Reduced positive evidence within activated self-schema may underpin increased
sensitivity to negative evaluation in socially anxious individuals

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Abstract

Positive self-beliefs are important for well-being, and are influenced by how others evaluate us during social interactions. Mechanistic accounts of self-beliefs have mostly relied on associative learning models. These account for choice behaviour but not for the explicit beliefs that trouble socially anxious patients. Neither do they speak to self-schemas, which underpin vulnerability according to psychological research. Here, we compared belief-based and associative computational models of social-evaluation, in individuals that varied in fear of negative evaluation (FNE). Using a novel analytic approach, ‘clinically informed model-fitting’, we replicated the finding that high-FNE participants learn faster from negative feedback about themselves. Crucially, this could be explained through reduced activation of positive self-schemas. The overall population could be characterized equally well by belief-based or associative models, but many individuals used either the one or the other perspective. Our findings have therapeutic importance, as belief activation may be used to specifically modulate learning.

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Introduction

‘We don’t see things as they are, we see things as we are’ - Anais Nin

We tend towards optimism instead of realism, often overestimating our competence and likeability (Sharot, Korn, & Dolan, 2011). This bias appears useful, allowing individuals who hold a positive self-view to benefit from better psychological well-being and mental health (Conversano et al., 2010; Korn, Sharot, Walter, Heekeren, & Dolan, 2014; Moore & Fresco, 2012). One’s self-view is theorised to be shaped by interpersonal interactions and the perceptions we think others have of us (Beck, 1971, 2008; Cooley, 1902; Will, Rutledge, Moutoussis, & Dolan, 2017). The nature of the social information individuals receive, and what they do with that information, is key to understanding how self-beliefs develop and are maintained (Spence & Rapee, 2016).

Cognitive theories of depression and social anxiety hold that repeated exposure to social adversity can teach an individual that the world is an unpredictable and hostile place, where they should expect criticism and poor social outcomes (Beck, 2008; Clark & Wells, 1995). This negative learning forms the schema, a system of beliefs and expectations through which future self-relevant social information is processed (Clark & Wells, 1995; Rapee & Heimberg, 1997). Once activated, the self-schema acts as an information filter, influencing attention, perception, learning and memory, such that the dysfunctional self-views are maintained (Beck, 2008). Schemas are disorder-specific; for social anxiety, their content relates to the core fear of being negatively evaluated by others.

It is important to understand the psychological mechanisms behind inferring evaluation of self and others, and how this integrates into our self-schema. Evidence indicates that the activation of self-beliefs, or self-schema, and the updating of such beliefs in response to social feedback is key (Button, Browning, Munafo, & Lewis, 2012; Korn, Prehn, Park, Walter, & Heekeren, 2012; Korn et al., 2014). However,

temperamental preparedness and operant learning routes to anxiety, such as behavioural inhibition and reinforcement via safety-behaviours, are also postulated to be important (Spence & Rapee, 2016).f

Individuals who show high fear of negative evaluation (FNE) display negatively biased processing of social-evaluative information (Winton, Clark, & Edelmann, 1995) and are prone to social anxiety (Stopa & Clark, 2001). Button and colleagues (Button et al., 2012, 2015) demonstrated negative bias about the self in a Social Evaluation Learning Task, wherein a computer persona described either themselves or an unknown other. Those more fearful of negative evaluation selected significantly fewer positive attributes when asked to predict how the computer persona would describe them, but displayed no bias when making predictions about unknown others. The fact that this negative bias specifically manifested when evaluations are related to the self, suggests that individuals integrate social information differently depending on the context and focus of the evaluation, which is consistent with the cognitive models (Beck, 1971; Cooley, 1902)

Computational cognitive studies have recently addressed self-evaluation (Koban et al., 2017; Will et al., 2017). So far, studies have mostly relied on associative learning models (Rescorla & Wagner, 1972) to capture phenomena such as healthy people giving more weight to positive, rather than negative, information about themselves. Koban et al. (2017) analysed self-evaluation using an associative model, to test whether learning rates – *association values* in learning theory (Hill, 1960) – depended on social anxiety. Social Anxiety Disorder patients were found to have higher learning rates for negative attributes about themselves, compared to healthy controls. Learning-rate based models give a good description of changes in moment-to-moment evaluation of the self, but learning rates are not stable psychological characteristics, depending on a host of factors (Browning, Behrens, Jocham, O'Reilly, & Bishop, 2015; Dorfman, Bhui, Hughes, & Gershman, 2019; Mathys, Daunizeau, Friston, & Stephan, 2011). Clinically, this maleability is useful, opening up maladaptive learning rates to therapeutic intervention (Kube et al., 2019).

