Modeling variation in empathic sensitivity using go/no-go social reinforcement learning

Katherine O'Connell^{1*}, Marissa Walsh², Brandon Padgett², Sarah Connell² & Abigail A. Marsh²

¹Interdisciplinary Program in Neuroscience, Georgetown University, Washington, DC, 20057

²Department of Psychology, Georgetown University, Washington, DC, 20057

Corresponding author e-mail: kmo52@georgetown.edu

Abstract

Empathic experiences shape social behaviors and display considerable individual variation. Recent advances in computational behavioral modeling can help rigorously quantify individual differences, but remain understudied in the context of empathy and antisocial behavior. We adapted a go/no-go reinforcement learning task across social and non-social contexts such that monetary gains and losses explicitly impacted the subject, a study partner, or no one. Empathy was operationalized as sensitivity to others' rewards, sensitivity to others' losses, and as the Pavlovian influence of empathic outcomes on approach and avoidance behavior. Results showed that 61 subjects learned for a partner in a way that was computationally similar to how they learned for themselves. Results supported the psychometric value of individualized model parameters such as sensitivity to others' loss, which was inversely associated with antisociality. Modeled empathic sensitivity also mapped onto motivation ratings, but was not associated with self-reported trait empathy. This work is the first to apply a social reinforcement learning task that spans affect and action requirement (go/no-go) to measure multiple facets of empathic sensitivity.

Keywords: Social learning; empathy; antisociality; behavioral modeling; reinforcement learning

Introduction

Empathic responding to the emotions of others—including representing, learning about, and responding to others’ outcomes—may be disrupted in populations with antisocial traits and behaviors (Blair, 2001, 2018; Decety et al., 2009; Lozier et al., 2014). The psychological and computational mechanisms underlying empathic responding are important to understand, but thus far remain opaque. Decades of research have shown how the anticipation of reward or punishment for the self can potentiate approach or avoidant behaviors, respectively (Estes & Skinner, 1941; Rescorla & Solomon, 1967). But comparatively little is known about how the anticipation of *others’* affective outcomes influences behavior, or how these processes may be disrupted in individuals with antisocial traits. For this study, we aimed to assess how reinforcement learning, which provides the prevailing framework to describe how organisms learn to obtain rewards and avoid punishments for themselves, can be extended to the social domain to help understand how we learn to make choices that result in outcomes for another person. This social reinforcement learning, or *learning for*, approach permits quantitative investigation of the influence of empathic affect on learning and behavior.

According to theories of shared representations, empathizing involves activation of neural processes involved in the first-hand experience of the target emotion (Bernhardt & Singer, 2012; Decety & Sommerville, 2003). For example, both winning money and viewing another person win money is associated with neural responses in ventral striatum (Burke et al., 2010; Fareri et al., 2012; Mobbs et al., 2009) and overlapping amygdala activation is observed during both experienced and empathic fear of shock (Lindström et al., 2018), suggesting similar neural processes. Shared responses to experienced and empathic events are also relevant for learning in social contexts. Neural reward prediction errors (i.e., modulations in activity based on the

difference between actual and expected reward outcomes) are observed in ventral striatum regardless of whether subjects learn for their own or a partner's monetary gain (Lockwood et al., 2016). Striatal prediction errors are also engaged when learning to avoid a shock to oneself or a partner (Lengersdorff et al., 2020). Both neural prediction error signals (Lockwood et al., 2016) and individualized model parameters that describe heightened sensitivity to others' outcomes—including learning rate (Lockwood et al., 2016) and value sensitivity (Lengersdorff et al., 2020)—have been positively associated with self-reported empathic abilities. This suggests that individual variation in learning when outcomes for another person are at stake reflects empathic traits. However, to our knowledge, no prior study has investigated links between learning across both rewarding and aversive social outcomes and antisociality.

We thus created a novel go/no-go social reinforcement learning paradigm in which monetary outcomes impacted the subject (the learner), a stranger (introduced to subjects as their study partner) or no one. Subjects learned to perform a go or a no-go action on trials associated with either win or loss, including two congruent trial types (go to win, no-go to avoid loss) and two incongruent trial types (no-go to win, go to avoid loss). This design capitalizes on the inflexibility of conserved, spontaneous behavioral responses to affective states—known as Pavlovian biases. In general, behavioral avoidance is facilitated in anticipation of aversive stimuli, whereas approach is facilitated during anticipation of appetitive stimuli (Chen & Bargh, 1999; Gray & McNaughton, 2000; Hershberger, 1986; Lang et al., 1990; Solarz, 1960). This fully-crossed design between action (go/no-go) and valence (win/lose) enables quantification of Pavlovian biases (Guitart-Masip et al., 2014; Guitart-Masip et al., 2012a; 2012b) and provides a deeper understanding of affect's influence on behavior than standard reinforcement learning designs, which typically require a go action (approach) on every trial and frequently assess only

one valence direction. Our design enabled us to quantify outcome sensitivities and Pavlovian biases for both positively and negatively valenced outcomes and to investigate whether people learn to obtain rewards and avoid punishments for others in a way that is computationally similar to how they learn for themselves.

Consistent with the shared representations view of empathy, we anticipated similarities in learning parameters for the self and social conditions. We also tested whether parameters indexing empathy during the task were associated with trait antisociality and empathy. We hypothesized a negative association between antisociality and modeled empathic sensitivity, particularly for others' loss. In the real-world, impaired empathy for others' distress is posited to be a primary factor contributing to maladaptive antisocial behaviors that cause harm to others' welfare directly or indirectly (Blair, 1995). Because we used a mixed-gender community sample, we focused on social aggression, which is also known as indirect or relational aggression (Archer & Coyne, 2005). This is a common form of antisocial behavior (Björkqvist et al., 1994; Burt et al., 2012) employed at relatively similar rates by females and males (Archer, 2004; Björkqvist et al., 1994; Burt et al., 2012; Czar et al., 2011; Eagly & Steffen, 1986; Slawinski et al., 2018), which involves the use or manipulation of social relationships as a means of harming others psychologically or detrimentally affecting their social status (Archer & Coyne, 2005; Burt & Donnellan, 2010). Examples include bullying, social exclusion, and spreading rumors. Like other forms of antisociality, social aggression is believed to reflect reduced empathic sensitivity (Decety, 2010; Marsh, 2016, 2018; Miller & Eisenberg, 1988), and, unlike physical aggression, is well distributed in community samples. However, few studies have applied computational modeling or reinforcement learning to quantify empathic deficits in social aggression. Lastly, and because measures of trait empathy have previously been linked to learning parameters for obtaining a

partner rewards (Lockwood et al., 2016) and avoiding a partner's shock (Lengersdorff et al., 2020), we hypothesized a positive association between trait empathy and model parameters capturing variation in empathy for both positive and negative social outcomes.

