal R^2 / Conditional R^2	0.039 / 0.759			

Note: Variance for the participant random effect was 0.046. Contrasts were set as follows: for social anxiety group, high social anxiety participants were coded 1 (vs. low social anxiety participants were coded -1); for prediction error valence, positive update weights were coded 1 (vs. negative update weights were coded -1). **p*<.05, ***p*<.01, ****p*<.001.

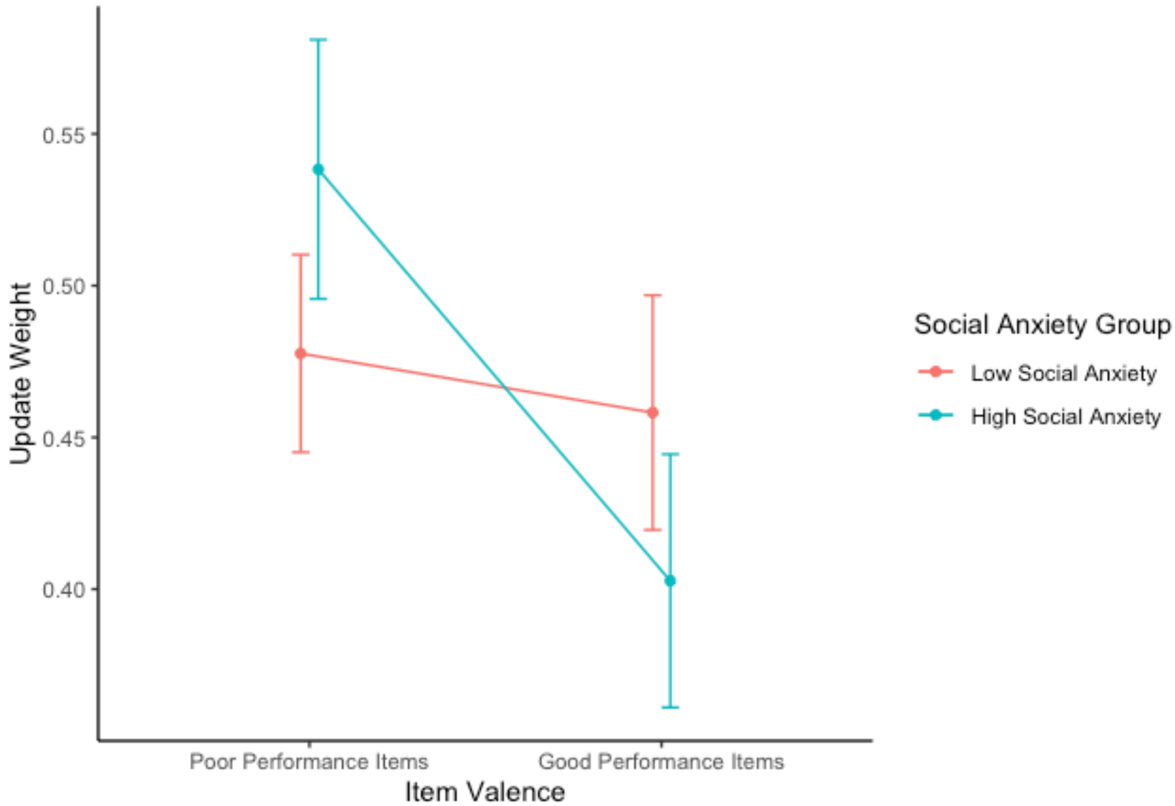
Figure 1

Speech Expectancies Task



Note: The Trier Social Stress Test sketch was created by Coetzee (2012). For the pre- and post-speech ratings tasks, participants saw the instruction and response screens below, here shown with one example item ("seem intelligent") of 20. The blue bar labeled "your prediction" was set based on each participant's pre-speech rating on that item, and the orange bar labeled "judge rating" was set based on a random integer between -50 and 50 added to the participant's pre-speech rating on that item.

Figure 2. Interaction Plot for Update Weights Estimated Separately for Items Measuring Poor versus Good Social Performance



Note: As compared to participants low in social anxiety, participants high in social anxiety tended to update their expectancies more in the direction of feedback on items related to poor (vs. good) performance.

Appendix A

Modified Perceptions of Speech Performance (adapted from Cody & Teachman, 2010) items.

Seem confident

Sound out of breath

Be interesting

Say "um" a lot

Speak fluently

Make a good impression

Speak too quickly

Blush visibly

Keep eye contact

Appear to be sweating

Seem well-prepared

Be understandable

Stammer over words

Look poised

Have a shaky voice

Speak audibly

Have long pauses

Tremble noticeably

Move around excessively

Seem intelligent

Supplementary Method

Procedure

This study was part of a larger data collection. In the larger study, all participants completed a laboratory session with the speech expectancy task, as well as other behavioral tasks and surveys. The high social anxiety group completed five weeks of ecological momentary assessment, followed by another laboratory session with the same tasks. Approximately half of the socially anxious participants were randomized to complete a week of interpretation bias modification training in week three of the ecological momentary assessment period. The present study included data from session one for the low social anxiety group and session two for the high social anxiety group who did not receive the intervention. Because the mobile app used for ecological momentary assessment only ran on certain versions of iOS and Android OS, participants who did not have a compatible smartphone were excluded. More information about the ecological momentary assessment component of the study, as well as other measures administered but not analyzed in this study, can be found at https://osf.io/utk7m/.

Measures

Subjective Units of Distress

Research assistants recorded participants' verbal reports of state anxiety using a Subjective Units of Distress Scale (SUDS; Wolpe, 1969), ranging from 0 (*not at all anxious*) to 100 (*the most anxious*). These ratings occurred at six timepoints throughout each session (see Supplementary Figure 1): after informed consent (T1); before any instructions were given about the speech (T2); immediately before the speech (after speech instructions, two minutes of silent preparation, and pre-speech ratings); T3); immediately after the speech, ratings of peak anxiety during the speech (T4); immediately after T4, ratings of current (post-speech) anxiety (T5); after post-speech rating task (T6).

Analytic Approach

Social Feedback Learning within the High Social Anxiety Group

Because symptoms of social anxiety exist along a continuum (McNeil, 2001), there may be meaningful variation in learning not just between the high and low social anxiety groups, but also within the high social anxiety group, whose SIAS scores ranged from 29 to 73. Some reinforcement learning studies have found effects of anxiety measured continuously in clinical groups, even in the absence of between-groups differences (e.g., Cavanagh et al., 2018). As a follow-up, we assessed the relationship between social anxiety and social feedback learning dimensionally within the high social anxiety group. We conducted a linear mixed effects model that predicted update weights from fixed effects of SIAS score, prediction error valence, and item valence, and all two- and three-way interactions. We included a random intercept for participant. Visual inspection of effects and post-hoc tests were performed to understand any significant interactions.

Supplementary Results

Descriptive Analyses

Pre-speech and Post-feedback Ratings

For poor performance items, there were significant main effects of both social anxiety group and time, such that high (vs. low) social anxiety participants endorsed greater agreement with poor performance items, and endorsement for poor performance items was lower post-feedback vs. pre-speech. The social anxiety group-by-time interaction was not significant. See Supplementary Table 1.

Consistent results were found for items related to good performance. There were significant main effects of both social anxiety group and time, such that high (vs. low) social anxiety participants endorsed lower agreement with good performance items, and endorsement with good performance items was higher post-feedback vs. pre-speech. The social anxiety group-by-time interaction was not significant. See Supplementary Table 2.

Together, these results suggest that while participants high in social anxiety expected to perform worse than did those low in social anxiety, both groups' self-ratings improved after giving the speech and receiving feedback, on items measuring both good and poor social performance.

Speech Feedback

To assess whether both participant groups received comparable computer-generated feedback, a 2X2 ANOVA was performed predicting feedback from group, item valence, and their interaction. There were significant main effects of both item valence and social anxiety group that are not interpreted because they were subsumed within a significant interaction. For poor performance items, high social anxiety participants received more negative feedback (*M* = 53.45, *SD* = 33.75) than low social anxiety participants (*M* = 44.52, *SD* = 31.40). For good performance items, high social anxiety participants received less positive feedback (*M* = 43.58, *SD* = 32.03) than low social anxiety participants (*M* = 55.07, *SD* = 33.65). Given feedback was generated around participants' pre-speech ratings, this difference between feedback on items related to good and poor performance was not surprising. See Supplementary Table 3.

Further, a 2x2 ANOVA predicting prediction error (the difference between feedback and pre-speech ratings) from group, item valence, and their interaction found no significant differences. See Supplementary Table 4. This suggests that there was no evidence of bias in the feedback-generating procedure (i.e., the high social anxiety group did not receive more negative feedback relative to their pre-speech ratings than the low social anxiety group).

Planned Analyses

Social Feedback Learning within the High Social Anxiety Group

Again, due to singular model fit, we dropped the random intercept from this planned mixed effect model. We removed two influential outliers (1.3% of the data). No significant differences were found in update weights as a function of SIAS severity (assessed dimensionally amongst individuals in the high social anxiety group), item valence, or prediction error valence, or any higher-order interactions (see Table 3). This suggests that expectancy updating did not differ in the high social anxiety group as a function of social anxiety severity, item valence, or prediction error valence.

Exploratory Analyses

State Anxiety

We performed explored effects of state anxiety on learning biases, motivated by past studies finding state anxiety-related changes in reinforcement learning that appear to differ for individuals varying in social anxiety symptoms (Müller-Pinzler et al., 2019; Voegler et al., 2019).

First, we sought to understand how participants with varying levels of social anxiety symptoms responded to the modified version of the Trier Social Stress Test. To investigate whether state anxiety, as measured by SUDS ratings, differed over the course of the experiment between social anxiety groups, a linear mixed effects model was performed predicting SUDS from social anxiety group, timepoint of measurement, and their interaction, with a random intercept for participant. The results of this model found that SUDS at T3 (pre-speech; b = 18.21, SD = 1.10, p < 0.001), T4 (peak anxiety during the speech; b = 26.89, SD = 1.10, p < 0.001), and T5 (post-speech; b = 14.18, SD = 1.10, p < 0.001) were all significantly greater than at T1 (baseline), as might be expected. There was not a significant main effect of social anxiety group, though, nor was there a significant interaction between timepoint and social anxiety group at any timepoint (ps > 0.05). This result suggests that both the low and high social anxiety symptom groups reported similar state anxiety throughout the session, and both groups experienced similar increases in state anxiety around the speech.

Next, we considered state anxiety's relations to learning biases, and whether state anxiety might induce different learning biases among individuals high and low in trait social anxiety symptoms. To assess whether state anxiety from the speech affected expectancy updating, a linear mixed effects model was performed predicting update weights from the mean SUDS around the speech (T3, T4, and T5), social anxiety group, prediction error valence, item valence, and all 2-, 3- , and 4-way interactions, covarying for baseline T1 SUDS, and with a random intercept for participant. However, this random intercept was dropped due to singular model fit. Mean SUDS around the speech was used instead of each individual SUDS rating due to their high correlations (see Supplementary Table 5) and to improve reliability. Outliers were identified and removed using the method described above, resulting in 4 observations (1.4%) of being removed. No main effects or interactions were significant (*p*s > 0.05), providing no evidence of a state-anxiety linked learning bias.

Extreme Ratings

We considered the possibility that extreme expectancy ratings (e.g., very low or very high self-ratings) might be related to feedback learning biases in two potential opposing directions: (1) perhaps participants learn more from feedback on items about which they have particularly strong beliefs, or (2) perhaps participants' strong beliefs are more resistant to change. To see if we had sufficient data to test these questions, we examined the extent to which participants low and high in social anxiety symptoms reported extreme expectancy ratings. We examined the percent of pre- and post-speech ratings at the extreme ends of the response scale (i.e., <10 and >90) for items related to good vs. poor performance for each social anxiety group (see Supplementary Table 6) and visually inspected the distributions (Supplementary Figure 2). We observed relatively infrequent extreme expectancy ratings, making further analysis difficult. However, the low social anxiety group had greater than chance extreme endorsements for agreement with good performance items and disagreement with poor performance items post-feedback, suggesting that their positive expectancies became stronger after feedback.

Supplementary Table 1

Mixed Effects Model Estimates Predicting Participant Self-Ratings on Items Assessing Poor Performance

	Participant Self-Ratings			
Predictors	*Estimates*	*CI*	*Statistic*	*p*
(Intercept)	47.23	43.88 – 50.58	27.67	<0.001***
SA	4.85	1.50 – 8.19	2.84	0.005***
Time	-2.26	-3.50 – -1.03	-3.60	<0.001***
SA1 X Time	0.12	-1.12 – 1.35	0.18	0.853
Random Effects				
σ^2	573.69			
$\tau_{00\ participant}$	183.01			
ICC	0.24			
$N_{participant}$	74			
Observations	1480			
Marginal R^2 / Conditional R^2	0.036 / 0.269			

Note: Contrasts were set as follows: for social anxiety group, high social anxiety participants were coded 1 (vs. low social anxiety participants were coded -1); for time, ratings after feedback were coded 1 (vs. before the speech were coded -1). ****p*<.001.

Supplementary Table 2

Mixed Effects Model Estimates Predicting Participant Self-Ratings on Items Assessing Good Performance

	Participant Self-Ratings			
Predictors	*Estimates*	*CI*	*Statistic*	*p*
(Intercept)	52.86	48.95 – 56.78	26.45	<0.001***
SA	-6.78	-10.69 – -2.86	-3.39	0.001**
Time1	2.12	1.10 – 3.15	4.05	<0.001***
SA X Time	-0.56	-1.59 – 0.47	-1.07	0.284
Random Effects				
σ^2	399.13			
$\tau_{00\ participant}$	270.25			
ICC	0.40			
$N_{participant}$	74			
Observations	1480			
Marginal R^2 / Conditional R^2	0.069 / 0.445			

Note: Contrasts were set as follows: for social anxiety group, high social anxiety participants were coded 1 (vs. low social anxiety participants were coded -1); for time, ratings after feedback were coded 1 (vs. before the speech were coded -1). ***p*<.01, ****p*<.001.