Instead of focusing on behaviour assumed to be gradually reinforced, belief-based frameworks focus how evidence, here provided by social information, updates beliefs. This framework can accommodate the top-down role of self-schema/beliefs, including trait-like views about the self activated given a social context, more naturally than associationist approaches. It also explicitly accounts for the role of uncertainty, which may be especially important for social learning (Kruschke, 2008).

A Bayesian approach is particularly well suited to modelling the top-down influence of beliefs (Stankevicius, Huys, Kalra, & Seriès, 2014), as it has belief update at its core and explicitly represents different strengths of belief. For example, I may believe that I am ‘80-90%’ socially competent but also allow for a socially incompetent 10-20%. Alternative beliefs are then strengthened or weakened as social information accumulates. The certainty of beliefs is informed by learning throughout an individual’s history. Certainty then determines how open existing (‘prior’) beliefs are to change, i.e. determines learning rates. Intuitively, someone with a negative self-view may be more likely to integrate negative evaluations, as they are more in line with their own initial beliefs (see SOM-U for a tutorial demonstration). Similarly biased belief-updating has been demonstrated in non-social reward-based tasks (Stankevicius et al., 2014).

We aimed to clarify the explanatory power of these two psychological frameworks in social-evaluation. We expected associative learning models to capture well the dynamics of learning, while a Bayesian cognitivist framework would provide insight into how beliefs evolve and affect learning. We were interested in mechanisms of biased learning in individuals with high fear of negative evaluation, and its potential basis in biased updating of beliefs about the self.

Methods and Materials

Measures

Published data was obtained from (Button et al., 2015). Data consisted of a Social Evaluation Learning Task (Figure ??) completed by 100 participants and a range of questionnaires, of which the primary measure was the Brief Fear of Negative Evaluation

(BFNE) scale (Leary, 1983). A higher BFNE score indicates greater fear of negative evaluation. For a full details of the task and sample please see (Button et al., 2015).

Figure 1. Each task block consisted of 32 trials. Participants had to choose between positive and negative words. There were 6 blocks in total, corresponding to 6 evaluative conditions, termed *personas* - Self-like, self-neutral, self-dislike, other-like, other-neutral, other-dislike. Self/other refers to who is being evaluated, like/neutral/dislike refers to the probability of a positive word being correct (0.8, 0.5, 0.2 for the like/neutral/dislike rules respectively)

Associative and belief-based models

To assess how choices evolved as a function of social feedback, we used computational models. We formalised how social feedback influenced subsequent choices about the self and other using adapted Rescorla-Wagner reinforcement learning models (Rescorla & Wagner, 1972) and novel belief-update models. Here we describe the key features of the models, with technical details to be found in the Supplement.

Associative Learning models. Associative learning models describe learning in terms of value. Here, participants learn the value of the action ‘choose the positive attribute’ or ‘choose the negative attribute’, based on feedback. These action-values $Q(action, context)$ are updated after each outcome. A discrepancy between choice and outcome forms a ‘prediction error’, PE . The PE is then multiplied by a learning rate, λ_c , a parameter weighing the impact of new evidence on existing values, and the result added to update the existing action-value. High learning rates correspond to new evidence having a strong impact, quickly replacing old learning. The *context* s_t simply indexes which state, i.e. computer persona $\times$ (self vs. other), the trial t was about.

$$\begin{aligned} PE_t &= r_t - Q_{t-1}(a_t, s_t) \\ Q_t(a_t, s_t) &= Q_{t-1}(a_t, s_t) + \lambda_c PE_t \end{aligned} \tag{1}$$

Table 1

Model families, grouped according to their defining core parameters.