Methods

Subjects

A sample size of $n=60$ was predetermined following a power calculation using previously reported data (Lockwood et al., 2016) that observed a positive correlation ($r=.44$) between trait empathy and social reinforcement learning rate, for which we anticipated a similar effect size (power=.80, $\alpha=.05/8$). We thus enrolled 71 community adults from the Washington, DC metro area in testing (recruitment sources included the ResearchMatch database, flyers, word of mouth, and Georgetown University's Research Volunteer Program that granted course/extra credit to undergraduate students) to yield our final sample ($n=61$; 40f, 21m; 23.0 ± 6.9 years old) that excluded 2 subjects who did not complete the study, 5 who responded to $\geq 90\%$ of trials with the same action, and 3 who stopped responding to the task for ≥ 6 consecutive blocks. Six additional subjects expressed significant doubt that the social condition would result in real monetary payout to the partner, but were included in the final sample with a coded variable for post-hoc evaluation. Characteristics of the final sample are reported in Supplementary Table 1. Data was collected in 2017 and 2018 and all study procedures were carried out in accordance with a protocol approved by the Institutional Review Board at Georgetown University in Washington, DC, and subjects provided written informed consent prior to testing.

Procedure

A go/no-go reinforcement learning task (Guitart-Masip et al., 2012a; 2012b), which harnesses the interaction between action (go, no-go) and valence (reward, punishment) was adapted to include social and non-social conditions. Subjects first completed paper and pencil forms that included information regarding demographics. Subjects were then briefly introduced to a stranger described to them as their study partner, who was actually a trained female confederate. Subjects did not otherwise interact with this stranger and were told that they would leave at separate times to help minimize social desirability biases.

Subjects were introduced to the paradigm through written and verbal instruction and practiced the task. Subjects were instructed to learn the correct action for each image, either a button press or no button press, and that points would be converted to real money at the end of the task. Each trial consisted of presentation of a fractal image for 1000 ms followed by a 250 ms fixation then a 1000 ms decision screen (Fig. 1). The decision screen presented a white circle on either the right or left side of a central fixation cross, and subjects were told to match button press responses to the circle side using the right or left arrow key if they chose to respond. After another 250 ms fixation screen, a 1000 ms feedback screen showed a green up-arrow for win, a red down-arrow for loss or a yellow horizontal bar for no change. Each fractal image was associated with only one possible affective valence—that is each image was associated with either: 1) win for correct answers and no change for incorrect answers, or 2) no change for correct answers and loss for incorrect answers. This enabled each image to be tethered to either wins or losses, but not both, resulting in discrete affective mapping. The mapping between action requirement and affect was orthogonalized such that win-associated cues sometimes required no-go responses while loss-associated cues sometimes required go responses, creating two difficult trial types and two easy trial types (Pavlovian biases render go to win easier than go to avoid loss and no-go to avoid loss

easier than no-go to win). Subjects were not made aware of this interaction and were not told that fractal images were discretely associated with either possible win or loss. Outcomes were probabilistic such that the correct feedback was provided 80% of the time, while the alternate feedback was randomly provided 20% of the time.

The three condition types were always explicitly known to subjects; each condition block was introduced by a 4 second screen that signaled the condition type (“You are now playing for [YOURSELF] / [YOUR PARTNER] / [NO ONE]”) and was associated with a specific border color presented throughout the condition block. Three 120 s computerized break periods were built into the paradigm, which split the task into 4 chunks of 9 alternating condition blocks. The task consisted of 720 total trials (240 for each condition, 60 for each trial type, 20 trials within each condition block). Subjects and their partners were separately endowed with \$5 at the beginning of the task, which subjects could lose from or add to, up to \$10. Subjects were physically given 5 \$1 bills to increase the saliency and reinforce that real money was at stake. The experimental task was adapted from resources made available from a prior study (Mkrtchian et al., 2017) and was programed in Psychtoolbox 3 (<http://psychtoolbox.org>).

Fig. 1 Task Design. (a) Subjects learned a go/no-go reinforcement learning paradigm in three conditions, for when monetary outcomes impacted themselves, their study partner, or no one. On each trial, a fractal image cue was followed by a go/no-go decision screen. Subjects had to learn

the correct response, either a button press (go) or no button press (no-go) over time based on outcome feedback (win, loss, no change). Condition blocks alternated and were signaled by an instruction screen (e.g. “you are now playing for your partner”). (b) All four trial types were present in each condition and were cued by distinct fractal images

Following completion of the task, subjects completed a computerized survey that included ratings of effort and motivation (see Supplementary Materials), the Subtypes of Antisocial Behavior Questionnaire (STAB) (Burt & Donnellan, 2009), the Interpersonal Reactivity Index (IRI) (Davis, 1983), and the Spielberger Trait Anxiety Inventory (STAI-Y2) (Spielberger, 2010). The IRI is a 28-item measure that assesses trait empathy and includes two subscales indexing cognitive empathy (Perspective Taking, Fantasy) and two subscales indexing affective empathy (Personal Distress, Empathic Concern). The STAB is a 32-item measure that separately assesses Physical Aggression, Social Aggression, and Rule Breaking by summing subscale items. The scale was developed and validated for use in college and community samples and shows good criterion-related and ecological validity (Burt et al., 2012; Burt & Donnellan, 2009, 2010). The STAI-Y2 is a 20-item measure of trait anxiety developed for use in community and clinical samples. Four subjects did not complete motivation ratings and 1 subject did not complete the STAI-Y2.

Reinforcement learning models

All models were adapted from the classic Rescorla-Wagner model (Rescorla & Wagner, 1972) and were similar to previously reported adaptations used for this go/no-go reinforcement task design (Guitart-Masip et al., 2011; Guitart-Masip et al., 2012b; Mkrtchian et al., 2017). The models, which examine trial-by-trial behavior, use an update rule to calculate action weight on

each trial, $Weight_{a,s}$, allowing for learning about the best action (a) for each trial type (s) over time. Outcomes, r , were coded as +1, 0, or -1, based on whether the subject won, stayed the same, or lost points, respectively, as provided by feedback to the subject after each decision. This adapted Rescorla-Wagner model multiplies r_{actual} by a sensitivity parameter, β , to allow for variations in the effective size of the reinforcement, then subtracts from this product the learned expected outcome resulting in a prediction error. Learning occurs over time by multiplying prediction errors by a learning rate, α , and consequently updating the action weight from the preceding trial by adding the new learning (Equation 1). The update rule was calculated separately for each trial type, s , meaning that the events occurring between two trials of the same trial type had no influence in the model.

$$Weight_{a,s} = Weight_{a,s-1} + \alpha((\beta * r_{actual}) - r_{expected}) \quad (\text{Equation 1})$$

Action weights were then passed through a softmax function (Sutton & Barto, 1998) (Equation 2) to obtain action probabilities that introduced an irreducible noise parameter, x , which allowed for added choice noise in the conversion between action weights and action probabilities (x was set to 0 for the model without an x parameter).

$$Probability_{a,s} = \left[\frac{\exp(Weight_{a,s})}{\sum \exp(Weight'_{a,s})} \right] (1 - x) + \frac{x}{2} \quad (\text{Equation 2})$$

Incremental modifications (Table 1) to the Rescorla-Wagner model included the following additions: 1) b : a constant go bias parameter that added to the go action weight, 2) π : the Pavlovian bias parameter which was multiplied by the affective state value (also calculated by a Rescorla-

Wagner update rule), and the product of which was added to the action weight of go for positive affective states and added to the action weight of no-go for negative affective states, 3) q: an initial go bias parameter which set the initial go action weight greater than 0 to account for subjects' initial tendency to perform go actions at the beginning of the task. Finally, additional models evaluated fits when allowing for separate sensitivities to win and loss (β_{win} , β_{loss}) and separate Pavlovian bias parameters for win and loss (π_{win} , π_{loss}). These modifications are highly similar to those described previously (Guitart-Masip et al., 2014; Guitart-Masip et al., 2012b; Mkrtchian et al., 2017).