Supplementary Table 3

ANOVA Table Predicting Speech Feedback Provided to Participants

Predictor	*Sum Sq*	*df*	*F*	*p*
(Intercept)	634,303	1	591.48	<0.001
SA	14,470	1	13.49	<0.001
Item Valence	17,798	1	16.60	<0.001
SA X Item Valence	37,851	1	35.30	<0.001
Residuals	1,582,857	1476		

Supplementary Table 4

ANOVA Table Predicting Prediction Errors

Predictor	*Sum Sq*	*df*	*F*	*p*
(Intercept)	19	1	0.03	0.867
SA	53	1	0.08	0.778
Item Valence	432	1	0.66	0.418
SA X Item Valence	197	1	0.30	0.584
Residuals	973576	1476		

Supplementary Table 5

Correlation Matrix of Subjective Units of Distress Scale Measurements Throughout the Session with 95% Confidence Intervals

	T1	T2	T3	T4	T5	T6
T1	-	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***
T2	0.90 (0.87, 0.92)	-	<0.001***	<0.001***	<0.001***	<0.001***
T3	0.65 (0.58, 0.72)	0.73 (0.66, 0.78)	-	<0.001***	<0.001***	<0.001***
T4	0.50 (0.41, 0.58)	0.56 (0.47, 0.63)	0.75 (0.69, 0.80)	-	<0.001***	<0.001***
T5	0.66 (0.59, 0.72)	0.69 (0.62, 0.75)	0.63 (0.55, 0.70)	0.67 (0.60, 0.73)	-	<0.001***
T6	0.74 (0.68, 0.79)	0.76 (0.71, 0.81)	0.70 (0.64, 0.76)	0.55 (0.46, 0.63)	0.64 (0.57, 0.71)	-

Note: T1 = Subjective Units of Distress Scale (SUDS) rating at timepoint 1, baseline at the start of the session. T2 = SUDS rating at timepoint 2, before any instructions were given about the speech. T3 = SUDS rating at timepoint 3, immediately before the speech (after speech instructions, two minutes of silent preparation, and pre-speech ratings). T4 = SUDS rating at timepoint 4, immediately after the speech, participants were asked to rate their peak distress during the speech. T5 = SUDS rating at timepoint 5, immediately after T4, participants were asked to rate their current distress. T6 = SUDS rating at timepoint 6, after post-speech rating task. Correlations and 95% confidence intervals are presented below the diagonal, and p-values are presented above the diagonal.

Supplementary Table 6

Proportions of Self-Ratings on the Speech Expectancies Task in Extreme Ranges of the Response Scale for Participants Low and High in Social Anxiety Symptoms

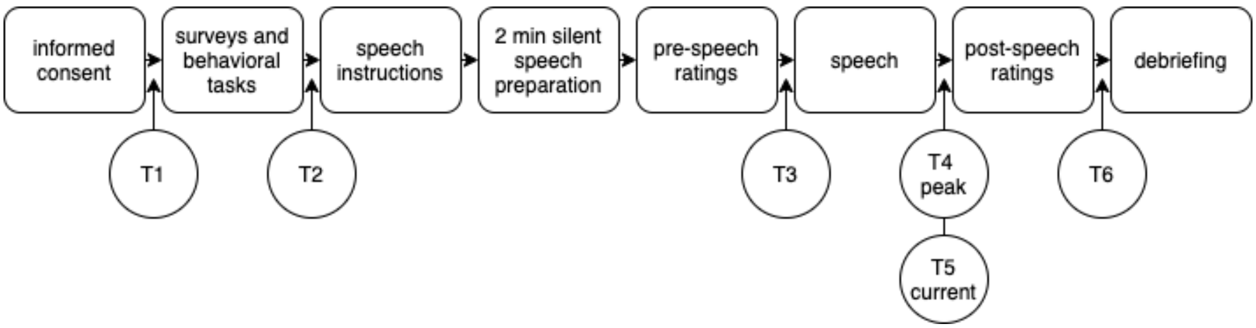
	Ratings < 10		Ratings > 90	
	Low SA	High SA	Low SA	High SA
Pre-speech				
Negative Items	8.13%	4.52%	3.13%	5.48%
Positive Items	5.00%	8.81%	8.44%	3.33%
Post-feedback				
Negative Items	15.31%	9.29%	3.44%	8.57%
Positive Items	3.13%	10.00%	16.56%	4.76%

	Ratings < 10		Ratings > 90	
	Low SA	High SA	Low SA	High SA
Pre-speech				
Negative Items	8.13%	4.52%	3.13%	5.48%
Positive Items	5.00%	8.81%	8.44%	3.33%
Post-feedback				
Negative Items	15.31%	9.29%	3.44%	8.57%
Positive Items	3.13%	10.00%	16.56%	4.76%

Note: SA = social anxiety group.

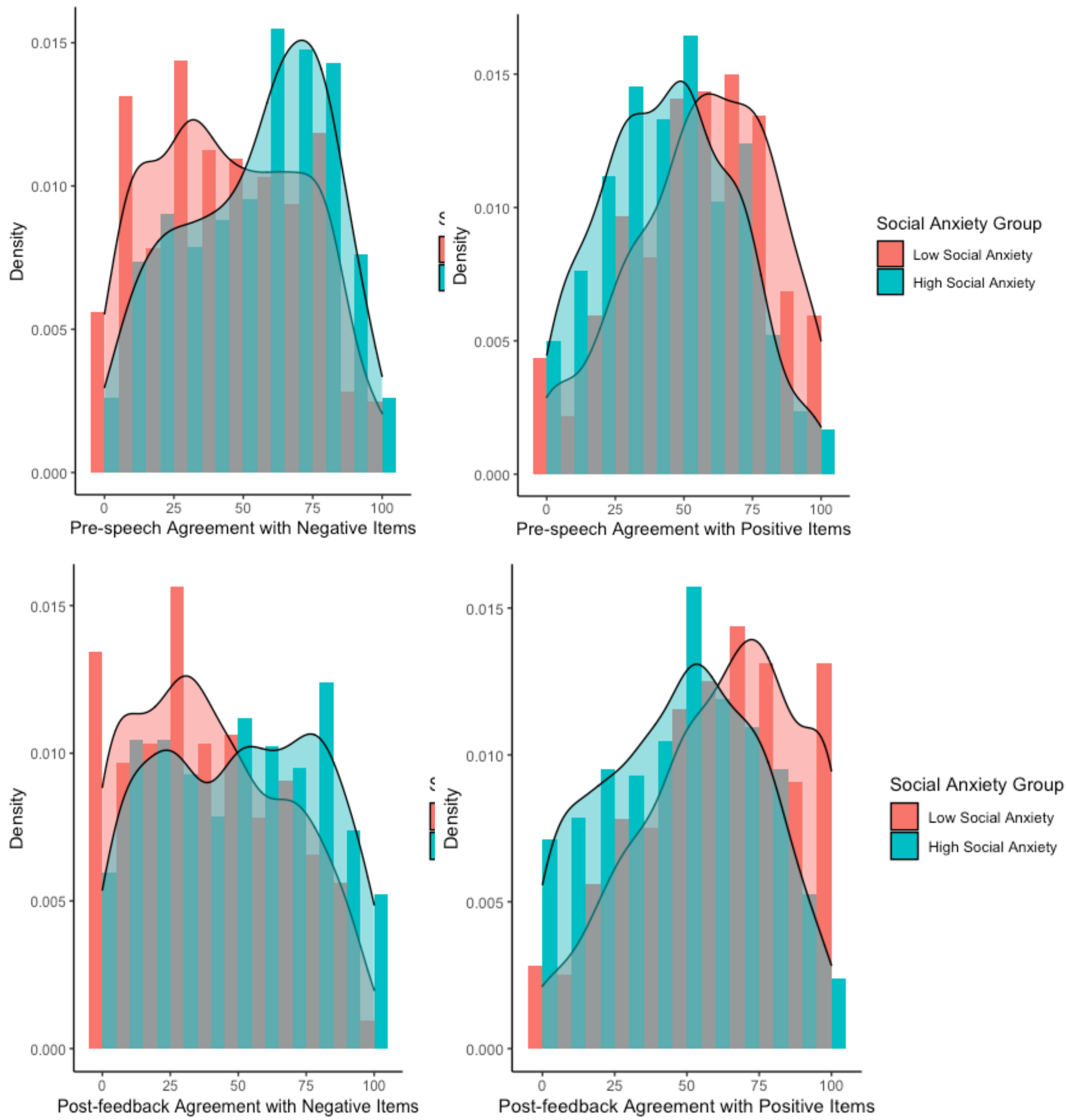
Supplementary Figure 1

Timing of Subjective Units of Distress Scale (SUDS) ratings. SUDS ratings were taken at the six timepoints labeled T1-T6. At all timepoints except T4, participants were asked, “On a scale of 0 to 100, what is your current level of anxiety?” At T4, participants were asked, “On a scale of 0 to 100, what was your highest level of anxiety during the speech?”



Supplementary Figure 2

Density Plots Overlaid on Histograms of Pre-speech and Post-feedback Ratings



Note: Participants high (vs. low) in social anxiety rated themselves more negatively and less positively across timepoints, but both groups' self-ratings on items related to both poor and good social performance (below, termed “Negative Items” and “Positive Items,” respectively) became similarly more positive and less negative after giving the speech and receiving feedback.

Study 3: Social Reinforcement Learning Parameters Change with Interpretation Bias Modification

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Abstract

Biases in social reinforcement learning, or the process of learning to predict and optimize behavior based on rewards and punishments in the social environment, may underlie and maintain some of the negative cognitive biases that are characteristic of social anxiety. This study assessed whether a computerized cognitive bias modification for interpretations (CBM-I) intervention changed social reinforcement learning biases in participants high in social anxiety symptoms. Participants (*N*=106) completed two laboratory sessions, separated by five weeks of tracking emotion regulation strategy use and affect using ecological momentary assessment. Approximately half (*n*=51) also completed up to six brief daily sessions of CBM-I in week three. Participants completed a task that assessed social reinforcement learning about other people at both laboratory sessions, and a task that assessed social reinforcement learning about one's own social performance at the second session. Behavioral data from these tasks were computationally modeled and analyzed with mixed effects models. Results suggested that after CBM-I, participants updated their beliefs about others more slowly but used what they learned to make more accurate decisions, choosing rewarding faces more frequently. They also showed less biased updating about their social performance compared to participants who did not complete CBM-I, learning similarly from positive and negative feedback, and from feedback on items related to poor (vs. good) social performance. Regardless of intervention condition, participants at session two (vs. one) updated their expectancies about others more from rewarding and less from punishing outcomes, and they became more accurate at learning to avoid punishing faces. Both CBM-I and tracking emotion regulation strategy use and affect may have beneficial effects on social reinforcement learning for socially anxious individuals.

Keywords: social anxiety, reinforcement learning, cognitive bias modification

Social Reinforcement Learning Parameters Change with Interpretation Bias Modification

Socially anxious individuals tend to see the world through rejection-colored glasses, perceiving ambiguous social situations as more negative than they are, and expecting to perform poorly in social situations (Hirsch & Clark, 2004; R M Rapee & Heimberg, 1997). Some of these negative cognitive biases, however, might be maintained in part by negative learning biases, wherein socially anxious individuals have difficulty using positive information to update their previously held negative beliefs (Everaert et al., 2018). For example, if a socially anxious person updated their beliefs about an acquaintance more from the few times that acquaintance seemed annoyed with them than from the many times the acquaintance was friendly, they might come to have an overly negative expectancy of interactions with that acquaintance. Similarly, negative expectancies about social performance might be partially explained by overweighting instances of negative versus positive feedback—learning more from criticism than praise. Changing those learning processes to be less negatively biased may have positive downstream effects for socially anxious individuals, like changing rigidly negative beliefs about social interactions and performance to be more balanced and flexible. In this study, we investigate whether a computerized intervention that trains more positive, flexible interpretation styles for socially anxious individuals also modifies the learning process by which they update their social expectancies from new experiences—i.e., social reinforcement learning. We use computational modeling to understand change in particular parameters of interest; specifically, learning rates, which are the weights given to positive and negative feedback when updating social expectancies.

Social Reinforcement Learning Biases

Reinforcement learning (RL) is the process by which people learn to predict outcomes and optimize behavior in an environment where taking actions leads to *rewards* (positive outcomes) and *punishments* (negative outcomes; Sutton & Barto, 1998). Social RL is the same learning process, but specific to the social environment: updating beliefs about different social actions based on social rewards (like acceptance and smiles from others) and social punishments (like rejection and scowls). Previous research has begun to explore social RL in social anxiety, finding that unlike healthy individuals, who update their beliefs about their social performance more from positive feedback from others, socially anxious individuals update more from negative feedback (Koban et al., 2017). Socially anxious individuals also tend to show greater learning from angry versus happy faces (Abraham & Hermann, 2015), and they have difficulty adapting their learning and behavior to changing probabilities of social punishment (Beltzer et al., 2019; Lamba et al., 2020; Piray et al., 2019). Together, these studies suggest that socially anxious individuals may have negative biases in social RL that may make it hard to learn from social interactions, even when they seemingly go well.

Changing Social RL

While there is a considerable literature on the neural underpinnings of RL and how pharmacological interventions may change RL, less is known about changing RL through cognitive and behavioral interventions. Researchers have demonstrated that patterns of RL-related neural activity can predict response to cognitive behavioral therapy (Burkhouse et al., 2016; Queirazza et al., 2019; Webb et al., 2021) and behavioral activation (Nagy et al., 2020), and that these therapies can change RL-related neural activity (Dichter et al., 2009; Webb et al., 2021). Further, several different pharmacological interventions have been used to normalize aberrant processing of rewards and punishments in various psychological disorders (Admon et al., 2017; Jocham et al., 2014; Palminteri et al., 2012; Whitton et al., 2019). Some of these studies have found that pharmacological interventions can specifically change punishment learning rates, in terms of the weights given to negative outcomes when updating expectancies (Herzallah et al., 2013; Pulcu et al., 2019). Taken together, this prior research suggests that RL processes can be changed through pharmacological interventions and that RL is relevant to cognitive behavioral interventions.

However, very little research has assessed whether cognitive behavioral interventions change RL processes, despite several researchers advocating for computationally modeling learning and cognitive change in cognitive behavioral therapy (Moutoussis et al., 2018; Nair et al., 2020). Cognitive remediation therapy has been shown to improve sensitivity to reward and punishment in individuals with schizophrenia (Cella et al., 2014), demonstrating that cognitive interventions can change RL processes, and this change can be detected by computationally modeling behavior. A recent proof-of-concept study demonstrated that a cognitive training paradigm that encouraged learning from negative outcomes could be used to increase punishment learning rates (the weights given to negative feedback in updating beliefs) in healthy individuals, suggesting that cognitive interventions can change RL processes, and specifically, learning rates (Overman et al., 2020). To our knowledge, the present study is the first to behaviorally assess change in RL through a different type of cognitive intervention, cognitive bias modification, and to assess this change in a population with elevated anxiety symptoms.

Cognitive Bias Modification

This study assesses whether several social RL biases—biases in learning from positive and negative social feedback to update beliefs about others and one's own social performance—can be changed through a scalable, computerized intervention called cognitive bias modification for interpretations (CBM-I). CBM-I programs aim to train people to make less threatening and more flexible interpretations of ambiguous stimuli, often by presenting scenarios that are emotionally ambiguous until the final word, with more frequent positive or neutral resolutions to the ambiguity aiming to train interpretive biases to be more benign. CBM-I is a targeted, mechanism-driven intervention that is easily scalable. Because socially anxious individuals can do it from the comfort of their own homes or wherever is convenient for them, it holds potential either as an adjunct to other treatments or as a way to engage individuals who are unwilling to seek in-person treatment or who lack access to psychotherapy, or who may simply believe that a less intensive intervention will work for them. CBM-I can effectively reduce cognitive biases, and to a smaller extent, symptoms of social anxiety disorder (Bowler et al., 2012; Hallion & Ruscio, 2011; Liu et al., 2017; Yeung & Sharpe, 2019). However, note that there has been mixed evidence for CBM-I's efficacy, including small effect sizes (Cristea et al., 2015; Fodor et al., 2020).