Model Family Name	NP	Core Parameters	Additional Parameters	
Valence model – 2λ	3-5	$\lambda_{+ve}, \lambda_{-ve}, \tau$	Initial bias	Pos. bias
Self/other asymmetric valence - 3λ	4-6	$\lambda_{self\ pos}, \lambda_{self, -ve}, \lambda_{other}, \tau$	Initial bias	Pos. bias
Self/other valence - 4λ	5-7	$\lambda_{self, +ve}, \lambda_{self, -ve}, \lambda_{other, +ve}, \lambda_{other, -ve}, \tau$	Initial bias	Pos. bias
Confirmation bias	3-5	$\lambda_{confirm}, \lambda_{disconfirm}, \tau$	Initial bias	Pos. bias
Confirmation bias valence	5-7	$\lambda_{confirm, +ve}, \lambda_{confirm, -ve},$ $\lambda_{disconfirm, +ve}, \lambda_{disconfirm, -ve}$	Initial bias	Pos. bias
Belief-update	4	$\alpha, \beta, \eta, \tau$		
Belief-update self/other	7	$\alpha_{self}, \beta_{self}, \alpha_{other}, \beta_{other}, \eta_{self}, \eta_{other}, \tau$		
Belief-update self/other initial bias	9	$\alpha_{self}, \beta_{self}, \alpha_{other}, \beta_{other}, \eta_{self}, \eta_{other}, \tau$	$\alpha_{initial}$	$\beta_{initial}$

Note. Additional parameters were used to explore variants within each family, for example, only including an initial bias for the self only, as opposed to both self and other. NP gives the range number of parameters for each family

We focused on learning rates, as these easily characterise which conditions have a major or minor impact on learning. Following Koban et al. (2017), we expected that learning could be valence dependent and therefore allowed separate learning rates for trials with a positive or negative outcome word (irrespective of action chosen). So, people might have $\lambda_{+ve\ outcome} > \lambda_{-ve\ outcome}$. Based on descriptive findings Button et al. (2015), we are interested in self/other distinction and therefore considered models that had separate learning rates depending on whether the object of learning was self or other, giving $\lambda_{self, +ve}, \lambda_{other, +ve}, \lambda_{self, -ve}$ etc. In addition, we tested whether learning

rates encoded an action-level confirmation bias (see table 1). Models could include an initial value parameter, allowing starting values $Q(+ve\ word, s_{t=0})$ to reflected an individuals starting tendency towards positivity.

Actions were chosen probabilistically, as a function of a propensity to choose each action. This propensity was the action value $Q(a, s)$ biased by a ‘positivity bias’ ρ , which quantified biases independent of learning (Eq. 2). $Q(a, s) + \rho$ then entered a standard softmax function, weighed by a ‘decision noise’ parameter $\tau > 0$:

$$P(a; s) = z \exp \frac{Q(a, s) + \rho}{\tau} \quad (2)$$

Where z ensured that probabilities add up to 1.

Belief-update models. Belief-update models conceptualised participants as holding beliefs about how approving each computer persona was, from 0 to 1. Such beliefs do not contain just one value (‘this persona will give me 80% +ve attributions’) but also embody an uncertainty (‘but it could be 70 to 90%). They can be formalized by a beta distribution, which conveniently describes beliefs through the amount of positive evidence α and that of negative evidence β held in mind. The mean probability of approval is just the average $p = \alpha / (\alpha + \beta)$.

The belief parameters were updated in every round by augmenting the evidence corresponding to the outcome (say, positive) by 1 piece of evidence. However, we sought to also model views about the self that participants brought to bear independent of learning. Greatly simplifying clinical theory (Pinto-Gouveia, Castilho, Galhardo, & Cunha, 2006), we represented this as the positive and negative evidence people brought to bear. People thus held two belief components. The first was trait-like, $(\alpha_{trait}, \beta_{trait})$, parametrized individual variability. It was fixed for the duration of the task, and represented the self- or other- view activated given the current context¹. The second was state-like, $(\alpha_{state}, \beta_{state})$, and it accumulated task information.