Table 1. Reinforcement learning models

Model (number of parameters)	Parameters					
	Sensitivity (β)	Learning rate (α)	Choice noise (x)	Constant go bias (b)	Pavlovian bias (π)	Initial go bias (q)
$\beta\alpha$ (2)	1	1				
$\beta\alpha x b$ (4)	1	1	1	1		
$\beta\alpha x b \pi$ (5)	1	1	1	1	1	
$2\beta\alpha x b \pi$ (6)	2	1	1	1	1	
$\beta\alpha x b 2\pi q$ (7)	1	1	1	1	2	1
$2\beta\alpha x b 2\pi q$ (8)*	2	1	1	1	2	1

* = winning model

The models were fit testing two distinct distributions; an unpooled distribution, in which models were fit to data from the self, social, and no one conditions separately, or a pooled distribution, in which models were fit to the entire dataset treating each condition and each subject as independent. Model comparison and assessment of distributions were analyzed using integrated Bayesian Information Criterion (iBIC) which penalizes models with more parameters. To

quantitatively compare the unpooled distribution model fit to the pooled distribution model fit, iBIC values were summed across the separately modeled self, social, and no one unpooled model fits (Mkrtchian et al., 2017).

Estimated parameters were fit for each subject and each condition using hierarchical expectation-maximization within `emfit_toolbox` code; <https://github.com/mpc-ucl/emfit>. Briefly, this process iterates between estimating parameters using maximum a posteriori inference and Laplacian approximation given group priors, then subsequently calculating new group mean priors from updated parameter estimates.

Statistical inference

To investigate within-subject effects, two-tailed repeated measures ANOVA tests evaluated mean accuracy and effect sizes are reported as partial eta squared (η^2) with the corresponding 95% CI. To test whether subjects performed significantly above chance overall, we applied a two-tailed, one-sample t-test against 50%; effect size is reported as Cohen's d with the corresponding 95% CI.

To investigate individual differences in model parameters, untransformed parameter estimates of interest from the winning model were Z-scored and submitted to a Pearson correlation test. Significance values for correlation tests (p_{perm}) were obtained using permutation testing implemented in Matlab; all tests were two-tailed and used 10,000 permutations to create a null distribution. Observation of a linear relationship was followed by multiple linear regression controlling for basic demographic variables and the corresponding parameter from the self condition.

Results

Traditional analyses of behavior

Mean accuracy was assessed to initially confirm the presence of predicted Pavlovian behavioral biases in the congruent and incongruent trial types that crossed action requirement and valence (Fig. 2). As expected, a three-way condition (self, social, no one) x action (go, no-go) x valence (win, avoid loss) repeated measures ANOVA revealed a significant action x valence interaction ($F(1,60)=32.39$, $p<.001$, $\eta^2=0.35$, 95% CI=[.16, .50]) such that the go action was potentiated by reward and the no-go action was potentiated by loss. The lack of a three-way interaction indicated that the action by valence interaction was similarly present across conditions ($F(2,120)=0.31$, $p=.733$). A main effect of condition ($F(2,120)=13.14$, $p<.001$, $\eta^2=.18$, 95% CI=[.06, .29]) and post-hoc testing with Bonferroni correction revealed that mean accuracy was significantly reduced in the social condition ($M=55.36\%$, $SD=1.29\%$, 95% CI=[52.78 %, 57.94%]) relative to the self ($M=60.68\%$, $SD=1.44\%$, 95% CI=[57.80%, 63.57%]; $p<.001$) and no one ($M=58.36\%$, $SD=1.16\%$, 95% CI=[56.04%, 60.69%]; $p=.019$) conditions; no statistically significant difference emerged between accuracy in the self and no one conditions ($p=.069$).

A significant main effect of action ($F(1,60)=52.07$, $p<.001$, $\eta^2=0.47$, 95% CI=[.27, .59]) indicated subjects were more accurate on go trials ($M=70.78\%$, $SD=2.03\%$, 95% CI=[66.73%, 74.84%]) relative to no-go trials ($M=45.48\%$, $SD=2.17\%$, 95% CI=[41.15%, 49.82%]) and a significant main effect of valence ($F(1,60)=16.57$, $p<.001$, $\eta^2=0.22$, 95% CI=[.06, .38]) indicated subjects were more accurate on avoid loss trials ($M=61.19\%$, $SD=1.39\%$, 95% CI=[58.42%, 63.97%]) than win trials ($M=55.08\%$, $SD=1.37\%$, 95% CI=[52.34%, 57.82%]). Subjects' overall accuracy was significantly above chance level ($M=58.14\%$, $SD=9.03\%$, 95% CI=[55.82%, 60.45%]; $t(60)=7.04$, $p<.001$, $d=0.90$, 95% CI=[0.60, 1.20]). The number of trials in which

subjects pressed the incorrect arrow key (right or left depending on circle side) accounted for very few trials (Mdn=4 out of 720 total trials, IQR=6.5).

Fig. 2 Overall performance accuracy. A significant action x valence interaction indicated that learning was impaired when action requirement was incongruent with valence (e.g. when no-go was required to win and when go was required to avoid loss). A main effect of condition indicated that accuracy was lowest for the social condition. Error bars represent 95% CI.

Winning model and validation

Models were compared for fit at the group level using iBIC, which penalizes models with more parameters. The winning model ($2\beta\alpha \times b2\pi q$) contained 8 parameters, which included one constant learning rate (α), separate sensitivities for rewards and punishments (β_{win} , β_{loss}), choice noise (x), a constant go bias (b), two separate Pavlovian bias parameters for wins and losses (π_{win} , π_{loss}), and an initial go bias (q). All models tested showed better performance when using the

pooled distribution (Supplementary Fig. 1), which fit data from all conditions in the same series of expectation-maximization steps, rather than fitting entirely separately for each condition. The pooled $2\beta\alpha \times 2\pi q$ model provides separate parameters for each subject and each condition. Transformed (Guitart-Masip et al., 2012b; Mkrtchian et al., 2017) parameters from the winning pooled model are plotted in Supplementary Fig. 2. Note that when modeling data separately by condition, the same $2\beta\alpha \times 2\pi q$ winning model performed best for both the self (iBIC= 1.50×10^4) and social (iBIC= 1.55×10^4) conditions; data collected during the no one condition was slightly better fit by the 7 parameter model ($\beta\alpha \times 2\pi q$; iBIC= 1.58×10^4), in which the same β parameter value was used for both wins and losses. Together, these findings support the prediction that subjects learn to obtain rewards and avoid punishments for others in a way that is computationally similar to how they learn for themselves.