CBM-I is a useful intervention to study changes in social RL because the cognitive mechanism targeted in training, rigid negative interpretive biases, may facilitate changes in social RL by priming awareness of potential social rewards and reducing expectations of social rejection. For example, in the CBM-I intervention used in this study, participants read emotionally ambiguous scenarios in which the ambiguity is only resolved in the final word, which is missing a letter that participants complete (e.g., "You are required to give a presentation to a group of work colleagues that you know well. They all are quiet during your presentation. As you think about the presentation later at home, you think that your colleagues found your presentation… stimul_ting"). As a socially anxious participant reads this scenario, they might start to think the scenario will end poorly because they expect punishment in socially threatening situations (e.g., that their colleagues hated their presentation), but the actual resolution of the ambiguity in a rewarding way (i.e., that their colleagues found their presentation stimulating) might train the participant to update their future expectancies to be less threatening. Notably, previous work has found that RL parameters predict response to cognitive bias modification to shift attention bias (i.e., selective focus on threat cues; Alon, Arad, Pine, & Bar-Haim, 2019); given their similar focus on shifting threat biases, CBM-I may also be related to RL.

Evidence for Social RL and CBM-I Change in these Data

Three previous studies that are relevant to the present study have been performed using data from the same dataset, and these studies informed our hypotheses. Two of these studies (Studies 1 and 2 of this dissertation; Beltzer et al., in prep) assessed social anxiety-related differences in social RL by comparing participants high in social anxiety symptoms (who had not completed CBM-I) with participants low in social anxiety symptoms. Participants completed two different social RL tasks, each of which has been analyzed in a previous study. In a task assessing learning about other people (the social probabilistic selection task, described more fully below), participants learned to choose between pairs of neutral faces, each of which had a different probability of becoming happy or angry when chosen (Study 1). In a task assessing learning about one's own social performance (the speech expectancies task, described more fully below), participants gave a speech to judges and then received feedback, which they used to update their beliefs about their performance (Study 2). For each of these studies, we used RL to computationally model how each participant weighted rewarding and punishing social outcomes when updating their beliefs, parameterized as reward and punishment learning rates. In Study 1, we also analyzed how participants used what they learned about other people to make decisions when they were no longer receiving social feedback. These studies did not find social anxiety-related differences in learning rates as a function of social anxiety group or whether social feedback was rewarding or punishing, but did find that, contrary to hypotheses, participants high (vs. low) in social anxiety symptoms were less accurate at avoiding punishing faces once feedback was no longer given (Study 1). Exploratory analyses found that participants (regardless of social anxiety group) updated their expectancies of their social performance more from positive than negative feedback, and that participants high (vs. low) in social anxiety symptoms used feedback to update their expectancies more for elements of poor social performance than good social performance (Study 2). These results suggest that negative social RL biases were not evident in this sample in the ways we had expected; instead, high social anxiety in this sample was characterized by impaired punishment learning accuracy and greater updating from feedback about feared, negative aspects of social performance.

Another study in this dataset (Daniel, Daros, et al., 2020) assessed effects of CBM-I on outcomes related to cognitive styles and social anxiety symptoms. Participants who completed

CBM-I and ecological momentary assessment (EMA) about their emotion regulation experienced greater reductions in trait negative interpretation bias than participants who completed EMA only, but CBM-I was not related to changes in any other trait cognitive styles (i.e., cognitive flexibility, cognitive reappraisal ability, social interaction anxiety, and fear of negative evaluation). CBM-I also increased daily self-reported ability to use cognitive reappraisal, but it did not change other daily cognitive style outcomes more than EMA-only. These results suggest that, in this dataset, the CBM-I intervention effectively changed negative interpretation biases, but did not have effects on many other processes related to social anxiety that it did not target as directly. Given social RL's close conceptual ties to interpretation biases, it is possible that even though null effects were found on many of these peripheral outcomes, CBM-I might still exert effects on social RL.

Overview and Hypotheses

This study examined whether social RL biases changed as a function of completing a week of CBM-I in the middle of a five-week EMA study tracking emotion regulation strategy use and affect (as compared to the comparison condition that also completed the five weeks of EMA but no CBM-I). We assessed whether CBM-I was associated with differences in the weights given to socially rewarding versus punishing information when updating beliefs in two domains: learning about other people and learning about one's own social performance. Given slight methodological differences, these are referred to as "learning rates" for learning about other people and "update weights" for updating social performance expectancies based on feedback. In the domain of learning about other people, we also assessed whether CBM-I was associated with differences in using what one has learned about others to guide one's own behavior to accurately choose rewarding people and avoid punishing people. To do this, we compared parameters extracted from a social probabilistic learning task administered at baseline and follow-up lab sessions, and of a speech expectancy updating task administered at follow-up, as a function of intervention group (CBM-I vs. EMA-only).

To our knowledge, no study to date has assessed change in RL as a function of CBM-I. We had competing hypotheses for most outcomes, as prior analyses of social RL in this dataset found results that diverged from hypotheses based on extant literature.

Hypotheses Based on Prior Literature

Based on conceptually related findings of decreased negative interpretation bias after completing a course of CBM-I (observed both in the literature and in this dataset; Daniel et al., 2020), we hypothesized that socially anxious participants would exhibit a decrease in parameters related to social punishment learning (punishment learning rate and accuracy in avoiding punishment) and/or an increase in parameters related to social reward learning (reward learning rate and accuracy in choosing reward). Modeling these parameters separately allowed us to pinpoint if CBM-I led to changes in learning from social reward and/or punishment, and whether those changes were reflected in the weight given to new social information and/or the accuracy of decisions made based on information learned about reward and/or punishment. Similarly, we hypothesized that socially anxious participants who completed CBM-I would update beliefs about their own social performance more based on positive feedback and/or less based on negative feedback, as compared to the EMA-only group.

Hypotheses Based on Prior Studies in This Dataset

Based on our prior analyses on the social probabilistic learning task finding no differences in learning rates as a function of social anxiety group, we hypothesized that we similarly would not find a difference between intervention groups in learning rates at either session. Based on our surprising finding of impaired accuracy in avoiding punishment in the high social anxiety group (Study 1), we hypothesized that CBM-I might mitigate this bias, evidenced as a greater increase in accuracy in avoiding punishment from baseline to follow-up for the CBM-I (vs. EMA-only) group. For speech expectancy updating, we hypothesized that there would be no difference between update weights in a model that included four update weights (estimated separately for positive and negative prediction errors on items assessing good vs. poor social performance), consistent with our earlier finding of no difference between social anxiety groups. However, based on our prior exploratory finding of greater updating on items assessing poor social performance in the high (vs. low) social anxiety group (Study 2), we hypothesized that a model with two update weights (estimated separately for items assessing good vs. poor social performance) would reveal a CBM-I vs. EMA-only intervention-related difference. Specifically, we hypothesized that CBM-I would mitigate this bias toward greater updating on items assessing poor social performance such that the CBM-I (vs. EMA-only) group would update their expectancies less from feedback on items measuring poor (vs. good) performance. Plans for analyses and competing hypotheses were preregistered at: https://osf.io/2g68x/.

Method

Participants

N=114 adults (18-45 years old) with high social anxiety symptoms were recruited from the University of Virginia undergraduate participant pool and the broader university and Charlottesville communities. Participants were recruited through advertisements sent to university email lists for undergraduate and graduate students and flyers posted in public areas. Prospective participants with moderate to severe social anxiety symptoms were eligible to participate (scoring 29 or greater out of a possible 80 points on the Social Interaction Anxiety Scale, approximately ¼ of a standard deviation below the mean in a sample diagnosed with social phobia; Mattick & Clarke, 1998). See Table 1 for demographic characteristics of the final sample of *N*=106 analyzed (described in Data Reduction in the Method section).

Procedure[4]

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[4] This study is part of a larger data collection. Because the mobile app used for EMA only ran on certain versions of iOS and Android OS, participants who did not have a compatible smartphone were excluded. More information about the EMA component of the study, as well as other measures administered but not analyzed in this study, can be found at https://osf.io/utk7m/.

All participants completed a baseline session in the lab that included questionnaires and the social probabilistic selection and speech expectancies tasks. Participants then completed five weeks of EMA about their emotion regulation (which is analyzed elsewhere; Beltzer et al., 2021; Daniel, Daros, et al., 2020; Daniel, Goodman, et al., 2020), followed by another laboratory session with the same tasks. Approximately half of the sample (*n*=59) were randomized to complete a week-long CBM-I intervention during week three.

Cognitive Bias Modification

Over the course of week three, participants assigned to the CBM-I condition were asked to complete six 10-15-minute CBM-I sessions on their personal computer or smartphone, once per day. Participants read a series of 30 ambiguous scenarios that raised the possibility of a threat (18 social threat, 8 physical threat, 5 other), which only became disambiguated once the final word of the scenario was read, from which one or two letters were missing (e.g., “While at the hairdresser's, you opt for a completely different haircut. When you see your friend afterwards, she gasps. Her gasp probably means that she thinks the new style makes you look… gre_t.”). After filling in the correct missing letter(s) to resolve the scenario’s emotional ambiguity (e.g., “gre**a**t”), the participant was asked a yes/no or multiple choice question about the scenario to ensure the participant had read it and understood the disambiguated ending. The disambiguation resolved the ambiguity in a benign, non-threatening way for 90% of scenarios, allowing participants to learn through practice that uncertain situations can end in a variety of ways (including in more rewarding ways than expected, counteracting their biased negative expectations). The full list of CBM-I materials (including scenarios, disambiguating words, and comprehension questions) is available at https://osf.io/8mhjw/.

Measures

Social Probabilistic Selection Task

The social probabilistic selection task (Abraham & Hermann, 2015) was used to assess social RL about other people. It was an adaptation of a widely used probabilistic category-learning paradigm (Frank et al., 2004) that used socially relevant information as stimuli (neutral faces) and socially evaluative reinforcement as feedback (reward: happy faces, punishment: angry faces). This task consisted of two phases: training and testing. In the training phase, participants were presented with two neutral faces at a time, and instructed that one face would become happy if chosen, but the other would become angry. They were instructed to select the face they thought was more likely to become happy. The pairs of faces had different, complementary reward contingencies (i.e., in one pair, one face became happy 80% of the times it was chosen and angry 20%, and the other face became happy 20% and angry 80%; the other pairs were 70/30 and 60/40) but participants had to learn which faces to choose through trial and error rather than ever explicitly being told the contingencies. In the testing phase, the faces were recombined into all possible pairs (e.g., the 80% rewarding face was now presented in pairs with the 70%, 60%, 40%, 30%, and 20% rewarding faces, rather than just the 20% rewarding face as in the training phase). Participants were instructed to select the more rewarding face based on what they had learned during the training phase, and no feedback was given (i.e., the neutral faces did not become happy or angry). See Study 1 for more detail about the social probabilistic selection task.

Speech Expectancies Task

The speech expectancies task (similar to Koban et al., 2017) was used to assess social RL about one's own social performance. Modified from the Trier Social Stress Test (Kirschbaum et al., 1993), participants had two minutes to mentally prepare to give a stressful speech for a panel of two confederate judges, who video-recorded the speech. Before the speech, participants rated how they expect to perform on ten items related to good social performance (e.g., "I will appear calm") and ten related to poor performance (e.g., "I will appear to be sweating") on a scale from 0 ("disagree") to 100 ("agree"; adapted from Cody & Teachman, 2010). After the speech at the second lab session[5], participants received false feedback on their performance, which was ostensibly from the judges, but which was actually randomly generated to fall within a range around the participant's pre-speech self-ratings. For each social performance-related item, participants were asked to rate how they expected to perform on a similar speech in the future. Before entering their post-speech expectancy rating, they were first shown their pre-speech rating, then the false feedback. See Study 2 for more detail about the speech expectancies task.

Plan for Analyses

This study assessed whether socially anxious individuals who completed CBM-I plus EMA (vs. only EMA) learned differently from positive and negative social feedback when updating their expectancies about other people and about their own social performance. To do this, we applied versions of a Q-learning model to the social probabilistic selection task and the speech expectancies task, then compared parameters related to learning (i.e., learning rates and update weights for positive and negative feedback) between groups. In the domain of learning about other people, we also assessed whether CBM-I changed participants' accuracy in choosing socially rewarding and avoiding socially punishing faces during the testing phase of the social probabilistic selection task. Reward and punishment learning accuracy were defined as the proportion of times the participant accurately selected the more rewarding face when the most rewarding (80% happy) and most punishing (80% angry) faces, respectively, were paired with all other faces during the testing phase.

Computational Modeling of the Social Probabilistic Selection Task

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5 We provided feedback only at the second session in order to be able to immediately debrief participants about the deception at the end of the session, and so this feedback would not influence other study measures. We also checked for suspicion using a funnel debriefing with open-ended questions that progressed from more general to specifically querying for suspicion about the speech task, ending with "Did you believe the judges' feedback on your speech?"

The social probabilistic selection task was computationally modeled using the hBayesDM package (Ahn et al., 2017) in R, which includes hierarchical Bayesian modeling of the Q-learning estimation procedure implemented in Frank et al. (2007). Q-learning models the process of updating expected values of each neutral face by learning from each experience of a rewarding (e.g., happy) or punishing (e.g., angry) outcome. We compared two candidate models. One model fitted the participants' choice data from the training phase of the task with separate reward and punishment learning rate parameters, which, respectively, represent the weights given to positive and negative prediction errors (the value difference between the observed and expected outcomes) when updating these expected values. The other model included a single learning rate parameter for all trials (and so was nested in the more complex model). We compared prediction accuracy for each condition at each session using leave-one-out information criterion (LOOIC) given our relatively small sample size (Vehtari et al., 2017). Because the more complex model had a lower LOOIC for one group, and the models provided relatively similar fit for the other groups, the more complex model was chosen as it was needed to explain response patterns in that group (see Supplemental Materials for LOOIC values). See Study 1 for more detail about computational modeling of this task and how model fit was assessed.

Computational Modeling of the Speech Expectancies Task

For the speech expectancies task, we used similar models to estimate how heavily each participant weighted positive and negative feedback when updating their post-speech expectancies of how they would perform on a future speech. For each participant, we estimated these update weights separately for feedback that was more positive than participants' pre-speech self-ratings (i.e., positive prediction errors) and feedback that was more negative than participants' pre-speech self-ratings (i.e., negative prediction errors). Note that these update weights were similar to the learning rates modeled for the social probabilistic selection task, but were estimated over only one instance of updating. See Study 2 for more detail about computational modeling of this task.

Results

Data Reduction

Eight participants of the *n*=59 assigned to the CBM-I group did not initiate any CBM-I training sessions (three dropped out of the study prior to CBM-I, five declined to initiate CBM-I but remained in the study) and were removed from analyses, leaving a final intent to treat sample of *N*=106 (*n*=51 in the CBM-I group and *n*=55 in the EMA-only group). All 51 participants who completed at least one CBM-I session were included in analyses, regardless of how many additional CBM-I sessions they completed. Of the *n*=51 participants in the CBM-I condition in the intent to treat sample, 41 participants completed all six CBM-I training sessions, two completed five sessions, one completed four sessions, three completed three sessions, two completed two sessions, and two completed one session.