¹ Strictly, the models only contain *notional* or effective evidence, i.e. a numerical representation of the weight of affective memories, images etc. activated in real people

$$\begin{aligned}\alpha_t &= \alpha_{trait} + \alpha_{state,t} \\ \beta_t &= \beta_{trait} + \beta_{state,t}\end{aligned}\tag{3}$$

Next, we considered that individuals may not integrate an indefinite amount of evidence, instead gradually discarding older task information. A memory decay parameter $0 < \eta < 1$ thus quantified a participant’s effective working memory. Belief-update models could include separate initial values $\alpha_{state,t=0}, \beta_{state,t=0}$. They could also be separated into self/other with respect to $\alpha_{trait,self}, \alpha_{trait,other}$ etc., and with respect to initial values, or indeed the memory decay parameter.

Belief distributions inherently contain uncertainty, which can affect decision variability (Moutoussis, Dolan, & Dayan, 2016). Hence, we considered two classes of probabilistic action choice. In the first, point estimates such as the mean of a belief distribution was used to determine policy. Here, choice variability was independent of belief uncertainty. In the second class, reduced belief uncertainty as a result of evidence accumulation resulted in reduced decision variability. We thus considered several ‘link functions’ from belief to choice (see Supplement), and determined the best by model comparison. The winning action-choice function was the one which only depended on the mean of the belief distributions (Eq. 4):

$$P(a = +ve\ word; context = s) = z \exp \frac{\alpha_t}{(\alpha_s + \beta_s)\tau}\tag{4}$$

A short summary of all models is displayed in Table 1. Detailed specifications and fit indices are given in the Supplement.

Parameter Estimation and Selection

All models were firstly estimated using Maximum Likelihood Estimation (MLE) to determine the best-fitting ones. The fit of competing models was compared using the Bayesian and Akaike information criteria (Akaike, 1998; Schwarz, 1978) at an individual level, which were then summed over participants.

$$\begin{aligned}
BIC &= -2 \ln p(d|\theta_{ML}) + k \ln(n) \\
AIC &= -2 \ln p(d|\theta_{ML}) + 2k
\end{aligned}
\tag{5}$$

Where k is the number of free parameters, n the number of trials, d the observed data and $p(d|\theta_{ML})$ the maximum-likelihood of the parameters given the data.

Modelling the relation to Fear of Negative Evaluation. Having screened a large number of models independent of BFNE scores to find the best candidates, we re-fitted the best ones, now including BFNE scores, in a *clinically informed model-fitting* procedure. This was necessary because conventional analyses (fixed-effects model-fitting by maximum-likelihood first, then correlation with symptoms) had difficulty capturing group differences evident in descriptive statistics of behaviour (Button et al., 2015). Traditional hierarchical modelling produces less noisy parameter estimates, but we have found that modelling using single or multiple group priors can increase the rates of Type 1 and Type 2 error respectively in subsequent correlation analyses with unmodelled psychometric measures (Moutoussis, Hopkins, & Dolan, 2018). Incorporating key psychological hypotheses in the model-fitting instead can give more accurate estimates of the relationship between model parameters and BFNE scores. As in traditional hierarchical modelling, individual parameters were estimated by taking into account the population distribution they come from, i.e. the ‘group prior distribution’. This was in turn estimated from the data, including BFNE scores. Let θ be a cognitive parameter that may correlate with BFNE. We modelled this correlation as a linear relationship between BFNE and the mean of θ over people with that value of BFNE:

$$\mu_{\theta}(BFNE) = w \text{ BFNE} + \theta_0 \tag{6}$$

Where θ_0 is an intercept. Then, the cognitive model can be fitted including Eq. 6, thus estimating w as a parameter of an overall model, including the distribution of θ .

The best-fitting associative learning and belief-update models according to summed BIC were fitted in this manner using RStan (Carpenter et al., 2017). We

specified several hierarchical models, testing for correlations between BFNE and different parameters. A hypothesis that a parameter correlated with BFNE was tested by determining whether the credible interval of w included zero. Markov-Chain Monte Carlo samples were drawn after 2000 burn-in samples from 4 chains, resulting in a total sample size of approximately 10,000. Convergence was determined by visual inspection of the trace plots and monitoring the Gelman-Rubin statistic for each parameter (Gelman & Rubin, 1992), with values close to 1.00 implying convergence.