The winning $2\beta\alpha \times 2\pi q$ model and estimated parameters for each subject were passed through a posterior predictive model to simulate behavior. Overall accuracy and learning curves of the simulated data follow closely with the subjects' real data (Fig. 3). The model performed well overall, but similar to a prior report (Mkrtchian et al., 2017), does not fully capture subjects' extremely poor performance on the no-go to win trial type. Plots of actual mean accuracy relative to simulated mean accuracy at the subject level are displayed in Supplementary Fig. 3.

Fig. 3 The posterior predictive model tracks subjects' actual performance. Colored bar graphs display subjects' mean accuracy in the self (a), social (b), and no one (c) conditions in comparison to simulated mean accuracy from the posterior predictive model (red). Line graphs show mean accuracy over time for real data (black) and simulated data (red)

Model parameters in relation to reported socioemotional traits

As hypothesized, bivariate tests found that antisociality was negatively associated with β sensitivity to the partners' outcomes. STAB Social Aggression subscale scores were negatively correlated with β sensitivity for the partner's loss ($r=-.273$, $p_{\text{perm}}=.034$; Fig. 4b; Supplemental Table 3) and, at a trend level, β sensitivity for the partner's win ($r=-.246$, $p_{\text{perm}}=.055$; Fig. 4a). In other words, increased antisociality was associated with reduced impact of the partners' affective outcomes on learning.

We next tested whether these relationships were retained after controlling for demographics and the corresponding β sensitivity for experienced (self) outcomes using multiple linear regression (Table 2). For the regression model predicting β_{loss} social, the association with antisociality persisted ($\beta=-.22$, $t(55)=2.06$, $p=.044$; model $R^2=.41$, $p<.001$) after accounting for age, sex, education level and β_{loss} during the self condition. That is, antisociality remains negatively associated with β sensitivity to a stranger's loss even when controlling for β sensitivity to experienced loss. Results of the regression model predicting the β_{win} social parameter, however, revealed that antisociality had no significant predictive value when accounting for age, sex, education and the β_{win} self parameter ($\beta=-.13$, $t(55)=1.16$, $p=.252$; model $R^2=.35$, $p<.001$). These results suggest that for negative affect, the empathic social condition appears to capture additional information relevant for antisociality beyond what could be explained by self-oriented learning. The relationship between β_{loss} social and antisociality was unaffected by removal of subjects that expressed significant doubt that the social condition would result in real monetary outcomes for the partner ($\beta=-.22$, $t(49)=2.02$, $p=.049$; model $R^2=.46$, $p<.001$).

Importantly, no significant associations were observed between antisociality and β_{loss} sensitivities obtained during the self ($r=-.127$, $p_{\text{perm}}=.328$) or no one ($r=-.206$, $p_{\text{perm}}=.111$)

conditions. Trend level negative associations were observed between antisociality and β_{win} sensitivities obtained during the self ($r=-.247$, $p_{\text{perm}}=.054$) and no one ($r=-.223$, $p_{\text{perm}}=.084$) conditions. Lastly, and further supporting the psychometric value of the social β_{loss} parameter, post-task ratings of motivation to avoid loss in the social relative to self condition positively correlated with this parameter ($r=.361$, $p_{\text{perm}}=.006$; Supplemental Fig. 4).

Fig. 4 Correlations between antisociality and model parameters β sensitivity and π

Pavlovian bias. Pearson correlations between z-scored model parameters obtained for the social (a-d) and self (e-h) conditions. Reported significance values are uncorrected and were obtained using two-tailed permutation tests

Table 2. Multiple linear regression models predicting β sensitivity for the partners' loss and win.

$\beta_{\text{loss}} \text{ Social}^a$	B [95% CI]	β	t	p
Constant	0.60 [-0.79, 1.98]		0.86	.394
Age	0.03 [-0.01, 0.06]	.18	1.41	.165
Sex ^c	0.13 [-0.33, 0.58]	.06	0.55	.582
Education ^d	-0.39 [-0.98, 0.19]	-.16	-1.35	.184
$\beta_{\text{loss}} \text{ Self}$	0.50 [0.28, 0.72]	.50	4.59	<.001*
Antisociality	-0.06 [-0.11, -.001]	-.22	-2.06	.044*
$\beta_{\text{win}} \text{ Social}^b$	B [95% CI]	β	t	p
Constant	0.13 [-1.36, 1.62]		0.18	.860
Age	0.03 [-0.01, 0.06]	.17	1.37	.175
Sex ^c	0.11 [-0.37, 0.58]	.05	0.45	.656
Education ^d	-0.35 [-0.95, 0.25]	-.14	-1.17	.249
$\beta_{\text{win}} \text{ Self}$	0.52 [0.29, 0.74]	.52	4.52	<.001*
Antisociality	-0.03 [-0.09, 0.02]	-.13	-1.16	.252

^a Model predicting $\beta_{\text{loss}} \text{ Social}$, $R^2=.41$, $p<.001$. ^b Model predicting $\beta_{\text{win}} \text{ Social}$, $R^2=.35$, $p<.001$. ^c

Sex was coded as 1 for female and 0 for male. ^d Education was coded as 1 for ≥ 4 -year degree and 0 for < 4 -year degree.

Contrary to expectations, antisociality did not show a significant relationship with Pavlovian bias parameters (π_{win} or π_{loss}) during the social or self conditions ($p_{\text{perm}} \geq .410$). However, similar to prior literature (Mkrtchian et al., 2017) we observed that high trait anxiety was associated with increased Pavlovian avoidance bias during self-experienced negative affect ($r=.258$, $p_{\text{perm}}=.045$; Supplementary Table 5), providing evidence that the Pavlovian bias parameter successfully captured meaningful socioemotional variance.

In addition, no significant association was observed between self-reported trait empathy and model parameters indexing empathic sensitivity (social β_{win} and β_{loss}) or empathic Pavlovian bias (social π_{win} and π_{loss}) (IRI Total; all $p_{\text{perm}} \geq .320$). Exploratory assessment of IRI subscales also

showed no significant association with these parameters (all $p_{\text{perm}} \geq .098$). Full statistics are displayed in Supplemental Table 4.

Bivariate correlation tables between social learning model parameters and self-reported traits are displayed in Supplemental Tables 3-5. Of note, antisociality was also positively correlated with social learning rate α ($r = .285$, $p_{\text{perm}} = .025$).

Discussion

Using a novel learning task that fully crossed valence, social context, and behavioral activation, we found that learning from experienced and empathic outcomes relies on similar computational processes and that individual differences in the weights of these computations meaningfully relate to socioemotional traits, particularly antisociality. Subjects were able to learn a task when monetary outcomes impacted a stranger study partner, but subjects who reported increased antisociality exhibited reduced sensitivity to the partner's outcomes, in line with theories that empathic deficits may lay the foundation for the development of antisocial behavior (Decety, 2010; Marsh, 2016, 2018; Miller & Eisenberg, 1988). Reduced empathic sensitivity for losses was associated with antisociality even after adjusting for demographic variables and self-oriented loss sensitivity, suggesting the social learning condition captured uniquely meaningful information about antisocial traits. To our knowledge, this is the first report to identify a link between antisociality and empathic sensitivity using a social reinforcement learning paradigm. Task ratings of self-reported motivation to avoid loss for the partner were also associated with increased empathic sensitivity for losses, and in line with a prior study (Mkrtchian et al., 2017), trait anxiety correlated with heightened Pavlovian avoidance bias when facing potential loss to the self (but not

the partner). These results indicate the task and modeling are suitable for assessing individual differences across distinct socioemotional traits.