Of the sample of *N*=106, five participants dropped out of the study between sessions and two were unable to come into the lab for the second session, so their data were only available for the baseline session. For the social probabilistic selection task, data were missing for two participants at session two due to technical problems (e.g., computer freezing). One participant's data for the testing phase were missing at the baseline session due to experimenter error.

For the speech expectancies task, three participants declined to complete the speech at the second session. Of those with complete speech expectancies task data, 18 participants indicated during the funnel debriefing that they did not believe the judges' feedback and were thus excluded from analyses, resulting in a final sample of 78 (*n*=36 in the CBM-I group and *n*=42 in the EMA-only group) participants included in analyses for the speech expectancies task.

Analyses of the Social Probabilistic Selection Task (RL About Other People)

Behavior on the social probabilistic selection task was analyzed to better understand how CBM-I affected social RL about other people. Specifically, we assessed reward and punishment learning rates, which described the weights given to happy and angry faces, respectively, in updating expectancies of other people during the training phase, and accuracy in choosing rewarding and avoiding punishing faces in the testing phase.

Learning Rates Estimated Over the Training Phase

To assess learning rate differences as a function of CBM-I condition, a mixed effects model was performed predicting learning rate from fixed effects of CBM-I condition, session, prediction error valence, and all two- and three-way interactions, with a random intercept for participant. There were significant session X condition and session X prediction error valence interactions. Post-hoc pairwise comparisons of estimated marginal means (with a Tukey adjustment)[6] revealed that, in the CBM-I condition, learning rates decreased from session one (M = 0.23, SE = 0.01) to session two (M = 0.20, SE = 0.01, t(303) = -2.04, p = 0.042, d = -0.29), but did not significantly change in the EMA-only condition (session 1: M = 0.22, SE = 0.01; session 2: M = 0.25, SE = 0.01, t(308) = 1.79, p = 0.074, d = 0.25). In other words, after completing CBM-I, participants updated their expectancies about other people less based on feedback, regardless of whether that feedback was a happy or angry face. Punishment learning rates decreased from session one (M = 0.25, SE = 0.01) to session two (M = 0.20, SE = 0.01, t(299) = -3.34, p = 0.001, d = -0.47), whereas reward learning rates increased from session one (M = 0.21, SE = 0.01) to session two (M = 0.26, SE = 0.01, t(299) = 3.04, p = 0.003, d = 0.43; Figure 1). This means that by the end of the study, participants (regardless of intervention condition) updated their expectancies about others less from angry faces and more from happy faces. See Table 2. These findings were partially in line with hypotheses based on prior literature. We hypothesized that punishment learning rates would decrease and/or reward

[6] For all post-hoc tests, note that estimated marginal means and odds ratios are presented on the logit scale.

learning rates would increase in the CBM-I condition, whereas results suggested that both of these changes were observed regardless of intervention condition (rather than specific to CBM-I). Furthermore, learning rates decreased in the CBM-I condition regardless of prediction error valence (rather than specific to negative prediction errors).

Accuracy Measured During the Testing Phase

To assess differences in accuracy at choosing the most rewarding face and avoiding the most punishing face in the testing phase as a function of CBM-I condition, a generalized linear mixed model was performed predicting the proportion of times the participant accurately chose the most rewarding face and accurately did not choose the most punishing face when each of them was paired with all other faces in the testing phase. This model included fixed effects of CBM-I condition, session, prediction error valence, and all two- and three-way interactions, with a random intercept for participant. There was a significant main effect of trial type (choose reward vs. avoid punishment) that is not interpreted because it was subsumed within a significant interaction. There were statistically significant session X condition, session X trial type, and condition X trial type interactions (Figure 2). See Table 3.

To better understand these statistically significant interactions, we performed post-hoc pairwise comparisons of the estimated marginal means (with a Tukey adjustment). Following up on the session X condition interaction, we found that testing phase accuracy increased from session 1 (M = 1.47, SD = 0.13) to session 2 (M = 1.67, SD = 0.13, OR = 2.84, p = 0.005, d = 0.20) in the CBM-I condition, but did not change in the EMA-only condition (session 1: M = 1.48, SD = 0.12; session 2: M = 1.44, SD = 0.12, OR = 0.56, p = 0.578, -d = 0.04). In other words, after completing CBM-I, participants used the probabilities they had learned to make better decisions about other people in the testing phase, regardless of whether that meant choosing rewarding faces or avoiding punishing faces.

Following up on the session X trial type interaction, we found that accuracy in avoiding punishment increased from session 1 (M = 1.13, SD = 0.09) to session 2 (M = 1.33, SD = 0.09, *OR* = 3.28, *p* = 0.001, *d* = 0.20), but accuracy in choosing reward did not (session 1: *M* = 1.82, *SD* = 0.10; session 2: *M* = 1.78, *SD* = 0.10, *OR* = -0.62, *p* = 0.535, *d* = -0.04). This suggests that by the end of the study, participants (regardless of CBM-I condition) became better at learning to avoid the most punishing face. These results were partially in line with hypotheses based on prior studies in this dataset. We hypothesized that accuracy in avoiding punishment would increase for the CBM-I condition, whereas results suggested that accuracy (not specific to punishment) increased for the CBM-I condition, and accuracy in avoiding punishment increased, but not specifically for the CBM-I condition.

Following up on the condition X trial type interaction, we found that accuracy in choosing reward was higher than accuracy in avoiding punishment for both the CBM-I (choose reward: *M* = 1.93, *SD* = 0.13; avoid punishment: *M* = 1.20, *SD* = 0.13, *OR* = 10.84, *p* < 0.001, *d* = 0.73) and EMA-only conditions (choose reward: *M* = 1.66, *SD* = 0.12; avoid punishment: *M* = 1.26, *SD* = 0.12, *OR* = 6.37, *p* < 0.001, *d* = 0.40). In other words, regardless of session, participants in both conditions made better decisions in the testing phase when selecting from a pair that included the most rewarding face instead of the most punishing face. Notably, examination of the effect sizes and visual inspection of the interaction plots suggested that this difference between accuracies in choosing reward and avoiding punishment was greater in the CBM-I (vs. EMA-only) condition. This result is partially in line with hypotheses based on prior literature. We hypothesized that learning biases would become less negative or more positive with CBM-I, and we found that learning biases were more positive in the CBM-I condition versus EMA-only (but regardless of session).

Analyses of the Speech Expectancies Task (RL About One's Own Social Performance)

Self-ratings before and after feedback on the speech expectancies task were analyzed to better understand how CBM-I affected social RL about one's own social performance. Specifically, we assessed update weights describing the extent to which feedback from the judges was weighted when participants updated their expectancies of their own public speaking performance. These update weights were conceptually similar to the learning rates on the social probabilistic selection task, but described learning in a different domain (about one's own social performance, rather than about other people).

Update Weights Estimated Separately by Prediction Error and Item Valence

To compare expectancy updating between social anxiety groups, a linear mixed effects model was performed predicting update weights, with update weights estimated separately over positive and negative prediction errors and items measuring good versus poor social performance (so, estimating four update weights per participant). This model included fixed effects of CBM-I condition, item valence, and prediction error valence, and all two- and three-way interactions, with a random intercept for participant. Four observations (1.5% of the data) were identified as influential outliers (classified as those whose Cook's distance was greater than four divided by the number of observations), and removed (Cook, 1977). The model's fit was singular, so the random intercept was dropped and a linear model was tested. The only statistically significant effect was a main effect of prediction error valence, such that participants more heavily weighted positive (vs. negative) feedback when updating their expectancies about their social performance (Figure 3). See Table 4.

Update Weights Estimated Separately by Prediction Error Valence

Given concerns in a previous study that twenty items were insufficient for reliably modeling four separate update weights per participant, follow-up analyses were performed estimating update weights over more trials—specifically, estimating separate update weights for positive and negative prediction errors, collapsing across item valence; estimating separate update weights for items measuring good and poor social performance, collapsing across prediction error valence; and estimating one update weight for all twenty items.

For update weights estimated separately by prediction error valence, a mixed effects model was performed predicting update weights from fixed effects of CBM-I condition, prediction error valence, and their interaction, with a random intercept for participant. Nine influential outliers were removed. A significant main effect of prediction error valence was observed but is not interpreted because it was subsumed within a significant interaction with CBM-I condition. Post-hoc pairwise comparisons of the estimated marginal means (with a Tukey adjustment) revealed that, contrary to hypotheses based on prior literature, participants in the EMA-only condition updated their expectancies about their social performance more from positive (M = 0.62, SE = 0.05) than negative feedback (M = 0.42, SE = 0.05, t(68.9) = 3.43, p = 0.001, d = -0.78), whereas participants in the CBM-I condition updated similarly from positive (M = 0.55, SE = 0.05) and negative feedback (M = 0.54, SE = 0.05; t(68.4) = 0.20, p = 0.846, d = -0.05; Figure 4). This suggests that EMA-only participants showed a bias towards learning from positive feedback about their social performance, whereas CBM-I participants did not learn significantly differently from positive versus negative feedback. See Table 5.

Update Weights Estimated Separately by Item Valence

For update weights estimated separately by item valence, a mixed effects model was performed predicting update weights from fixed effects of CBM-I condition, item valence, and their interaction, with a random intercept for participant. Ten influential outliers were removed. A significant main effect of item valence was observed but is not interpreted because it was subsumed within a significant interaction with CBM-I condition. Post-hoc pairwise comparisons of the estimated marginal means (with a Tukey adjustment) revealed that, in line with hypotheses based on prior work in this dataset, participants in the EMA-only condition updated their expectancies more from feedback on items measuring poor (M = 0.52, SE = 0.04) versus good social performance (M = 0.41, SE = 0.04, t(70.2) = -4.60, p < 0.001, d = 1.04), whereas participants in the CBM-I condition updated similarly from feedback on both types of items (poor items: M = 0.51, SE = 0.04; good items: M = 0.51, SE = 0.04, t(69.6) = -0.12, p = 0.909, d = 0.03; Figure 5). This suggests that EMA-only participants showed a bias towards learning from feedback about poor aspects of social performance, like speaking too quickly, versus good aspects, like seeming confident, whereas CBM-I participants did not learn significantly differently from feedback on poor vs. good items. See Table 6.

Update Weights Estimated Over All Items Together

A t-test was performed comparing a single update weight estimated over all items between CBM-I conditions, and found no significant difference between the EMA-only (M = 0.45) and CBM-I (M = 0.53) conditions (t(74.25) = -1.33, p = 0.187, d = 0.30). When speech expectancy updating was modeled with no regard for item or prediction error valence, no differences were found between intervention groups.

Discussion

This study assessed CBM-I's effects on social reinforcement learning in socially anxious individuals, focusing on two important domains: learning about other people, and learning about one's own social performance. For the most part, we did not find evidence supporting the three-way interactions we had hypothesized (i.e., interactions between session, intervention condition, and prediction error valence), but we did find evidence of several related two-way interactions. After (vs. before) CBM-I, participants updated their expectancies of other people on the social probabilistic selection task more slowly from new social information, and they used what they learned to make more accurate decisions. These changes were not observed in the EMA-only condition, suggesting that they were likely related to the CBM-I intervention. Further, participants who completed CBM-I used social feedback to update their expectancies of their own performance on the speech expectances task in less biased ways than EMA-only participants in that they learned similarly from positive and negative feedback and learned similarly from feedback on items related to poor (vs. good) social performance. We also observed several effects as a function of session (i.e., change over time), regardless of intervention condition, which might be a result of either practice with the social probabilistic selection task or from the five weeks of EMA tracking affect and emotion regulation that all participants completed. Specifically, at the end of the study, participants updated their expectancies about others more from reward and less from punishment, and they became more accurate at avoiding punishment, as compared to at the start of the study. While these were some of our major findings, we also found several other statistically significant effects along with a number of null effects, which we discuss below, grouped by the types of learning they describe.

Updating Expectancies Based on New Social Information

We assessed how socially anxious individuals update their beliefs based on new social information by analyzing learning rates on the social probabilistic selection task (to measure updating expectancies about other people) and update weights on the speech expectancies task (to measure updating expectancies about one's own social performance). There were a total of five models that asked this conceptual question about updating: one for learning about other people, and four for learning about one's own performance (because update weights were estimated over different numbers of trials to address questions about the number of trials needed to do this estimation reliably).

CBM-I's Effects on Expectancy Updating

We found slightly different effects of CBM-I on expectancy updating in the two domains assessed. Participants in the CBM-I but not EMA-only condition updated their expectancies about other people on the social probabilistic selection task more slowly at session two (vs. one). We did not find any similar main effects of CBM-I on updating expectancies about one's own social performance on the speech expectancies task for any of the four models for this task. However, we did find evidence of biased updating about one's social performance in the EMA-only group on the speech expectancies task (learning more from positive than negative feedback, and learning more from feedback on items related to poor (vs. good) social performance), but did not observe these biases in the CBM-I group. This suggests that CBM-I might be associated with different changes in social RL in these two domains relevant to social anxiety: slower updating about other people, and less biased updating about one's own social performance. (Of course, the results could also be due to other task differences besides the focus on updating about others vs. oneself given the tasks and self/other updating focus are perfectly confounded in this study.)

Slower Updating about Other People. Learning rates on the social probabilistic selection task decreased from session one to session two for participants who completed CBM-I, but not for participants who completed EMA-only. This suggests that CBM-I led socially anxious individuals to update their beliefs about other people less based on each new happy or angry face. This unexpected finding may be due to the format of CBM-I training, in which participants read through each emotionally ambiguous scenario sentence by sentence, accumulating information slowly, and they cannot come to an emotional resolution until the final word. This intervention may work to slow learning rates by training participants to rely less on any one piece of information when figuring out what to expect of a situation or a person. Slower updating about other people is likely clinically useful in situations where the probabilities of reward and punishment are stable; another person might sometimes respond positively and sometimes negatively to different things you do, but because these probabilities would be relatively stable, it would be adaptive not to change your expectancies too much based on each new reaction from them. Socially anxious individuals tend to revise their impressions of others more quickly than do less anxious individuals (Haker et al., 2014), so decreasing these learning rates, as appears to happen through CBM-I, might be beneficial. However, it is also worth considering potential downsides of slower updating about others. If a socially anxious individual already has negatively biased expectancies about others (e.g., “Other people will reject me.”), these biases may be corrected more slowly if the person updates their prior beliefs more slowly from new information that is overall more positive than expected. While these beliefs would eventually move towards less biased expectancies through unbiased updating from both positive and negative outcomes (i.e., similar learning rates for reward and punishment, as we observed), this change would occur more slowly for people who update their beliefs about others more slowly. Other work in this dataset (Daniel, Daros, et al., 2020), though, found that CBM-I was associated with a decrease in negative interpretation bias (the target of CBM-I), suggesting that the slower updating elicited by CBM-I does not preclude a shift towards more positive beliefs in uncertain situations.

Less Biased Updating about One's Own Performance. Note that because speech expectancy updating was only measured at session two, we cannot draw conclusions about a change in these biases as a function of CBM-I, but we can consider what a difference in updating between people who completed CBM-I versus EMA-only might mean. When updating expectancies of one's own social performance based on feedback on the speech expectancies task, two different modeling approaches (i.e., update weights estimated separately by item valence, and estimated separately by prediction error valence) found that two different updating biases (learning more from feedback on aspects of poor vs. good social performance, and learning more from positive than negative feedback) occurred in the EMA-only but not in the CBM-I condition.