Results

Fixed-Effects Modeling

Model comparisons using summed BIC showed that associative learning models that included separate learning rates for self and other outperformed ones that did not distinguish between agents. There were also big improvements in model fit upon including an initial bias parameter that allowed individuals to vary in an initial propensity to choose a positive word, and upon including a constant ‘positivity bias’ boosting the action-value of positive information. The belief-update models that included separate beta distribution parameters for self and other also performed much better than models without, emphasizing a necessary distinction between self and other in learning.

Table 2

The best models according to fixed-effects maximum-likelihood fitting from each family.

Model Family Name	N. param.	AIC	BIC
Valence model - 2λ	3-5	19024.74	19029.47
Self/other asymmetric valence model - 3λ	4-6	20634.49	20640.15
Self/other valence model - 4λ	5-7	18445.82	18452.43
Confirmation bias model	3-5	19631.34	19634.17
Confirmation bias valence model	5-7	18774.45	18780.12
Belief-update	4	19480.49	19511.94
Belief-update self/other	6	18598.59	18653.63
Belief-update self/other initial bias	9	18325.00	18395.76

Note. The associative model with separate learning rates for (self vs. other) $\times$ (positive vs. negative attributes) had the best BIC score, and the belief update model with separate schemas for self and other had the best AIC (in bold)

As shown in Table 2, the best-fitting associative learning model was a self/other valence model, which contained 4 learning rates, an initial bias parameter and a positive bias parameter. The best-fitting belief-update model contained separate self/other alpha, beta and memory parameters and also had free initial bias parameters that allowed starting beliefs to vary between individuals. A Wilcoxon Signed-Ranks Test using individual BICs from the best-fitting models indicated these models did not significantly differ from each other, $Z = 1.74$, $p = .08$. We also estimated protected exceedance probabilities (PEPs), which measure the likelihood that any given model is more frequent than all other models in the comparison set. PEPs account for the possibility that observed differences in model evidences (over subjects) are due to chance and are therefore more reliable than other fit measures. Exceedance probabilities of 0.99 indicate strong evidence in favour of one model. In our data, the belief-update model had a protected exceedance probability of 0.63. There was therefore no strong

evidence for a difference between the two best models. There were, however, large individual differences in model-fit, as shown in Figure 2. Here, we computed the difference in log-likelihoods between the two models, with larger differences indicative of one model describing the data better than the other. We correlated these log-likelihood difference scores with BFNE, and found a non-significant correlation, $r = .16$, $p = .10$. There was no significant correlation of log-likelihood with BFNE when models were analysed separately.

Figure 2. Individual log likelihoods for associative learning vs belief-update model.

Positive values indicates greater evidence for the associative learning model. The horizontal bars indicate log likelihood differences of ± 3 and ± 6 , conventionally mild and strong evidence in favour of one model over the other.

Hierarchical, Clinically informed Model Fitting

The best-fitting associative learning and belief-update models were then fitted hierarchically, to test the hypotheses that self-learning rates and self-trait beliefs would correlated with higher BFNE scores. We did this by embedding BFNE scores into hierarchical priors and using the package RStan (Carpenter et al., 2017). We assessed each of the BFNE weight parameters to determine whether their credible interval overlapped 0, which would go against an effect of BFNE on that parameter.

Table 3

Parameter weights on FNE, derived from clinically informed model-fitting.