By incorporating go/no-go action requirements, we quantified Pavlovian behavioral biases—the inflexible mappings between behavioral approach/ avoidance and positive/ negative affective states—for both self and social learning. Analyses of overall accuracy and model fitting confirmed the presence of Pavlovian biases across conditions; however, we found no clear link between Pavlovian biases and antisociality. These results point to the utility of our paradigm to separately quantify sensitivity to empathic outcomes (β) and the influence of empathic affect on approach and avoidance Pavlovian biases (π), with only the former associated with antisociality in our sample. Other paradigms have indicated generally reduced influence of affect on approach/avoidance behavior in violent incarcerated samples (Ly et al., 2016) and impaired inhibition in response to punishment cues during passive avoidance learning in youths with clinical-level conduct problems (White et al., 2014, 2016)—suggesting that variations in the Pavlovian bias parameter may be associated with more extreme forms of antisociality.

Many experimental paradigms used to study antisociality measure affective responding only as it applies to outcomes for the self—for example, behavioral, physiological or neural responses to affective events experienced first-hand (Arnett, 1997; Buckholtz et al., 2010, 2017; De Brito et al., 2013; Lorber, 2004; Murray et al., 2017, 2018; White et al., 2014, 2016). But antisocial behaviors are—by definition—fundamentally about disrupted social behaviors that impact other individuals. Thus, understanding antisociality and its computational origins may be better achieved by the techniques we report here and through incorporation of explicitly social (empathic) task conditions.

While antisociality, trait anxiety and post-task motivation ratings all showed largely expected correlations with model parameters, we observed no significant relationship with self-reported empathy measured using IRI Total Score. These findings contrast with previous reports of increased social reinforcement learning rate α (Lockwood et al., 2016) and choice sensitivity (referred to here as choice noise, x) (Lengersdorff et al., 2020) being associated with heightened self-reported empathy. Both of these previous investigations used the Questionnaire of Cognitive and Affective Empathy—a scale developed by selecting optimal items from prior empathy questionnaires including IRI (Reniers et al., 2011), which may account for the absence of similar results in the present study. The α learning rate parameter from the current investigation may also not be well suited for comparison with learning rates obtained from prior social reinforcement learning designs. Due to the orthogonalization of action and valence in the current study, half of the trial types require that learning overcome affective Pavlovian biases. For example, high sensitivity to partner outcomes in the current investigation was expected to—and did—inhibit learning on the go to avoid loss and no-go to win trials, which may explain why antisociality was correlated with increased social α learning rate but reduced β empathic sensitivity. The absence of a relationship between model parameters and self-reported empathy may also reflect the generally poor reliability of self-reported empathy measures, given their poor predictive validity in interpersonal settings (Bernardo et al., 2018; Ickes et al., 2000; Marsh et al., 2007; Vachon et al., 2014) and subjectivity to strong bias and demand characteristics (Zhou et al., 2003).

Some additional limitations should be considered in interpreting results. Although subjects met their study partner before the task to increase ecological validity, it remains to be determined whether present results would apply to more complex or face-to-face social situations. In addition, the task operationalized empathic affect as discrete parameters constrained within the framework

of reinforcement learning. Although defining empathy in this stringent way carries strengths, fully understanding empathic affect and its behavioral consequences will require implementing diverse modeling techniques (e.g., drift diffusion, hyperbolic discounting) across various social paradigms and across species (Lockwood et al., 2020).

We obtained relatively small learning rates across conditions (median α values ranged from .046 to .053). Although subjects overall performed significantly above chance and our model simulated data well, future investigations—especially those that involve brain imaging—should consider the tradeoff between task complexity and the potential speed of learning, particularly in relation to trial-by-trial signals of interest (e.g. action values). Lastly, the effect sizes observed in the current study were small, suggesting that replication in a large and diverse sample will be important and that future work may benefit from refining the task or methods to increase specificity (e.g., removing the no one condition, which rather than serving as a non-active comparator may capture participation effort or social desirability, which may be related to socioemotional traits of interest).

This *learning for* paradigm appears to aptly model empathic responding for both positive and negative valence, and in combination with go/no-go requirements, aids in understanding how empathic affect influences behavioral approach and avoidance. We provide the first evidence linking antisociality to impaired sensitivity to others' monetary outcomes during learning, supporting the utility of computational learning models for understanding the processes shaping variance in socioemotional traits.

Acknowledgments

The authors thank Lydia Meena for help with data collection and Shawn A. Rhoads for helpful feedback.

Funding

This work was supported by the National Center for Advancing Translational Sciences of the National Institutes of Health under Award Number TL1TR001431 to KO and by internal Georgetown University funding provided to AAM.

Conflicts of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

Availability of data and material

The datasets generated and analyzed in the current study are available in the Open Science Framework Repository, osf.io/u9fx3/.

Code availability

Code specific to this study is made available osf.io/u9fx3/. The emfit_toolbox code was provided by Q.J.M. Huys and is available at <https://github.com/mpc-ucl/emfit>.

Authors' contributions

KO conceptualized study, programmed tasks, collected data, analyzed data, and wrote manuscript; MW, BP, and SC collected data; AAM conceptualized study, acquired funding, and

provided critical revisions to the manuscript. All authors approved the final version of the manuscript.

References

- Archer, J. (2004). Sex differences in aggression in real-world settings: A meta-analytic review. *Review of General Psychology*, 8(4), 291–322. <https://doi.org/10.1037/1089-2680.8.4.291>
- Archer, J., & Coyne, S. M. (2005). An Integrated Review of Indirect, Relational, and Social Aggression. *Personality and Social Psychology Review*, 9(3), 212–230. https://doi.org/10.1207/s15327957pspr0903_2
- Arnett, P. A. (1997). Autonomic responsivity in psychopaths: A critical review and theoretical proposal. *Clinical Psychology Review*, 17(8), 903–936. [https://doi.org/10.1016/S0272-7358\(97\)00045-7](https://doi.org/10.1016/S0272-7358(97)00045-7)
- Bernardo, M. O., Cecílio-Fernandes, D., Costa, P., Quince, T. A., Costa, M. J., & Carvalho-Filho, M. A. (2018). Physicians' self-assessed empathy levels do not correlate with patients' assessments. *PLoS ONE*, 13(5), e0198488. <https://doi.org/10.1371/journal.pone.0198488>
- Bernhardt, B. C., & Singer, T. (2012). The Neural Basis of Empathy. *Annual Review of Neuroscience*, 35(1), 1–23. <https://doi.org/10.1146/annurev-neuro-062111-150536>
- Björkqvist, K., Österman, K., & Lagerspetz, K. M. J. (1994). Sex differences in covert aggression among adults. *Aggressive Behavior*, 20(1), 27–33. [https://doi.org/10.1002/1098-2337\(1994\)20:1<27::AID-AB2480200105>3.0.CO;2-Q](https://doi.org/10.1002/1098-2337(1994)20:1<27::AID-AB2480200105>3.0.CO;2-Q)
- Blair, R. J. R. (1995). A cognitive developmental approach to mortality: investigating the psychopath. *Cognition*, 57(1), 1–29. [https://doi.org/10.1016/0010-0277\(95\)00676-P](https://doi.org/10.1016/0010-0277(95)00676-P)
- Blair, R. J. R. (2001). Neurocognitive models of aggression, the antisocial personality disorders,

and psychopathy. *Journal of Neurology, Neurosurgery & Psychiatry*, 71(6), 727–731.