It is not clear, though, that the unbiased updating observed in the CBM-I condition is uniformly beneficial, given the nature of the biases observed in the EMA-only condition. The biases observed in the EMA-only condition were towards learning more from feedback on items related to poor (vs. good) social performance and towards learning more from positive than negative feedback. The bias towards learning more from feedback on aspects of poor (vs. good) social performance was previously found in this dataset to characterize participants high, but not low, in social anxiety symptoms. This bias may be related to socially anxious individuals being more motivated to avoid embarrassment than to aim for excellent performance. As such, it may be good that participants who completed CBM-I did not show this bias. However, participants in the EMA-only condition also learned more from positive than negative feedback, which is likely adaptive as it would lead to updating expectancies of one's own social performance to be more positive, and these types of positive biases are usually associated with psychological well-being (e.g., Romano et al., 2020; Sharot, 2011). So, it is likely not good that participants who completed CBM-I did not show this healthy, positive bias. Although participants who completed CBM-I showed less biased updating from feedback about their own social performance than participants who completed EMA only, this unbiased updating seems adaptive in mitigating a bias towards learning from feedback about poor performance and maladaptive for mitigating a bias towards learning from positive feedback.

More Positively Biased Expectancy Updating Over Time

Because the social probabilistic selection task was administered at both sessions but the speech expectancies task was only administered at session two, we were able to analyze change in expectancy updating about other people over time, but only had a snapshot of expectancy updating about one's own performance at the end of the study. We found that at the end of the study, participants (regardless of intervention condition) showed more positively biased updating about other people on the social probabilistic selection task, updating their beliefs more from reward and less from punishment at session two than at session one. This change over time is consistent with the session two snapshot of updating expectancies about one's social performance on the speech expectancies task, which found more updating from positive than negative feedback on the four-weight model. Note, though, that the two-weight model, but not the four-weight model, found that this effect was qualified by an interaction with intervention condition, as described in the preceding section, suggesting that the way in which item valence is treated in the model may have implications for this effect. Overall, though, these findings of more positively biased updating about others over time and about one's own performance at the end of the study suggest that the EMA portion of the study completed by all participants might have had positive effects on social RL in both the self and other domains. Tracking one's emotions multiple times each day for several weeks and bringing attention to one's use of emotion regulation strategies and their associated effectiveness might have increased participants' motivation to regulate their emotions, which might be accomplished by learning in positively biased ways. We know from prior work in this dataset that trait and state social anxiety symptoms and fear of negative evaluation decreased over the course of this study, regardless of intervention condition (Daniel, Daros, et al., 2020), further supporting the helpful effects of EMA about emotion regulation. However, we did not find evidence of social anxiety-linked biases in expectancy updating in prior studies in this dataset (Studies 1 and 2 of this dissertation; Beltzer et al., in prep). So, although high social anxiety participants came to update their expectancies in more positively biased ways over the course of the study, their expectancy updating was not significantly different from participants low in social anxiety.

Learning to Choose Social Reward and Avoid Social Punishment

In addition to assessing CBM-I's effects on how socially anxious individuals use different types of social information to update their expectancies, we also analyzed how socially anxious individuals use what they have learned about other people to make decisions. This process was only measured in the domain of learning about other people, not learning about one's own social performance. Although we did not find evidence of the hypothesized three-way interaction, we did find evidence of all of the composite two-way interactions. First, CBM-I, but not EMA-only, participants' decision accuracy improved over the course of the study, such that they were able to more frequently select the more rewarding face during testing phase trials that included the most rewarding and most punishing faces. This suggests that CBM-I may improve social decision-making in socially anxious individuals, which may manifest in choosing to interact with people who are more likely to respond positively to them, or in choosing actions that are more likely to elicit a positive response. Second, participants became better at avoiding social punishment, but not at choosing social reward, over the course of the study. This effect was not specific to CBM-I, and suggests that either EMA about emotion regulation or practice with the task might improve accuracy in learning to avoid social punishment. This finding is particularly noteworthy because previous research, both in this dataset (Study 1) and elsewhere (Lamba et al., 2020), has found that anxious individuals may show impairments in learning to avoid people who respond negatively to or take advantage of them. Frequent monitoring of emotions (as occurred in the EMA portion of this study) might help make socially anxious participants more aware of when certain people make them feel bad, which might help them learn to avoid these types of punishing people. Lastly, we found that participants in both conditions tended to be more accurate at choosing social reward than avoiding social punishment, but this difference was larger in the CBM-I than EMA-only condition. Because this effect was found regardless of session, we cannot say whether completing CBM-I contributed to this difference. This finding of higher accuracy at choosing reward than avoiding punishment is consistent with prior work in this dataset (Study 1) that found that participants high in social anxiety symptoms had impaired punishment learning accuracy relative to participants low in social anxiety symptoms.

Clinical Implications

This study was the first to our knowledge to examine the effects of CBM-I and EMA about emotion regulation on RL. Both CBM-I and EMA are digital interventions that can be scaled up at low cost to increase access to treatment, which may help bridge the treatment gap for socially anxious individuals. We found that CBM-I was associated with several changes in social RL that might be helpful for socially anxious individuals. Participants who completed CBM-I were slower to change their beliefs about others based on each instance of facial feedback. In real life, this might mean that CBM-I could help socially anxious people resist the urge to jump to a conclusion about a person based on a single bad (or good) interaction. CBM-I also improved the accuracy of social decision-making about other people (as evidenced by their more frequently selecting more rewarding faces on the social probabilistic selection task at follow-up vs. baseline). This higher accuracy might help socially anxious individuals navigate social situations more successfully, resulting in more positive interactions with others and better relationships. Participants who completed CBM-I also used feedback to update their beliefs about their own social performance in less biased ways than participants who completed EMA only, but this unbiased updating seems a bit of a mixed blessing. CBM-I seems to have mitigated the bias (that was observed in the EMA-only group) towards learning more from feedback on poor than good aspects of speech performance, and having this type of unbiased updating is likely healthier for the CBM-I group (than the bias observed in the EMA-only group). However, CBM-I also seems to have mitigated the bias (that was observed in the EMA-only group) towards learning more from positive than negative feedback. The EMA-only group's bias towards learning from positive feedback would likely lead to more positive expectancies of one's own social performance over time, which is likely healthier than the CBM-I group's unbiased learning from positive and negative feedback.

Effects observed over time regardless of intervention condition suggest that tracking emotions and emotion regulation may also be helpful for social RL, possibly increasing learning from positive feedback and decreasing learning from negative feedback. Given all participants completed EMA, it is hard to disentangle what mechanisms might be at work. Emotion tracking might make socially anxious individuals more aware of the outcomes of their emotion regulation attempts, or it might encourage them to regulate in ways that promote positive affect, increasing motivation to learn from positive social outcomes. Or, they may pay more attention to when people treat them poorly and learn to make better decisions accordingly to avoid that treatment. Empirical questions regarding mechanisms of change in social RL remain to be addressed in future studies.

Other work in this dataset has found that CBM-I decreased participants' trait negative interpretation bias and increased their ability to use cognitive reappraisal day-to-day, but was not associated with changes in cognitive flexibility, and decreases in social anxiety symptoms occurred regardless of intervention condition (Daniel, Daros, et al., 2020).That we found intervention-related changes in social RL and interpretation bias but non-specific changes in symptoms brings up interesting questions of the relations among these cognitive, emotional, and behavioral processes. The current research design does not allow us to disentangle the temporal relations between changes in social RL and changes in interpretation bias and symptoms. However, it seems possible (and worth testing empirically in future research) that changes in social RL precede changes in social anxiety symptoms. For example, improvements in social decision-making accuracy may lead to more rewarding social interactions, which may in time decrease social avoidance and fears of negative evaluation.

Limitations

There are several limitations worth noting in this study's methodology. First, while the CBM-I intervention included mostly social scenarios, it also included several non-social scenarios. Its effects on social RL might have been stronger if the intervention had specifically targeted negative interpretation bias in social situations. Second, all participants, including those in the comparison condition, completed five weeks of EMA about their emotion regulation, which may have increased self-reflection about participants' emotions and social situations that prompted those emotions (Boswell et al., 2015; Roth et al., 2017), making it harder to identify CBM-I-specific effects. Third, this study might have been underpowered to detect the hypothesized three-way interactions. Unfortunately, we did not conduct a power analysis before data collection. Relevant effect sizes in other studies with fewer participants were medium-large (Abraham & Hermann, 2015: $d = 0.54$ for high social anxiety participants avoiding punishing faces more frequently than low social anxiety participants; Koban et al., 2017: partial $\eta^2 = 0.26$ for the feedback valence by social anxiety group interaction in updating beliefs about one's past speech performance), but sample sizes need to be increased fourfold to detect three-way versus two-way interactions, as were tested in those studies (Heo & Leon, 2010). Fourth, characteristics of our sample, including their relative homogeneity in age, race, and ethnicity, and that they were not clinically diagnosed with social anxiety disorder, limit generalizability to clinical populations more broadly.

Future Directions

Given our initial findings of several positive changes in social RL associated with CBM-I, future research may help illuminate mechanisms of change, as well as how changes in social RL relate to changes in other important constructs, like interpretation bias and social anxiety symptoms. Researchers may also consider other potential relations between social RL and CBM-I (e.g., do certain patterns of social RL predict response to CBM-I in terms of interpretation bias and symptom change?). Further, studies may look at how social RL changes over the course of other interventions, like cognitive behavioral therapy, may predict response to treatment. Updating rigidly negative expectancies and beliefs is at the heart of cognitive behavioral therapy; continued work on social RL in social anxiety may help us understand why certain biases persist and how we might work to change them.

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Table 1

Demographic Characteristics of the Intent-to-Treat Sample

	CBM-I	EMA-only
n	51	55
Sex		
Females (%)	38 (74.51%)	40 (72.73%)
Males (%)	13 (25.49%)	15 (27.27%)
Non-binary (%)	0 (0%)	0 (0%)
M_{age} in years (SD_{age})	20.67 (2.92)	20.24 (3.12)
Undergraduates (%)	36 (70.59%)	46 (83.64%)
Ethnicity		
Latinx/Hispanic (%)	1 (1.96%)	2 (3.64%)
Not Latinx/Hispanic (%)	50 (98.04%)	52 (92.55%)
Prefer Not to Answer (%)	0 (0%)	1 (3.81%)
Race		
White (%)	39 (76.47%)	40 (72.73%)
Asian (%)	11 (21.57%)	10 (18.18%)
African American/Black (%)	2 (3.92%)	6 (10.91%)
Middle Eastern (%)	1 (1.96%)	2 (3.64%)
Native American (%)	0 (0.00%)	0 (0.00%)
Hawaiian/Pacific Islander (%)	1 (1.96%)	2 (3.64%)

Table 2

Model Estimates Predicting Learning Rate in the Training Phase of the Social Probabilistic Selection Task

	Learning Rate			
Predictors	*Estimates*	*CI*	*Statistic*	*p*
(Intercept)	0.23	0.21 – 0.24	32.10	**<0.001**
Session	-0.00	-0.01 – 0.01	-0.21	0.833
Condition	-0.01	-0.02 – 0.00	-1.39	0.163
PE Valence	0.00	-0.01 – 0.01	0.63	0.528
Session X Condition	-0.02	-0.03 – -0.00	-2.71	**0.007**
Session X PE Valence	0.03	0.01 – 0.04	4.53	**<0.001**
Condition X PE Valence	0.01	-0.00 – 0.02	1.13	0.259
Session X Condition X PE Valence	0.01	-0.00 – 0.02	1.16	0.247
Random Effects				
σ^2	0.01			
$\tau_{00\ subjID}$	0.00			
ICC	0.13			
N_{subjID}	106			
Observations	404			
Marginal R^2 / Conditional R^2	0.067 / 0.185			

Note: Condition = intervention condition (CBM-I vs. EMA-only). PE Valence = prediction error valence (positive vs. negative).

Table 3

Model Estimates Predicting Accuracy in the Testing Phase of the Social Probabilistic Selection Task

	P(correct)			
Predictors	*Odds Ratios*	*CI*	*Statistic*	*p*
(Intercept)	4.55	3.85 – 5.38	17.71	**<0.001**
Session	1.04	0.99 – 1.09	1.67	0.094
Condition	1.05	0.89 – 1.25	0.62	0.538
Trial Type	1.33	1.27 – 1.39	12.25	**<0.001**
Session X Condition	1.06	1.01 – 1.11	2.44	**0.015**
Session X Trial Type	0.94	0.90 – 0.98	-2.67	**0.008**
Condition X Trial Type	1.09	1.04 – 1.14	3.54	**<0.001**
Session X Condition X Trial Type	1.02	0.98 – 1.07	0.99	0.324
Random Effects				
σ^2	3.29			
$\tau_{00\ id}$	0.70			
ICC	0.18			
N_{id}	106			
Observations	12863			
Marginal R^2 / Conditional R^2	0.024 / 0.195			

Note: Condition = intervention condition (CBM-I vs. EMA-only). Trial Type = choose reward vs. avoid punishment.

Table 4

Model Estimates Predicting Update Weights Estimated Separately by Prediction Error and Item Valence in the Speech Expectancies Task

	Update Weight			
Predictors	*Estimates*	*CI*	*Statistic*	*p*
(Intercept)	0.56	0.45 – 0.66	10.63	**<0.001**
Condition	0.03	-0.08 – 0.13	0.50	0.617
PE Valence	0.10	0.00 – 0.21	2.00	**0.047**
Item Valence	-0.04	-0.14 – 0.07	-0.69	0.492
Condition X PE Valence	0.05	-0.05 – 0.16	1.00	0.318
Condition X Item Valence	-0.00	-0.11 – 0.10	-0.09	0.928
PE Valence X Item Valence	0.05	-0.05 – 0.15	0.96	0.340
Condition X PE Valence X X Item Valence	-0.06	-0.16 – 0.05	-1.11	0.268
Observations	281			
R^2 / R^2 adjusted	0.027 / 0.002			

Note: Condition = intervention condition (CBM-I vs. EMA-only). PE Valence = prediction error valence (positive vs. negative). Item Valence = items measuring good vs. poor social performance.

Table 5

Model Estimates Predicting Update Weights Estimated Separately by Prediction Error Valence in the Speech Expectancies Task

	Update Weight			
Predictors	*Estimates*	*CI*	*Statistic*	*p*
(Intercept)	0.53	0.48 – 0.58	20.15	**<0.001**
PE Valence	0.05	0.01 – 0.09	2.48	**0.013**
Condition	0.01	-0.04 – 0.07	0.56	0.576
PE Valence X Condition	-0.05	-0.09 – -0.00	-2.19	**0.028**
Random Effects				
σ^2	0.06			
$\tau_{00\ participant}$	0.02			
ICC	0.24			
$N_{participant}$	78			
Observations	147			
Marginal R^2 / Conditional R^2	0.061 / 0.286			

Note: Condition = intervention condition (CBM-I vs. EMA-only). PE Valence = prediction error valence (positive vs. negative).