Associative Learning	Mean w [Lower CI – Upper CI 95%] parameter	Belief-update parameter	Mean w [Lower CI – Upper CI 95%]
$\lambda_{self,+ve}$	0.01 [−0.09 0.10]	α_{self}	−0.44 [− 0.80 − 0.04]
$\lambda_{self,-ve}$	0.11 [0.01 0.22]	β_{self}	−0.04 [−0.73 0.81]
$\lambda_{other,+ve}$	−0.06 [−0.14 0.03]	α_{other}	−0.05 [−0.18 0.09]
$\lambda_{other,-ve}$	−0.01 [−0.08 0.07]	β_{other}	0.14 [−0.24 0.52]
τ	−0.01 [−0.08 0.07]	η_{self}	−0.33 [−0.79 0.13]
Initial bias	−0.58 [−1.22 0.07]	η_{other}	−0.10 [−0.47 0.26]
Pos. bias	−0.04 [−0.19 0.10]	τ	−0.09 [−0.25 0.06]
		$\alpha_{initial}$	−0.14[−0.32 0.04]
		$\beta_{initial}$	−0.09[−0.04 0.22]

Note. Mean weights and 95% credible intervals for self/other valence model and self/other belief-update model are shown, with intervals not containing zero shown in bold.

The only associative weight parameter that did not have credible intervals overlapping 0 was for the self-negative learning rate (see table 3). This weight parameter was positive, indicating the higher the individual is in FNE, the larger the

self-negative learning rate will be. Therefore, it appears that in an associative learning framework, fear of negative evaluation is specifically related to over weighting of negative information, while positive information processing appears intact. Inspection of parameter estimates themselves indicate that positive learning rates averaged across self/other were overall significantly higher than the negative learning rates, consistent with an optimism bias $t(99) = 4.20$, $p < 0.01$.

The only belief-update weight parameter that did not have credible intervals overlapping 0 was between BFNE score and the $\alpha_{self,+ve}$ parameter (see 3). This weight parameter was negative, indicating the higher the individual is in FNE, the lower the amount of positive evidence in the self-schema, $\alpha_{trait,self}$, will be. The more negative balance of the self-schema then decreases the mean belief in approval in individuals with higher FNE.

The MLE fitted values of $\alpha_{trait,self}$ were strongly anticorrelated with the $\lambda_{-ve,self}$, Spearman $r = -0.46$, raw $p = 2.21e - 06$ and $\beta_{trait,self}$, Spearman $r = -0.34$, raw $p = 6.72e - 04$ (Spearman’s rho was used due to non-normality). $\lambda_{-ve,self}$ was also correlated with $\beta_{trait,other}$, Spearman $r = -0.22$, $p = 0.03$, and τ , Spearman $r = 0.28$, $p = 0.01$, but none of the other parameters of the belief-model. $\lambda_{-ve,self}$ was also strongly anticorrelated to the proportion of activated positive self-beliefs (Spearman $r = -0.27$, $p < 0.01$).

Generative Performance

We wanted to establish that the best-fitting models not only statistically fit the data well, but were also able to capture the processes of interest, as recommended by (Palminteri, Wyart, & Koechlin, 2017). The best-fitting associative learning model and belief-update models were used to generate pseudo-data from 100 sample datasets consisting of 1000 participants each. Using computational models to run simulations allows for the estimation of effects under ‘ideal experiment’ conditions, e.g. with more subjects than resource constraints allow. We checked that these could reproduce the pattern of data published in Button et al. (2015), and then formally ran the same

statistical tests and examined the credible intervals of each result over simulated samples. We computed the percentage positive response for each persona from the generated data as the number of positive word choices made/32 (number of trials). We ran linear mixed models including BFNE scores, persona (like/neutral/dislike) and referential condition (self/other) as predictor variables and percent positive response as outcome variable.

Figure 3. Generative performance; mean cumulative positive words chosen for actual data (first column) vs. data generated from ‘clinically informed fitting’ for associative learning and belief-update models. The generated data naturally includes stochasticity, so a representative example is shown here. All data is visualised using median-split FNE scores. Shaded zones represent $\pm$ SEM. The generated data reproduces many features of the real data, capturing the asymmetries in positive vs. negative word selection and the group differences between high and low FNE for the self-referential condition only. However, both models show slower initial learning and more optimistic minima in the self condition. The belief model underestimates, and the associative may overestimate, the group $\times$ condition $\times$ persona differences.