<https://doi.org/10.1136/jnnp.71.6.727>

Blair, R. J. R. (2018). Traits of empathy and anger: Implications for psychopathy and other disorders associated with aggression. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 373, 20170155. <https://doi.org/10.1098/rstb.2017.0155>

Buckholtz, J. W., Karmarkar, U., Ye, S., Brennan, G. M., & Baskin-Sommers, A. (2017). Blunted Ambiguity Aversion during Cost-Benefit Decisions in Antisocial Individuals. *Scientific Reports*, 7, 2030. <https://doi.org/10.1038/s41598-017-02149-6>

Buckholtz, J. W., Treadway, M. T., Cowan, R. L., Woodward, N. D., Benning, S. D., Li, R., ... & Zald, D. H. (2010). Mesolimbic dopamine reward system hypersensitivity in individuals with psychopathic traits. *Nature Neuroscience*. <https://doi.org/10.1038/nn.2510>

Burke, C. J., Tobler, P. N., Baddeley, M., & Schultz, W. (2010). Neural mechanisms of observational learning. *Proceedings of the National Academy of Sciences of the United States of America*, 107(32), 14431–14436. <https://doi.org/10.1073/pnas.1003111107>

Burt, S. A., & Donnellan, M. B. (2009). Development and validation of the subtypes of antisocial behavior questionnaire. *Aggressive Behavior*, 35(5), 376–398. <https://doi.org/10.1002/ab.20314>

Burt, S. A., & Donnellan, M. B. (2010). Evidence that the Subtypes of Antisocial Behavior questionnaire (STAB) predicts momentary reports of acting-out behaviors. *Personality and Individual Differences*, 48(8), 917–920. <https://doi.org/10.1016/j.paid.2010.02.021>

Burt, S. A., Donnellan, M. B., & Tackett, J. L. (2012). Should social aggression be considered “antisocial”? *Journal of Psychopathology and Behavioral Assessment*, 34(2), 153–163. <https://doi.org/10.1007/s10862-011-9267-0>

518 Chen, M., & Bargh, J. A. (1999). Consequences of Automatic Evaluation: Immediate Behavioral
519 Predispositions to Approach or Avoid the Stimulus. *Personality and Social Psychology*
520 *Bulletin*, 25(2), 215–224. <https://doi.org/10.1177/0146167299025002007>

521 Czar, K. A., Dahlen, E. R., Bullock, E. E., & Nicholson, B. C. (2011). Psychopathic personality
522 traits in relational aggression among young adults. *Aggressive Behavior*, 37(2), 207–214.
523 <https://doi.org/10.1002/ab.20381>

524 Davis, M. H. (1983). Measuring individual differences in empathy: Evidence for a
525 multidimensional approach. *Journal of Personality and Social Psychology*, 44(1), 113–126.
526 <https://doi.org/10.1037/0022-3514.44.1.113>

527 De Brito, S. A., Viding, E., Kumari, V., Blackwood, N., & Hodgins, S. (2013). Cool and Hot
528 Executive Function Impairments in Violent Offenders with Antisocial Personality Disorder
529 with and without Psychopathy. *PLoS ONE*, 8(6), e65566.
530 <https://doi.org/10.1371/journal.pone.0065566>

531 Decety, J. (2010). The neurodevelopment of empathy in humans. *Developmental Neuroscience*,
532 32(4), 257–267. <https://doi.org/10.1159/000317771>

533 Decety, J., Michalska, K. J., Akitsuki, Y., & Lahey, B. B. (2009). Atypical empathic responses in
534 adolescents with aggressive conduct disorder: A functional MRI investigation. *Biological*
535 *Psychology*, 80(2), 203–211. <https://doi.org/10.1016/j.biopsycho.2008.09.004>

536 Decety, J., & Sommerville, J. A. (2003). Shared representations between self and other: A social
537 cognitive neuroscience view. *Trends in Cognitive Sciences*, 7(12), 527–533.
538 <https://doi.org/10.1016/j.tics.2003.10.004>

539 Eagly, A. H., & Steffen, V. J. (1986). Gender and Aggressive Behavior. A Meta-Analytic
540 Review of the Social Psychological Literature. *Psychological Bulletin*, 100(3), 309–330.

541 <https://doi.org/10.1037/0033-2909.100.3.309>

542 Estes, W. K., & Skinner, B. F. (1941). Some quantitative properties of anxiety. *Journal of*
543 *Experimental Psychology*, 29(5), 390–400. <https://doi.org/10.1037/h0062283>

544 Fareri, D. S., Niznikiewicz, M. A., Lee, V. K., & Delgado, M. R. (2012). Social network
545 modulation of reward-related signals. *Journal of Neuroscience*, 32(26), 9045–9052.
546 <https://doi.org/10.1523/JNEUROSCI.0610-12.2012>

547 Gray, J. A., & McNaughton, N. (2000). *The Neuropsychology of Anxiety: An Enquiry into the*
548 *Functions of the Septo-Hippocampal System, Second Edition*. Oxford University Press.

549 Guitart-Masip, M., Chowdhury, R., Sharot, T., Dayan, P., Duzel, E., & Dolan, R. J. (2012a).
550 Action controls dopaminergic enhancement of reward representations. *Proceedings of the*
551 *National Academy of Sciences of the United States of America*, 109(19), 7511–7516.
552 <https://doi.org/10.1073/pnas.1202229109>

553 Guitart-Masip, M., Duzel, E., Dolan, R., & Dayan, P. (2014). Action versus valence in decision
554 making. *Trends in Cognitive Sciences*, 18(4), 194–202.
555 <https://doi.org/10.1016/j.tics.2014.01.003>

556 Guitart-Masip, M., Fuentemilla, L., Bach, D. R., Huys, Q. J. M., Dayan, P., Dolan, R. J., &
557 Duzel, E. (2011). Action dominates valence in anticipatory representations in the human
558 striatum and dopaminergic midbrain. *J Neurosci*, 31(21), 7867–7875.
559 <https://doi.org/10.1523/JNEUROSCI.6376-10.2011>

560 Guitart-Masip, M., Huys, Q. J. M., Fuentemilla, L., Dayan, P., Duzel, E., & Dolan, R. J. (2012b).
561 Go and no-go learning in reward and punishment: Interactions between affect and effect.
562 *NeuroImage*, 62(1), 154–166. <https://doi.org/10.1016/j.neuroimage.2012.04.024>