Table 6

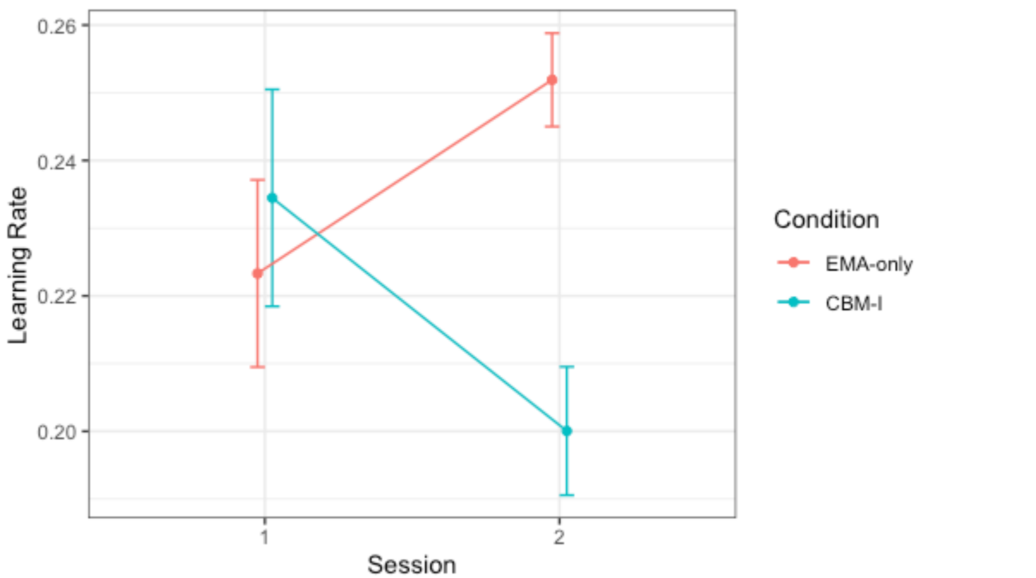
Model Estimates Predicting Update Weights Estimated Separately by Item Valence in the Speech Expectancies Task

	Update Weight			
Predictors	*Estimates*	*CI*	*Statistic*	*p*
(Intercept)	0.49	0.43 – 0.54	17.81	**<0.001**
Item Valence	-0.03	-0.05 – -0.01	-3.17	**0.002**
Condition	0.02	-0.03 – 0.08	0.79	0.431
Item Valence X Condition	0.03	0.01 – 0.05	3.00	**0.003**
Random Effects				
σ^2	0.01			
$\tau_{00\ participant}$	0.05			
ICC	0.80			
$N_{participant}$	75			
Observations	146			
Marginal R^2 / Conditional R^2	0.036 / 0.810			

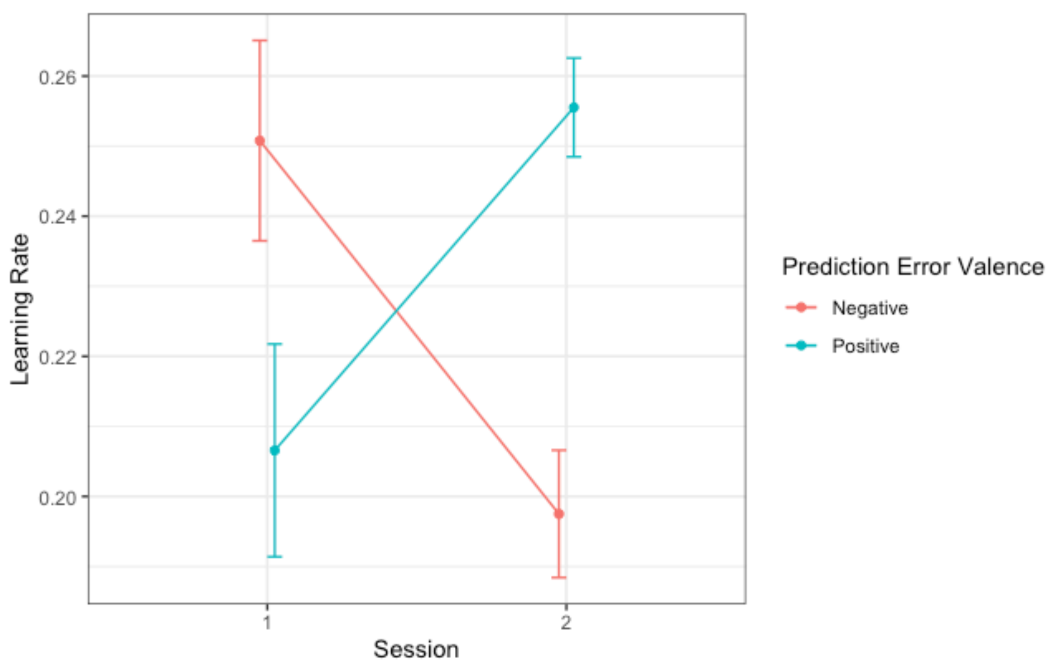
Note: Condition = intervention condition (CBM-I vs. EMA-only). Item Valence = items measuring good vs. poor social performance.

Figure 1

Learning Rates in the Social Probabilistic Selection Task



a.

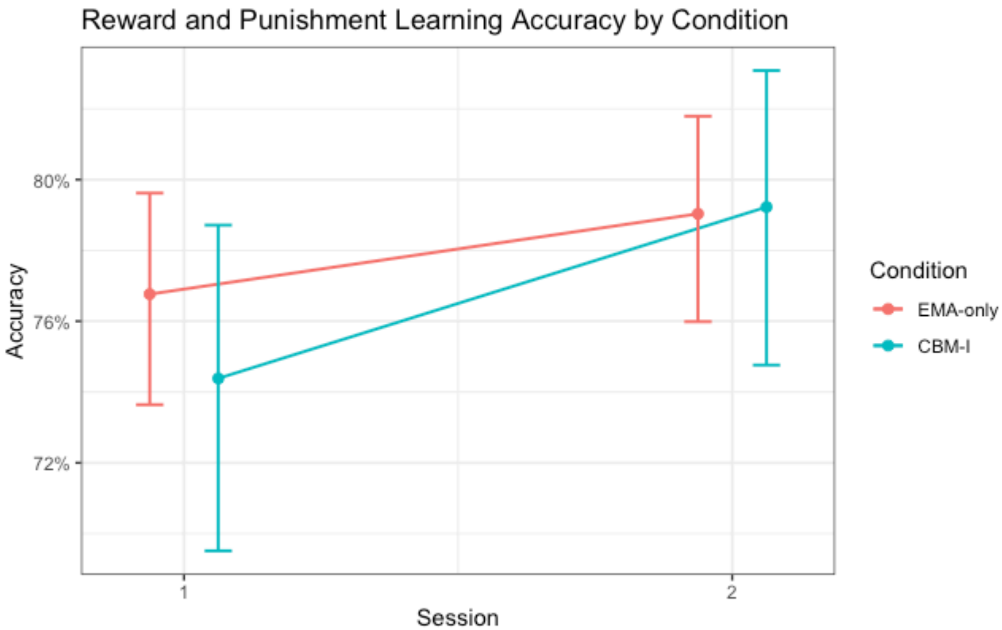


b.

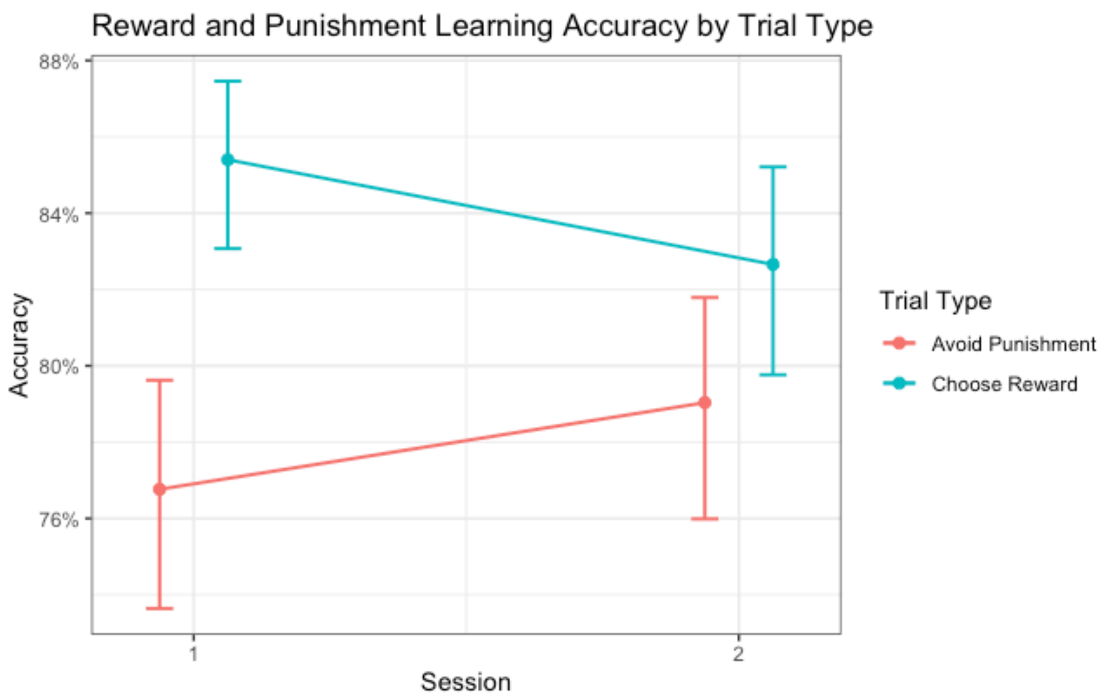
Note: Condition = intervention condition (CBM-I vs. EMA-only).

Figure 2

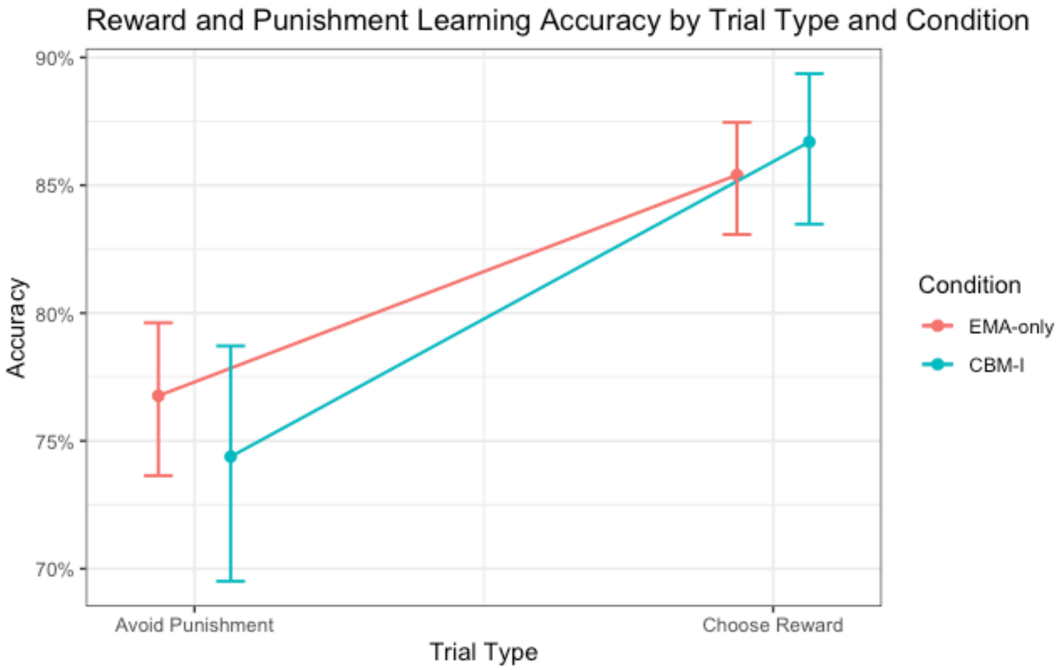
Decision Accuracy in the Social Probabilistic Selection Task



a.



b.

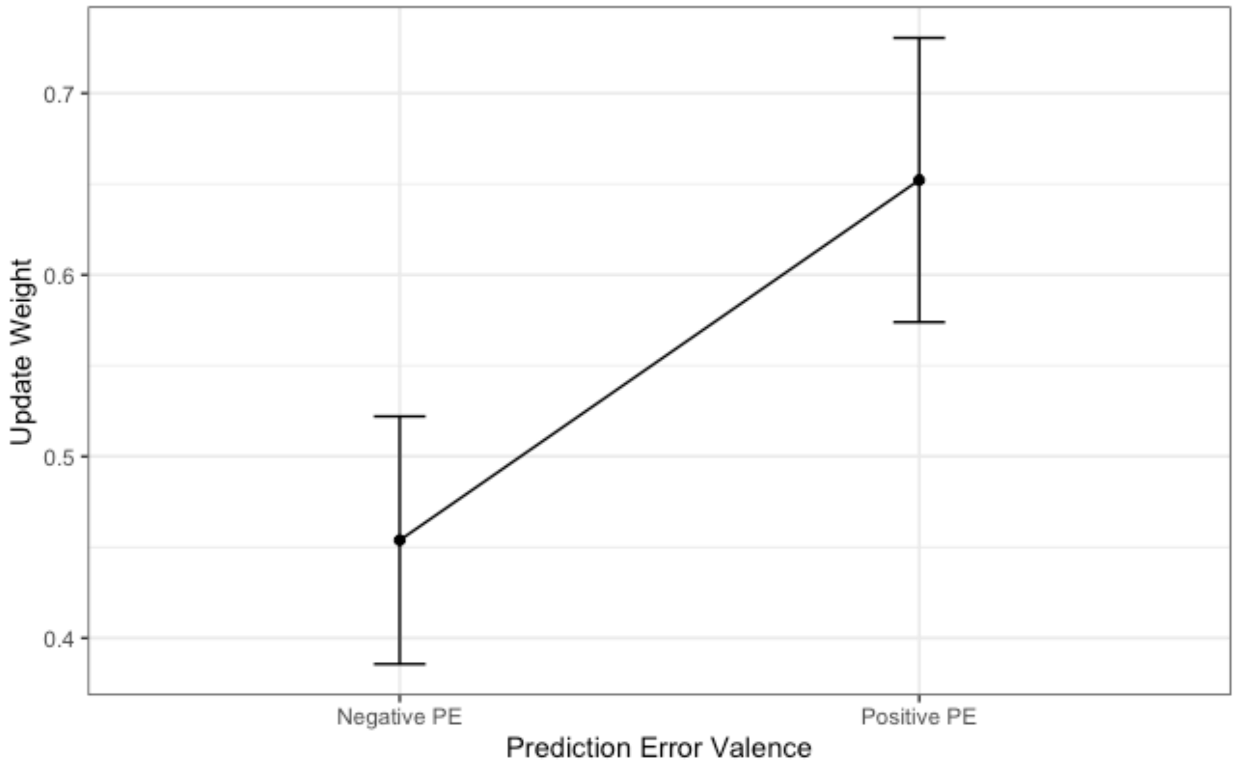


c.

Note: Condition = intervention condition (CBM-I vs. EMA-only).