As seen in Figure 3, the generated data reproduced many features of the actual participant data. With generated data from the best-fitting associative learning model, we replicated all of the main and interaction effects from the linear mixed effects model

presented in (Button et al., 2015) in over 95% of the samples (Table). The associative learning model also provided evidence for a significant three-way BFNE X persona X condition interaction in over 95% of the samples. Using generated data from the belief-update model, we replicated all of the main and interaction effects in over 95% of the samples. The three-way interaction, however did not consistently reach significance. Implications for model performance in light of this are discussed.

Table 4

Generative performance statistics.

Contrast	Associative learning model		Belief-update model	
	Mean β coefficient	% of sig samples	Mean β coefficient	% of sig samples
Main effect BFNE	-0.66 [-0.67 -0.65]	100	-0.73 [-0.74 -0.72]	100
Main effect self/other	-10.76 [-11.04 -10.49]	100	-13.45 [-13.76 -13.14]	100
Main effect persona: like	21.68 [21.09 22.27]	100	25.61 [25.08 26.13]	100
Main effect persona: neutral	16.86 [16.16 17.56]	98	15.61 [14.80 16.41]	92
BFNE X self/other	0.27 [0.26 0.28]	100	0.27 [0.27 0.28]	100
BFNE X persona: like	0.63 [0.62 0.64]	100	0.72 [0.71 0.73]	100
BFNE X persona: neutral	0.16 [0.14 0.17]	22	0.28 [0.26 0.30]	64
BFNE X self/other X persona	-0.22 [-0.22 -0.23]	98	-0.23 [-0.24 0.22]	94

Note. [Lower CI–Upper CI 95%]

Discussion

We aimed to understand learning about self and others in those fearful of social evaluation, by formalizing and comparing two classic psychological perspectives. This is important, as the way in which belief-based accounts used by clinicians should be formalized is unknown, as is how valid they are and whether they are distinct from associationist accounts. Using a well-established Social Evaluation Learning task, we showed that reduced positive content within activated self-schemas may underpin increased sensitivity to negative evaluation in socially anxious individuals. Associative

learning and belief-based models described social learning well, associative models capturing somewhat better the interaction between task context and participant disposition.

We replicated, and also refined, influential findings on associative learning in social anxiety (Koban et al., 2017). Using a highly reproducible task Button et al. (2012, 2015), we confirmed that socially anxious (high-FNE) individuals showed higher learning rates governing the impact of negative information on predictions about the self. Overall, learning was faster for positive feedback, yet this did not fully account for participants' optimistic predictions about the self. We finessed the associative model by including a 'positivity parameter', thus better accounting for this optimism bias (Sharot et al., 2011).

Detecting the dependence of task parameters on FNE in this subclinical sample owed its success to *clinically informed model-fitting*, which makes use of a fundamental property of hierarchical statistical models. These infer the characteristics of each individual not only from the data they provided, but also from the specific population from which they are drawn. Here, the analysis considered whether a better model-fit would be obtained if the population was modelled to have cognitive parameters (say, learning rates) that varied systematically with FNE (Moutoussis et al., 2018). This allowed the fitting procedure to detect that significant correlations provided for a better fit to the overall data. Future research may benefit from clinically informed model-fitting.

To examine whether learning rates or positivity biases were understandable in terms of self-beliefs, which statistically account for improvement during therapy (Gregory & Peters, 2017), we formulated a very simple model of social belief update. We assumed that upon entering a context of evaluation of self or other, individuals activate beliefs about themselves (or others), over and above the evidence gleaned during the task. These beliefs are trait-like for the duration of the task, but may differ according to the contextual focus of evaluation. This activated self-schema consisted of positive and negative 'notional' evidence that each individual brought to mind. We

hypothesised that ordinary beliefs could be modelled as Bayesian beliefs, so that the strength of belief could be quantified much like in CBT ('I believe 70-80% that I will be judged positively'). This meant that belief change not only depended on evidence, but also on the certainty of prior beliefs (Moutoussis et al., 2016). Overall, the success of belief-based models suggested that this was indeed the case. Next, we hypothesized that the amount of evidence that each individual processed would be variable, in effect a working memory capacity. Again, the evidence supported this hypothesis. Another 'signature' of belief-based cognition might be that more uncertain participants would show increased decision variability. However, model comparison provided evidence against this.