563 Hershberger, W. A. (1986). An approach through the looking-glass. *Animal Learning &*

564 *Behavior*, 14(4), 443–451. <https://doi.org/10.3758/BF03200092>
 565 Ickes, W., Buysse, A., Pham, H., Rivers, K., Erickson, J. R., Hancock, M., ... & Gesn, P. R.
 566 (2000). On the difficulty of distinguishing “good” and “poor” perceivers: A social relations
 567 analysis of empathic accuracy data. *Personal Relationships*, 7(2), 219–234.
 568 <https://doi.org/10.1111/j.1475-6811.2000.tb00013.x>
 569 Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (1990). Emotion, Attention, and the Startle
 570 Reflex. *Psychological Review*, 97(3), 377–395. <https://doi.org/10.1037/0033-295X.97.3.377>
 571 Lengersdorff, L., Wagner, I., Lockwood, P. L., & Lamm, C. (2020). When implicit prosociality
 572 trumps selfishness: the neural valuation system underpins more optimal choices when
 573 learning to avoid harm to others than to oneself. *The Journal of Neuroscience*, 40(38),
 574 7286–7299. <https://doi.org/10.1523/JNEUROSCI.0842-20.2020>
 575 Lindström, B., Haaker, J., & Olsson, A. (2018). A common neural network differentially
 576 mediates direct and social fear learning. *NeuroImage*, 167, 121–129.
 577 <https://doi.org/10.1016/j.neuroimage.2017.11.039>
 578 Lockwood, P. L., Apps, M. A. J., & Chang, S. W. C. (2020). Is There a ‘Social’ Brain?
 579 Implementations and Algorithms. *Trends in Cognitive Sciences*, 24(10), P802-813.
 580 <https://doi.org/10.1016/j.tics.2020.06.011>
 581 Lockwood, P. L., Apps, M. A. J., Valton, V., Viding, E., & Roiser, J. P. (2016).
 582 Neurocomputational mechanisms of prosocial learning and links to empathy. *Proceedings*
 583 *of the National Academy of Sciences of the United States of America*, 113(35), 9763–9768.
 584 <https://doi.org/10.1073/pnas.1603198113>
 585 Lorber, M. F. (2004). Psychophysiology of aggression, psychopathy, and conduct problems: a
 586 meta-analysis. *Psychological Bulletin*, 130(4), 531–552. <https://doi.org/10.1037/0033->

2909.130.4.531

- Lozier, L. M., Cardinale, E. M., Vanmeter, J. W., & Marsh, A. A. (2014). Mediation of the relationship between callous-unemotional traits and proactive aggression by amygdala response to fear among children with conduct problems. *JAMA Psychiatry*, 71(6), 627–636. <https://doi.org/10.1001/jamapsychiatry.2013.4540>
- Ly, V., von Borries, A. K. L., Brazil, I. A., Bulten, B. H., Cools, R., & Roelofs, K. (2016). Reduced Transfer of Affective Value to Instrumental Behavior in Violent Offenders. *Journal of Abnormal Psychology*, 125(5), 657–663. <https://doi.org/10.1037/abn0000166>
- Marsh, A. A. (2016). Understanding amygdala responsiveness to fearful expressions through the lens of psychopathy and altruism. *Journal of Neuroscience Research*, 94(6), 513–525. <https://doi.org/10.1002/jnr.23668>
- Marsh, A. A. (2018). The caring continuum: Evolved hormonal and proximal mechanisms explain prosocial and antisocial extremes. *Annual Review of Psychology*, 70, 347–371. <https://doi.org/10.1146/annurev-psych-010418-103010>
- Marsh, A. A., Kozak, M. N., & Ambady, N. (2007). Accurate identification of fear facial expression predicts prosocial behavior. *Emotion*, 7(2), 239–251. <https://doi.org/10.1037/1528-3542.7.2.239>
- Miller, P. A., & Eisenberg, N. (1988). The relation of empathy to aggressive and externalizing/antisocial behavior. *Psychological Bulletin*, 103(3), 324–344. <https://doi.org/10.1037/0033-2909.103.3.324>
- Mkrtchian, A., Aylward, J., Dayan, P., Roiser, J. P., & Robinson, O. J. (2017). Modeling avoidance in mood and anxiety disorders using reinforcement learning. *Biological Psychiatry*, 82(7), 532–539. <https://doi.org/10.1016/j.biopsych.2017.01.017>

- Mobbs, D., Yu, R., Meyer, M., Passamonti, L., Seymour, B., Calder, A. J., Schweizer, S., Frith, C. D., & Dalglish, T. (2009). A key role for similarity in vicarious reward. *Science*, 324(5929), 900. <https://doi.org/10.1126/science.1170539>
- Murray, L., Shaw, D. S., Forbes, E. E., & Hyde, L. W. (2017). Reward-related neural correlates of antisocial behavior and callous–unemotional traits in young men. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, 2(4), 346–354. <https://doi.org/10.1016/j.bpsc.2017.01.009>
- Murray, L., Waller, R., & Hyde, L. W. (2018). A systematic review examining the link between psychopathic personality traits, antisocial behavior, and neural reactivity during reward and loss processing. *Personality Disorders: Theory, Research, and Treatment*, 9(6), 497–509. <https://doi.org/10.1037/per0000308>
- Reniers, R. L. E. P., Corcoran, R., Drake, R., Shryane, N. M., & Völlm, B. A. (2011). The QCAE: A questionnaire of cognitive and affective empathy. *Journal of Personality Assessment*, 93(1), 84–95. <https://doi.org/10.1080/00223891.2010.528484>
- Rescorla, R. A., & Solomon, R. L. (1967). Two-process learning theory: relationships between pavlovian conditioning and instrumental learning. *Psychological Review*, 74(3), 151–182. <https://doi.org/10.1037/h0024475>
- Rescorla, R. A., & Wagner, A. R. (1972). A theory of Pavlovian conditioning: Variations in the effectiveness of reinforcement and nonreinforcement. In A. H. Black & W. F. Prokasy (Eds.), *Classical Conditioning II Current Research and Theory* (pp. 64–99). Appleton-Century-Crofts.
- Slawinski, B. L., Klump, K. L., & Burt, A. S. (2018). No sex differences in the origins of covariation between social and physical aggression. *Psychological Medicine*, 49(15), 1–9.

<https://doi.org/10.1017/s0033291718003392>

Solarz, A. K. (1960). Latency of instrumental responses as a function of compatibility with the meaning of eliciting verbal signs. *Journal of Experimental Psychology*, 59(4), 239–245.

<https://doi.org/10.1037/h0047274>

Spielberger, C. D. (2010). State-Trait Anxiety Inventory. In *The Corsini Encyclopedia of Psychology*.

Sutton, R. S., & Barto, A. G. (1998). *Introduction to Reinforcement Learning*. Cambridge: MIT press.

Vachon, D. D., Lynam, D. R., & Johnson, J. A. (2014). The (non)relation between empathy and aggression: Surprising results from a meta-analysis. *Psychological Bulletin*, 140(3), 751–773. <https://doi.org/10.1037/a0035236>

White, S. F., Fowler, K. A., Sinclair, S., Schechter, J. C., Majestic, C., Pine, D. S., & Blair, R. J. R. (2014). Disrupted Expected Value Signaling in Youth With Disruptive Behavior Disorders to Environmental Reinforcers. *Journal of the American Academy of Child and Adolescent Psychiatry*, 53(5), 579–588. <https://doi.org/10.1016/j.jaac.2013.12.023>

White, S. F., Tyler, P. M., Erway, A. K., Botkin, M. L., Kolli, V., Meffert, H., Pope, K., & Blair, J. R. (2016). Dysfunctional representation of expected value is associated with reinforcement-based decision-making deficits in adolescents with conduct problems. *Journal of Child Psychology and Psychiatry*, 57(8), 938–946.