Figure 3

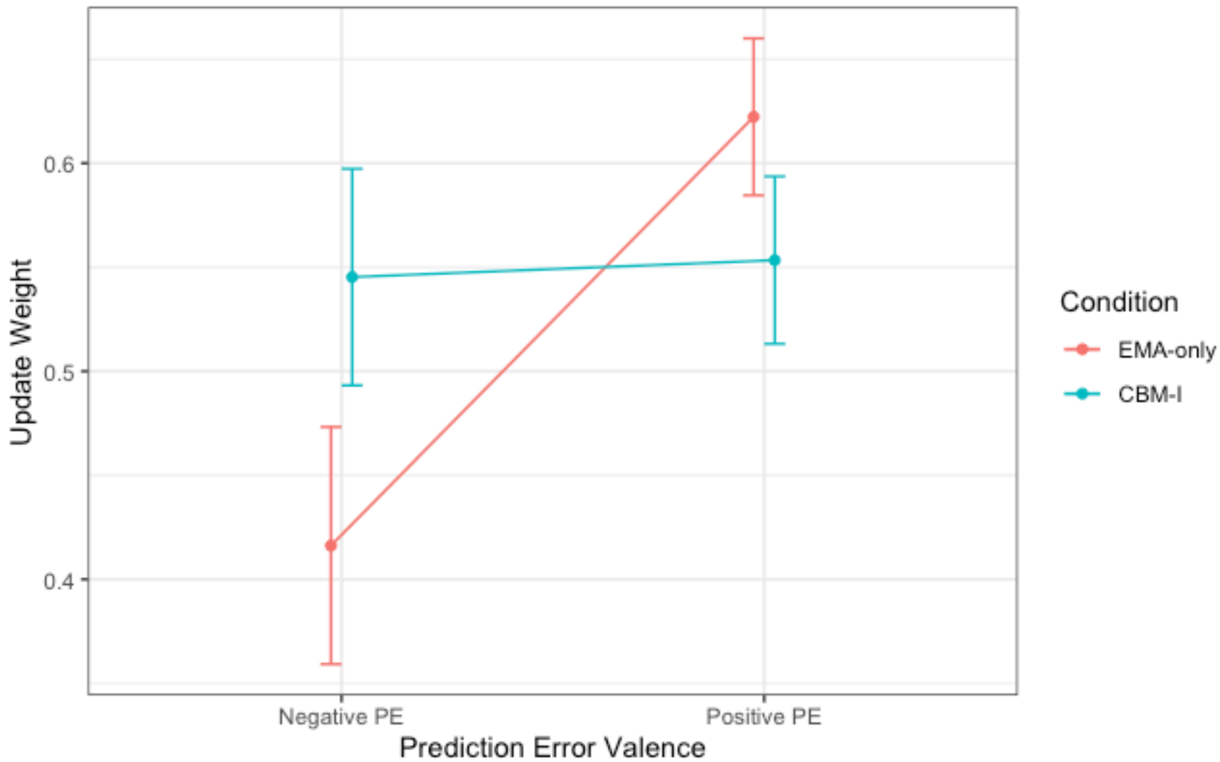
Update Weights in the 4-Weight Model for the Speech Expectancies Task



Note: In the 4-weight model, update weights were estimated separately for items measuring good vs. poor social performance on which feedback was more negative vs. positive than participants' pre-speech expectancies (prediction error valence).

Figure 4

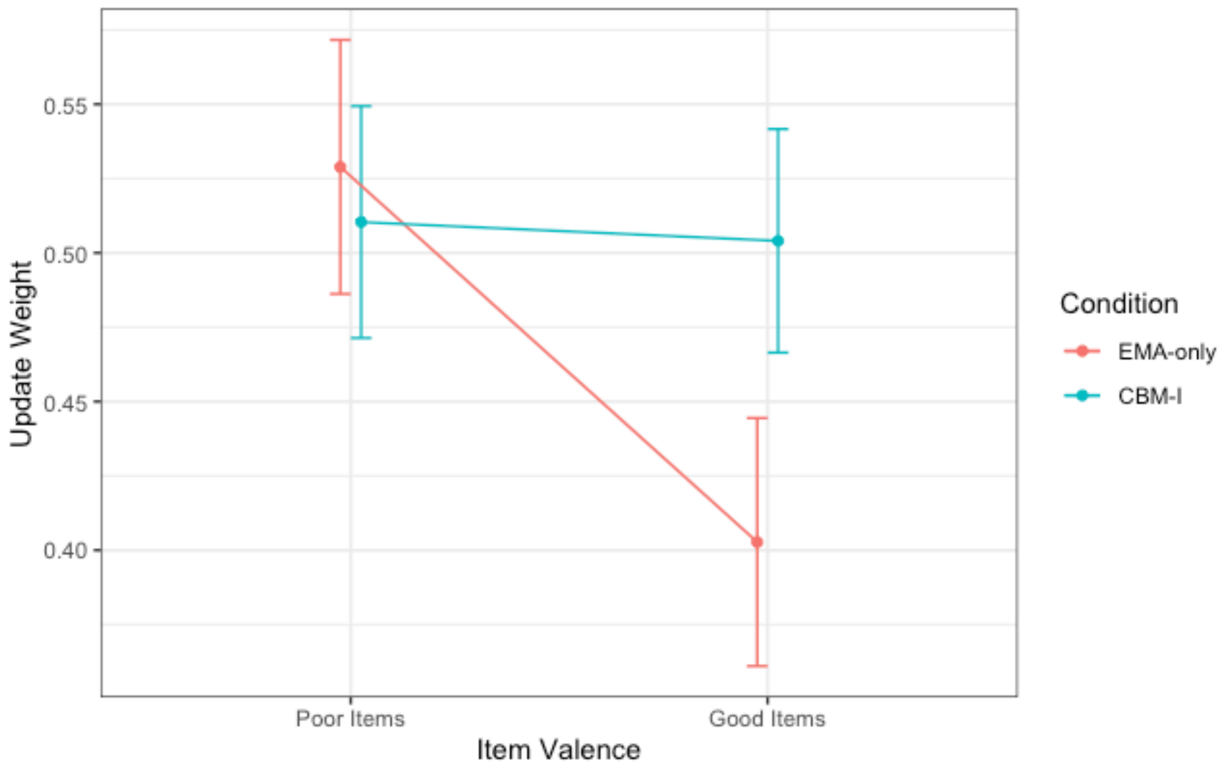
Update Weights in the 2-Weight (Prediction Error Valence) Model for the Speech Expectancies Task



Note: Condition = intervention condition (CBM-I vs. EMA-only). In the 2-weight (prediction error valence) model, update weights were estimated separately for items on which feedback was more negative vs. positive than participants' pre-speech expectancies (prediction error valence), without regard for item valence (items measuring good vs. poor social performance).

Figure 5

Update Weights in the 2-Weight (Item Valence) Model for the Speech Expectancies Task



Note: Condition = intervention condition (CBM-I vs. EMA-only). In the 2-weight (item valence) model, update weights were estimated separately for items measuring good vs. poor social performance, without regard for whether feedback was more negative vs. positive than participants' pre-speech expectancies (prediction error valence).

Supplemental Materials

Supplemental Results

Exploratory Bayesian Comparisons. Given the Bayesian computational modeling approach, group-level posterior distributions, and not just individual-level point estimates, were estimated for learning rates. Exploratory pairwise comparisons were performed on these posterior distributions to better understand possible learning rate differences in this sample by computing the 95% highest density interval (HDI) of the difference between the two posterior distributions.

Comparing learning rates across sessions within the EMA-only condition, the HDI for reward learning rates did not cross zero [0.0075, 0.2025], but the HDI for punishment learning rates did [-0.0709, 0.1317], suggesting that reward, but not punishment, learning rates credibly increased from session one to session two. Comparing across sessions within the CBM-I condition, HDIs for both reward [-0.0021, 0.0187] and punishment learning rates [-0.1732, 0.019] both crossed zero, but just barely. This suggests, for the CBM-I condition, that there was a trend towards reward learning rates increasing and punishment learning rates decreasing from session one to session two, but that it was not quite at 95% credibility.

Comparing learning rates across prediction error valence at each session within the EMA-only condition, the HDIs at session one [-0.1455, 0.0705] and session two [-0.0623, 0.1405] both crossed zero, suggesting no credible difference between reward and punishment learning rates at either session. Comparing across prediction error valence at each session within the CBM-I condition, the HDI at session one [-0.1851, 0.0378] crossed zero, though just barely, but the HDI at session two did not [0.0148, 0.1787]. This suggests that, for the CBM-I group, at session one, there was a trend towards reward learning rates being lower than punishment learning rates, but at session two, reward learning rates became credibly higher than punishment learning rates. Taken together, these exploratory results suggest a pattern (though not all at 95% credibility) of higher punishment than reward learning rates at baseline, with reward learning rates increasing between sessions for both conditions but punishment learning rates increasing only for the CBM-I condition, such that reward learning rates were credibly higher than punishment at session two for those in the CBM-I condition.

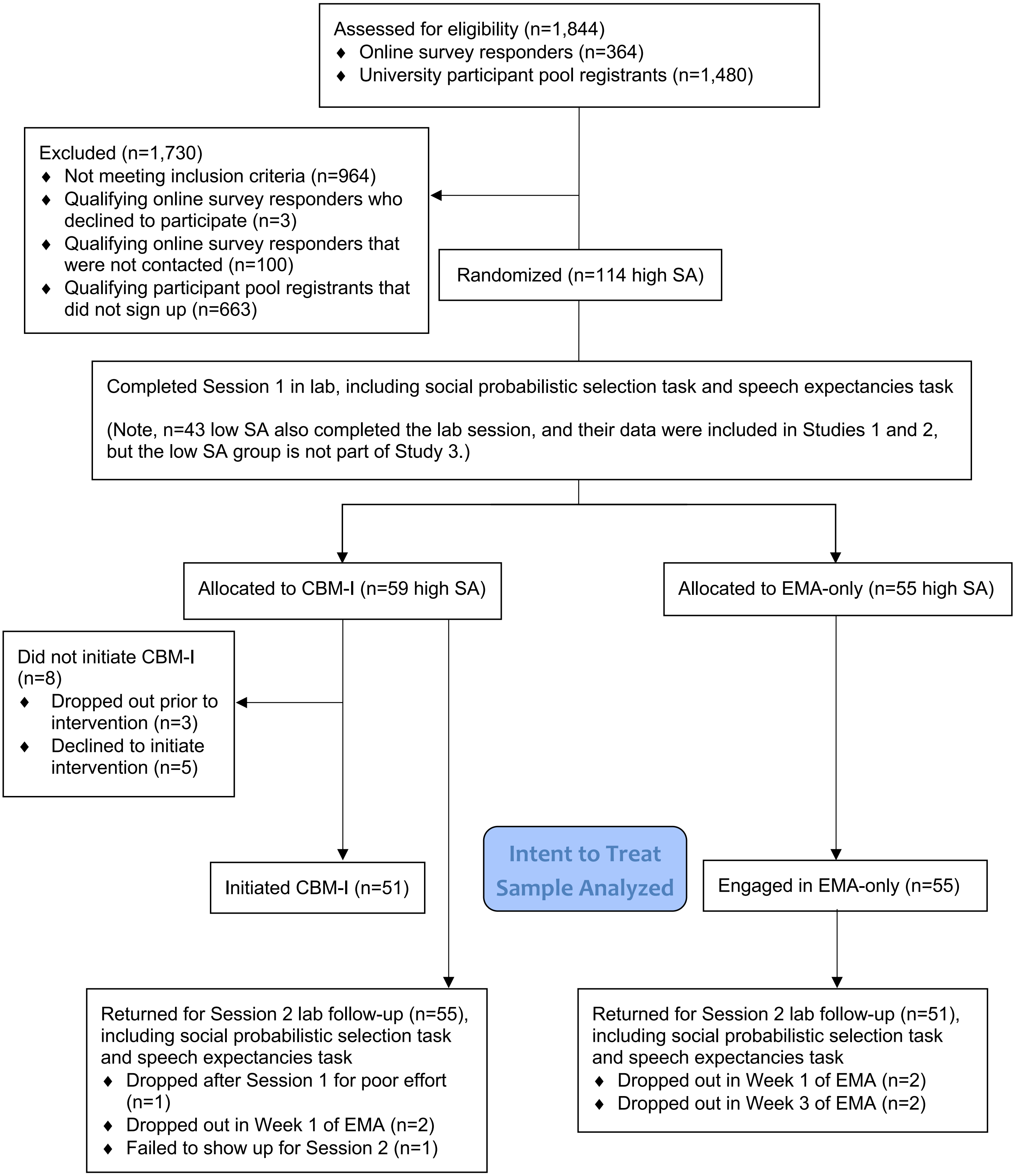
Supplemental Table 1

LOOIC of Candidate Models

	EMA-only, S1	EMA-only, S2	CBM-I, S1	CBM-I, S2
Two LRs	12352.45	10071.98	10367.72	7390.60
Single LR	12398.83	10072.02	10358.86	7385.28