Most importantly, FNE was predicted by the amount of positive evidence about the self that was held in mind independent of task feedback. The variation in this positive self-evidence accounted for almost half the variance in self-negative learning rates, however was not the only important relationship as there was also evidence for reduced negative self-evidence which, combined, may signal greater uncertainty in ones beliefs, similar to biases found in individuals with low self-esteem (Will et al., 2017). Importantly, the proportion of positive to negative self-evidence was greater in those with lower self-negative learning rates. Thus an activated self-schema including more positive evidence correlated strongly with diminished association value for negative attributes, largely reconciling cognitivist and behaviourist perspectives.

There was little evidence to favour belief-based vs. association models in the overall sample, but some individuals favoured associative learning, while others belief-updating. Belief-based models were a simple case of model-based cognition, updating the probability of a transition in the environment (that a persona will judge one positively), while the association models are model-free, incrementally associating values to actions. Thus, some people may be more model-based, whereas others more model-free, as in impersonal cognition (Daw, Gershman, Seymour, Dayan, & Dolan, 2011; Shahar et al., 2019).

Our study has the potential to inform treatments for social anxiety. Simple tasks,

like the one used here, may assess both the extent of biases and also the patient's predominant cognitive style, belief-based or associationist. Being able to quantify individuals self-views may prove to be particularly useful for assessing the outcome of therapies, as this is often the proposed object of intervention (Taylor & Montgomery, 2007). Patients characterized by slow learning may need to undergo longer treatments. Psychoeducation may be strengthened by incorporating rigorous research showing that patients are excessively influenced by negative feedback. Importantly, our findings support teaching patients to activate positive evidence about themselves 'on line', specifically upon exposure to negative feedback, consistent with the work of Kube et al. (2019).

In terms of limitations, our study induced social learning in an ecologically unrealistic setting. Ecologically realistic variants may induce stronger effects, important for detecting individual differences. Next, our modeling of evidence about the self was rudimentary, compared to the sophistication of clinical research on self representations (Calvete, Orue, & Hankin, 2013; Pinto-Gouveia et al., 2006). Limitations of model fidelity included over-slow initial learning (Fig. 3), possibly because real participants learn to fit personas into a few classes (kind, neutral etc.) rather than gradually infer degrees of approval.

In conclusion, non-clinical individuals high in fear of negative evaluation are more affected by negative social feedback, compared to those unafraid of feedback. The robustness of typical individuals is consistent with activation of more positive beliefs about themselves independently of feedback, acting as a 'buffer' against developing negative expectations. If replicated, this finding would offer support for therapeutic interventions aiming at activating positive views of self when people are in the crucible of social judgment.

CRedit Author Contributions

Conceptualisation, A.K.H, K.S.B. and M.M.; Methodology, A.K.H. and M.M.; Investigation, K.S.B.; Software, A.K.H; Writing - Original draft, A.K.H. and M.M.;

Writing - Review & editing, A.K.H., R.J.D., M.M. and K.S.B.; Supervision, M.M. and K.S.B.; Funding R.J.D. and K.S.B; Project Administration, R.J.D. All authors approved the final version of the manuscript for submission. (after <https://casrai.org/credit>).

Acknowledgments

We thank Geert-Jan Will and An-Ye Low for advice and discussions.

Funding

AH is a pre-doctoral fellow of the International Max Planck Research School on Computational Methods in Psychiatry and Ageing Research (IMPRS COMP2PSYCH). The participating institutions are the Max Planck Institute for Human Development, Berlin, Germany, and University College London, London, UK. For more information, see: <https://www.mps-ucl-centre.mpg.de/en/comp2psych>. A.K.H., R.J.D. and M.M. are funded by a Strategic Award by the Wellcome Trust (ref 095844/7/11/Z). M.M. is also supported by the NIHR UCLH Biomedical Research Center. Ray Dolan is supported by a Wellcome Trust Senior Investigator Award (ref 098362/Z/12/Z). The Max Planck - UCL Centre for Computational Psychiatry and Ageing Research is jointly funded by University College London and the Max Planck Society. The original study was funded by a Medical Research Council studentship awarded to K.S.B.

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