<https://doi.org/10.1111/jcpp.12557>

Zhou, Q., Valiente, C., & Eisenberg, N. (2003). Empathy and its measurement. In S. J. Lopez & C. R. Snyder (Eds.), *Positive psychological assessment: A handbook of models and measures* (pp. 269–284). American Psychological Association.

Modeling variation in empathic sensitivity using go/no-go social reinforcement learning

Supplementary Materials

Katherine O'Connell*, Marissa Walsh, Brandon Padgett, Sarah Connell & Abigail A. Marsh

Supplementary Text

Immediately following completion of the task subjects were directed to complete a computerized survey, which first asked them to rate for each condition how motivated they were to earn additional money (1–not at all motivated, 7–extremely motivated), how motivated they were to avoid losing money (1–not at all motivated, 7–extremely motivated), and their overall effort exerted (1–no effort, 7–maximal effort).

Results of a 3 condition (self, social, no one) x 2 valence (win, avoid loss) repeated measures ANOVA on motivation revealed a significant main effect of condition ($F(2,112)=43.53$, $p<.001$, $\eta^2=.44$, 95% CI=[.30, .54]) driven by reduced reported motivation during the no one condition (Supplementary Table 2). Subjects reported similarly moderate-to-high motivation to win and avoid losing money during both the self and social conditions. No significant main effect of valence ($F(1,56)=2.30$, $p=.135$) nor a condition x valence interaction ($F(2,112)=0.38$, $p=.686$) emerged. Ratings of effort also revealed a main effect of condition ($F(2,112)=22.17$, $p<.001$, $\eta^2=.28$, 95% CI=[.14, .40]) such that effort was lowest during the no one condition, but showed no difference between the self and social conditions ($p>.999$).

Supplementary Tables

Supplementary Table 1. Characteristics of the final sample

		Min-Max
N	61	
Age, <i>M (SD)</i>	23.0 (6.9)	18-49
Male/Female (% Female)	21/40 (66%)	
Race		
White/ Caucasian	32 (53%)	
Black/African-American	8 (13%)	
Asian	15 (25%)	
Other	5 (8%)	
Trait Anxiety STAI-Y2, <i>M (SD)</i>	43.7 (12.4)	23-71
Interpersonal Reactivity Index (IRI)	68.5 (12.9)	28-91
Perspective Taking, <i>M (SD)</i>	18.5 (4.7)	5-27
Fantasy, <i>M (SD)</i>	17.4 (5.3)	7-26
Empathic Concern, <i>M (SD)</i>	20.9 (4.6)	7-28
Personal Distress, <i>M (SD)</i>	11.7 (5.3)	1-25
Subtypes of Antisocial Behavior (STAB)		
Physical Aggression, <i>M (SD)</i>	18.0 (4.5)	12-36
Social Aggression, <i>M (SD)</i>	21.5 (4.0)	15-30
Rule-Breaking, <i>M (SD)</i>	12.4 (2.2)	11-21

Note: One subject did not report their race and one subject did not complete the STAI-Y2.

Supplementary Table 2. Self-reported motivation and effort

	Self	Social	No One
Motivated to win	5.07 [4.71, 5.44]	5.09 [4.69, 5.49]	3.54 [3.13, 3.96]
Motivated to avoid loss	4.95 [4.58, 5.32]	5.05 [4.64, 5.46]	3.39 [2.96, 3.81]
Effort exerted	3.46 [3.24, 3.68]	3.46 [3.22, 3.70]	2.74 [2.50, 2.98]

Note: Four subjects did not complete motivation and effort ratings. 95% CI of the mean provided in brackets.

Supplementary Table 3. Model parameters during social learning in relation to antisociality

	β_{win}	β_{loss}	π_{win}	π_{loss}	α	x	b	q
STAB Social	-.25 (.055)	-.27 (.034)	-.07 (.622)	-.07 (.573)	.29 (.025)	-.23 (.076)	-.13 (.329)	.18 (.152)

Note: Cells show Pearson r values. The p_{perm} in parentheses is uncorrected for multiple comparisons.

Supplementary Table 4. Model parameters during social learning in relation to trait empathy

	β_{win}	β_{loss}	π_{win}	π_{loss}	α	x	b	q
IRI PT	.08 (.548)	.11 (.375)	.21 (.098)	-.01 (.900)	-.12 (.339)	.01 (.921)	-.06 (.672)	.11 (.403)
IRI F	.03 (.831)	-.04 (.780)	.16 (.210)	-.01 (.929)	-.14 (.286)	-.09 (.470)	-.16 (.226)	.28 (.028)
IRI EC	.10 (.455)	.14 (.297)	.02 (.886)	.09 (.509)	-.22 (.098)	.07 (.578)	.00 (.992)	.10 (.459)
IRI PD	.13 (.333)	.03 (.782)	-.10 (.448)	.15 (.262)	-.14 (.283)	-.13 (.317)	.17 (.195)	-.02 (.891)
IRI Total	.13 (.320)	.09 (.488)	.11 (.386)	.08 (.534)	-.24 (.070)	-.06 (.642)	-.02 (.911)	.18 (.159)

Note: Cells show Pearson r values. The p_{perm} in parentheses is uncorrected for multiple comparisons.

Supplementary Table 5. Model parameters in relation to trait anxiety

	Social							
	β_{win}	β_{loss}	π_{win}	π_{loss}	α	x	b	q
STAI-Y2	.04 (.762)	-.01 (.921)	.06 (.663)	.10 (.480)	-.07 (.617)	-.15 (.245)	.00 (.997)	.07 (.579)
	Self							
	β_{win}	β_{loss}	π_{win}	π_{loss}	α	x	b	q
STAI-Y2	-.13 (.318)	-.13 (.309)	-.11 (.389)	.26 (.045)	-.22 (.090)	.08 (.550)	.22 (.085)	-.15 (.240)

Note: Cells show Pearson r values. The p_{perm} in parentheses is uncorrected for multiple comparisons.

Supplementary Figures

Supplementary Fig. 1 Model comparison. An adapted Rescorla-Wagner model with 8 parameters outperformed other models and the pooled distribution across conditions fit better than the unpooled distributions. Note the x-axis is on a logarithmic scale. The red asterisk indicates the best fitting model (Pooled distribution for $2\beta\alpha x b 2\pi q$; $iBIC = 4.62 \times 10^4$)

Supplementary Fig. 2 Transformed model parameters by condition. Note the logarithmic scale for the β and π parameters. Self = black, social = orange, no one = light gray

Supplementary Fig. 3 Posterior predictive model mean accuracy plotted by subjects' actual mean accuracy. Simulated mean accuracy (x-axis) in relation to actual mean accuracy (y-axis) for each subject. The model performs well but can overestimate accuracy, especially in the no-go to win trial type

Supplementary Fig. 4 Correlation between motivation to avoid loss for the partner and β_{loss} sensitivity. Pearson correlation between z-scored β_{loss} sensitivity obtained during the social condition and reported motivation to avoid loss in the social relative to self condition