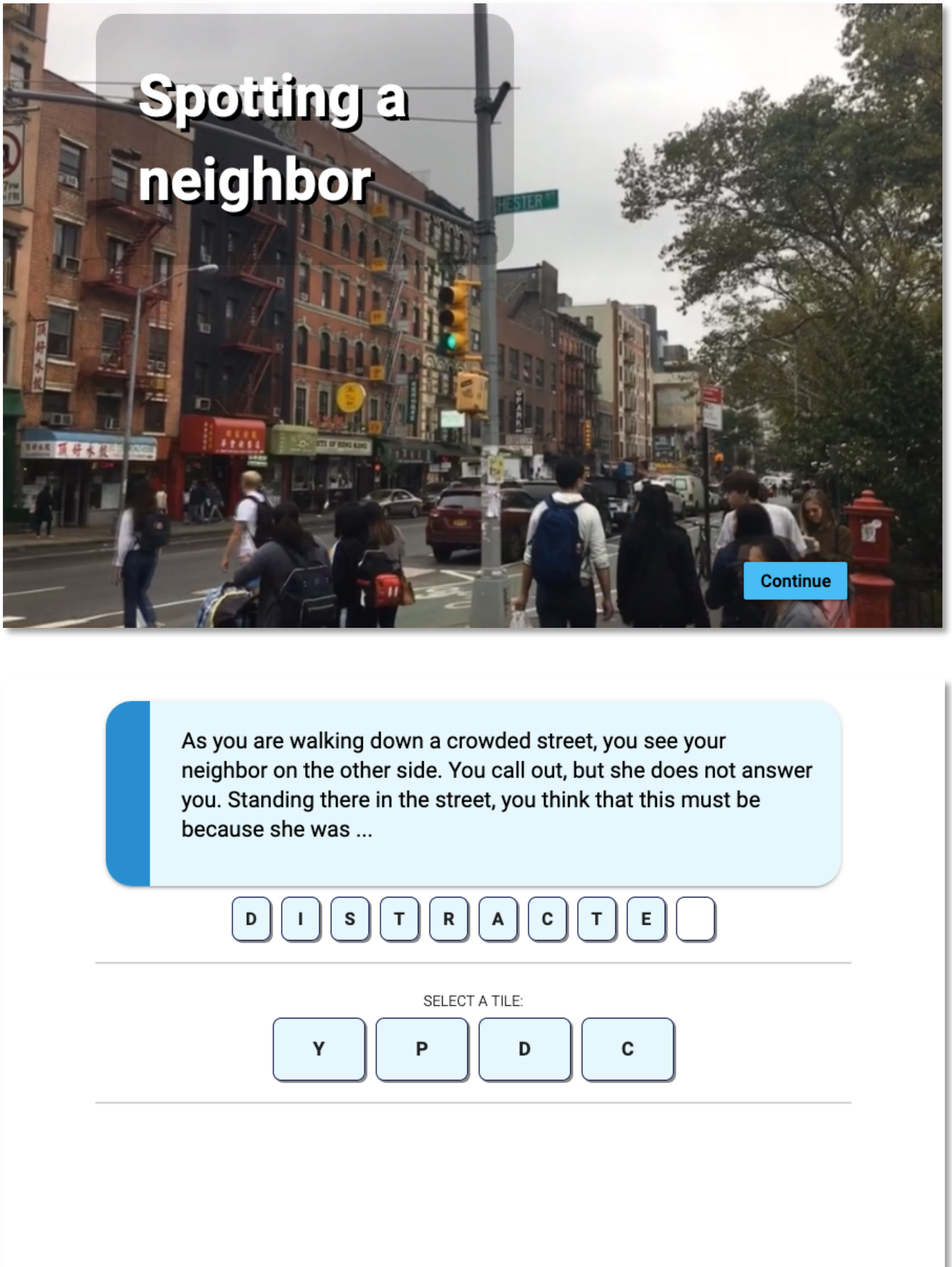
Supplementary Figure 1

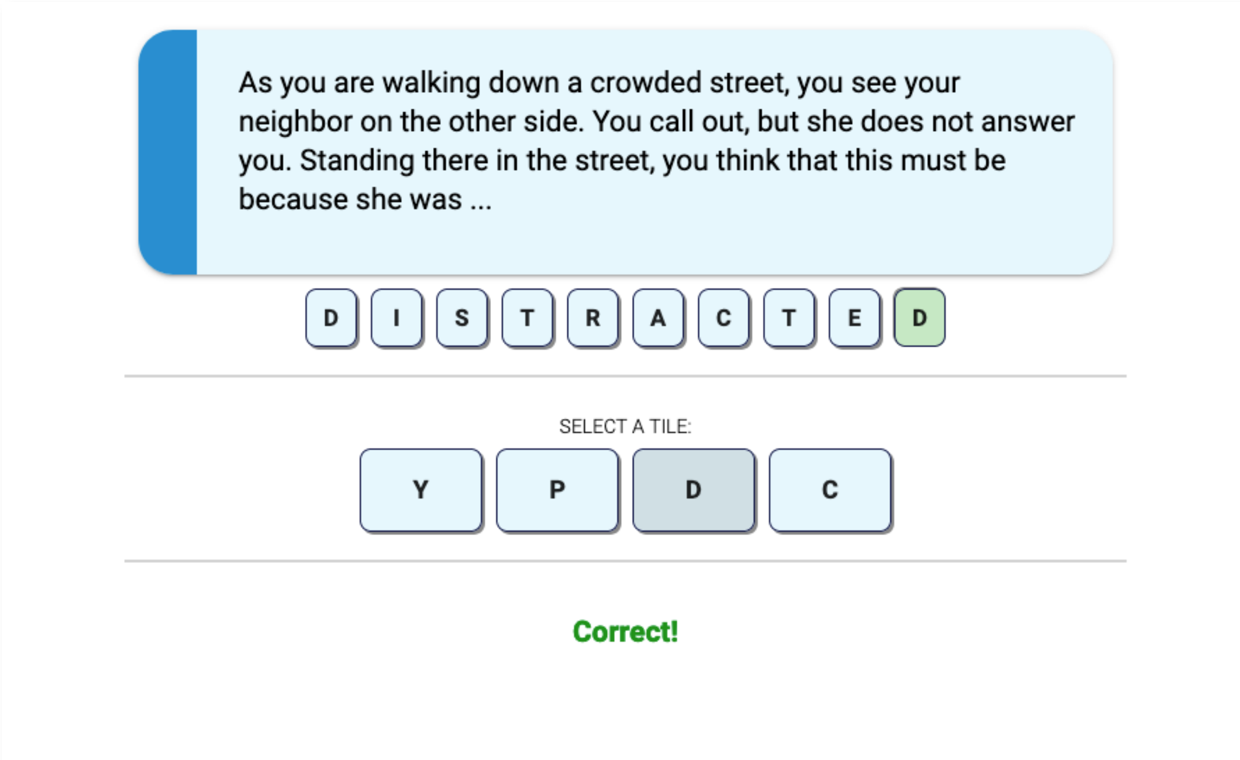
CONSORT Diagram



Supplementary Figure 2

Screenshots of CBM-I Training




As you are walking down a crowded street, you see your neighbor on the other side. You call out, but she does not answer you. Standing there in the street, you think that this must be because she was ...
D I S T R A C T E D
SELECT A TILE:
Y P D C
Correct!


Did your neighbor purposely ignore your call to her in the street?
No
Yes

General Discussion

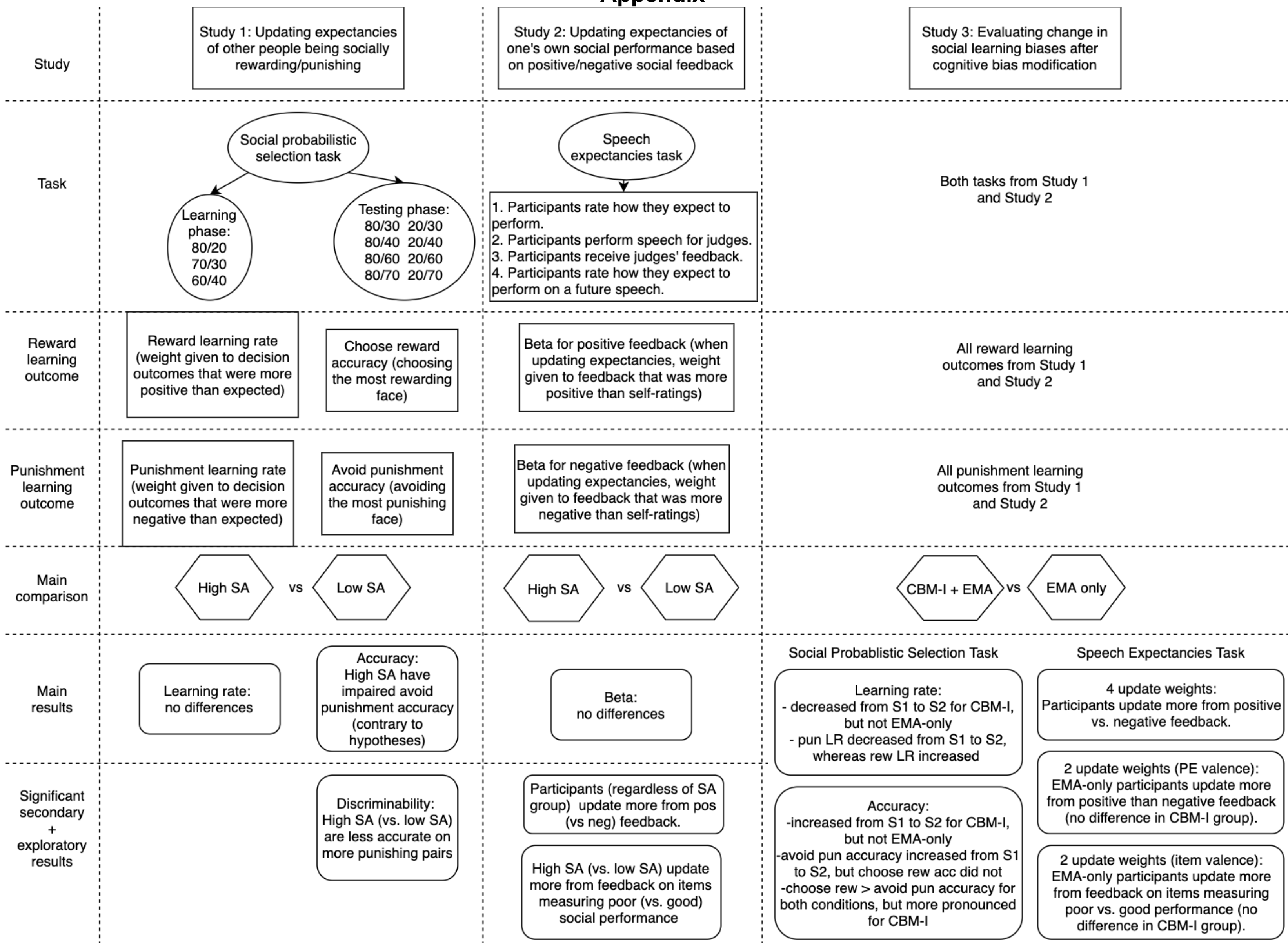
In this dissertation, I aimed to conduct a more comprehensive examination of social reinforcement learning in social anxiety than had previously been done in the literature. In Studies 1 and 2, I examined how individuals high versus low in social anxiety symptoms use positive and negative social feedback to update their beliefs about other people and about their own social performance on a speech. In Study 3, I assessed whether a computerized cognitive intervention, CBM-I, could be used to change social reinforcement learning biases. I hypothesized that compared to less anxious individuals, more socially anxious individuals would tend to show more negative learning biases, learning more from negative than positive social feedback, and I thought these effects were more likely to be evident on certain outcomes (e.g., accuracy at selecting rewarding faces and avoiding punishing faces) than others (e.g., learning rates). I also hypothesized that CBM-I would mitigate these negative social reinforcement learning biases.

Several of our results were surprising (as summarized in the Appendix)—perhaps most importantly, in our planned analyses, we did not find evidence of a social anxiety-linked bias towards learning more from negative than positive social feedback in either of the domains assessed in Studies 1 and 2. In fact, Study 1 found that high social anxiety participants were less accurate at avoiding punishing faces than were low social anxiety participants, contrary to hypotheses. Though unexpected (and in need of replication), this result might suggest that socially anxious individuals are worse at using what they have learned about other people to avoid social rejection. More frequent rejection might reinforce negative expectancies about social interactions and contribute to a process of avoidance behavior that may worsen social interactions–essentially, a process that could be thought of as interpersonal stress generation. Study 3 found that this improved over the course of the study: socially anxious participants became more accurate at avoiding punishing faces from session 1 to session 2. This suggests that something that occurred between sessions might help to change this process, but because this effect was not specific to intervention condition, we cannot attribute it to CBM-I. However, overall accuracy at selecting the more rewarding face (regardless of whether that meant choosing reward or avoiding punishment) increased across sessions only in the CBM-I condition and not in the EMA-only condition, which points to a potentially beneficial effect of CBM-I.

Planned analyses for Studies 1 and 2 did not find evidence of social anxiety-linked biases in the weights given to new information (i.e., learning rates/update weights). These null effects were not altogether surprising given learning rate’s greater relevance to learning in volatile than in stable environments (and learning in volatile environments was not a component of in this dissertation). Exploratory analyses for Study 2, however, suggested that participants high in social anxiety symptoms might learn more from feedback about aspects of poor social performance than good social performance. Further, Study 3 found that high social anxiety participants who completed CBM-I did not show this bias towards learning from feedback about poor social performance, whereas those who completed EMA only did. This is an encouraging result for CBM-I, and bears replication given the exploratory nature of the initial result. Study 3 also found other changes in learning rates/update weights across time and intervention condition, suggesting that both CBM-I and EMA tracking emotion regulation may be able to change how socially anxious people learn from social feedback. CBM-I might decrease the weight given to new feedback when updating expectancies about other people, essentially making each new piece of social feedback less important. This effect makes sense, considering how CBM-I aims to train people not to jump to negative conclusions about ambiguous situations. From session 1 to session 2, high social anxiety participants (regardless of intervention condition) came to update their beliefs about others more from positive feedback and less from negative feedback. Because this effect was not specific to the CBM-I condition, it could be attributed to EMA, practice, time, or something else that occurred between sessions. To our knowledge, though, these are the first results suggesting that CBM-I and tracking emotion regulation may change reinforcement learning processes.

Taken together, the results of the three studies comprising this dissertation found evidence of some social anxiety-linked differences in social reinforcement learning, but not in the ways that were expected. Importantly, Study 3 found that the biases observed in Studies 1 (impaired punishment learning accuracy) and 2 (learning more from feedback about aspects of poor vs. good social performance) might be normalized with CBM-I and EMA about emotion regulation. This dissertation established that the relations between social anxiety and social reinforcement learning might be more nuanced than an overall negative bias, might vary by learning domain (i.e., about other people vs. about one's own performance), and that CBM-I might act not only on interpretation biases, but also on social reinforcement learning.

Appendix


Study
Study 1: Updating expectancies of other people being socially rewarding/punishing
Study 2: Updating expectancies of one's own social performance based on positive/negative social feedback
Study 3: Evaluating change in social learning biases after cognitive bias modification
Task
Social probabilistic selection task
Learning phase: 80/20 70/30 60/40
Testing phase: 80/30 20/30 80/40 20/40 80/60 20/60 80/70 20/70
Speech expectancies task
1. Participants rate how they expect to perform.
2. Participants perform speech for judges.
3. Participants receive judges' feedback.
4. Participants rate how they expect to perform on a future speech.
Both tasks from Study 1 and Study 2
Reward learning outcome
Reward learning rate (weight given to decision outcomes that were more positive than expected)
Choose reward accuracy (choosing the most rewarding face)
Beta for positive feedback (when updating expectancies, weight given to feedback that was more positive than self-ratings)
All reward learning outcomes from Study 1 and Study 2
Punishment learning outcome
Punishment learning rate (weight given to decision outcomes that were more negative than expected)
Avoid punishment accuracy (avoiding the most punishing face)
Beta for negative feedback (when updating expectancies, weight given to feedback that was more negative than self-ratings)
All punishment learning outcomes from Study 1 and Study 2
Main comparison
High SA vs Low SA
High SA vs Low SA
CBM-I + EMA vs EMA only
Main results
Learning rate: no differences
Accuracy: High SA have impaired avoid punishment accuracy (contrary to hypotheses)
Beta: no differences
Social Probabilistic Selection Task
Learning rate: - decreased from S1 to S2 for CBM-I, but not EMA-only - pun LR decreased from S1 to S2, whereas rew LR increased
Speech Expectancies Task
4 update weights: Participants update more from positive vs. negative feedback.
Significant secondary + exploratory results
Discriminability: High SA (vs. low SA) are less accurate on more punishing pairs
Participants (regardless of SA group) update more from pos (vs neg) feedback.
High SA (vs. low SA) update more from feedback on items measuring poor (vs. good) social performance
Accuracy: -increased from S1 to S2 for CBM-I, but not EMA-only -avoid pun accuracy increased from S1 to S2, but choose rew acc did not -choose rew > avoid pun accuracy for both conditions, but more pronounced for CBM-I
2 update weights (PE valence): EMA-only participants update more from positive than negative feedback (no difference in CBM-I group).
2 update weights (item valence): EMA-only participants update more from feedback on items measuring poor vs. good performance (no difference in CBM-I group).