Reinforcement learning performance in at-risk youth

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Supplementary Methods

Computational model

The gain-loss Q-learning model (Frank et al 2007) is implemented by using separate learning rates α_G and α_L for positive and negative feedback. For each trial t, the expected value Q for the chosen stimulus *i* is updated as a function of learning rate (α_G or α_L) and actual outcome $r(t)$ such that,

(1) if
$$
r(t) > 0
$$
, $Q_i(t+1) = Q_i(t) + \alpha_G \cdot [r(t) - Q_i(t)]$
(2) if $r(t) = 0$, $Q_i(t+1) = Q_i(t) + \alpha_L \cdot [r(t) - Q_i(t)]$,

where $Q_i(t)$ is initialized to 0 and r(t) can be 1 for positive feedback and 0 for negative feedback. According to softmax distribution, the probability of choosing stimulus i over other stimuli in trial t is defined as

$$
(3) P_i(t) = \frac{exp[\beta \cdot Q_i(t)]}{\sum_{k=1}^n exp[\beta \cdot Q_k(t)]}
$$

where n is the total number of choices in each trial and β is the inverse temperature parameter, which reflects the randomness of responses.

The model described above was fit to each participant's training data and a set of best fit learning parameters (α _G, α _L, and β) was found by optimizing log-likelihood estimate (LLE), where LLE is defined as the log product of all probabilities,

$$
LLE = log[\prod_t P_i(t)].
$$

The model comparison was evaluated by Akaike's Information Criterion (AIC), which estimates the complexity of a given model used to represent the data:

$$
AIC = -2 \cdot LLE + 2 \cdot k
$$

where k is the number of parameters and the model with the lowest AIC is the best fitting model. The AIC for random model AIC_0 was also calculated using LLE_0 , which is the likelihood for random performance. If $AIC > AIC₀$, the model is penalized for additional parameters and

therefore the behavior of subject cannot be represented by the model. Individuals whose data satisfied the fitting criterion ($AIC < AIC₀$) were said to demonstrate "better-than-chance" behavior (because a model of purely random choices was not the best-fitting model). Individuals whose data did *not* satisfy the fitting criterion were said to demonstrate "at-chance" behavior.

To provide another measure of fit, we calculated pseudo- R^2 values, defined as

$$
(LLE - r)/r,
$$

where r is the log likelihood of the data under a model of purely random choices ($p = 0.5$ for all choices; Daw et al., 2006). The resulting pseudo- R^2 statistics reveal how well the model fits the data compared to a model predicting chance performance, and is independent of the number of trials to be fit in each set.

We performed second-level statistical analyses on individual estimates of learning parameters (α_G , α_L , and β). In addition, we performed second-level statistical analyses on the products of the inverse temperature parameter and learning rates ($\beta^* \alpha_G$ and $\beta^* \alpha_L$), because, when viewed separately, inverse temperature and learning rate can have large estimation error and therefore a large standard deviation across subjects. The product of the two parameters, however, is generally more stable. Furthermore, the product of the two parameters is of theoretical interest, in that choice preference, at time $f(P_i(t))$, shown in Equation 3], is a function of the product of inverse temperature and learning rate ($β[*]α$), as $Q_i(t)$ is a function of α. We performed two sets of analyses: 1) Mann-Whitney U-tests, comparing individuals demonstrating better-than-chance behavior and individuals showing at-chance behavior; and 2) Spearman correlation analyses between individual estimates of learning parameters (as well as $\beta^* \alpha_G$ and $\beta^* \alpha_L$) and clinical symptoms.

Following the estimation of parameters for each individual participant, we performed simulations using each individual's best fitting parameters. The simulation of each subject's performance was generated by the number of correct responses in each condition in 100 iterations. In order to capture performance during the Early Acquisition Phase (the first two

blocks, which were completed by all participants), only the first 120 trials of the simulation were included. The 40 trials in each reinforcement probability condition were divided into 10 bins of 4 trials each, and the mean proportion of optimal responses for each bin across subjects/iterations was plotted for each reinforcement probability condition. Actual and simulated behavioral data are shown for both the entire sample of 70 subjects (Supplementary Figure 1A) and the sample of 57 subjects showing above-chance performance (Supplementary Figure 1B).

Supplementary Results

Computational modeling results

Individual parameter estimates are shown in Supplementary Table 4. The fitting criterion $(AIC < AIC₀)$ was satisfied by 57 participants (showing better-than-chance behavior), and 13 participants were said to exhibit at-chance behavior. Supplementary Table 5 shows mean parameter values across subjects in each of the two groups. The fact that mean values for Temperature, (AIC - AIC₀), and Pseudo-R² were close to zero reflects the random nature of the choices in the group of participants showing at-chance behavior. The experimental behavioral data in Supplementary Table 6 (all three measures close to 50%) also clearly demonstrate the random nature of the choices in the group of participants showing at-chance behavior. The fact that mean values for Temperature, (AIC - AIC₀), and Pseudo-R² were significantly different from zero reflects the *systematic* nature of the choices in the group of participants showing betterthan-chance behavior. In these participants, values for $\beta^* \alpha_G$ and $\beta^* \alpha_L$ were interpretable and indicative of the impact of gains and losses on learning and subsequent choices. Importantly, we observed significant correlations between $\beta^* \alpha_G$, a measure of gain-driven learning, and the severity of negative symptoms and deficits in social function (Supplementary Table 7).

Simulation results

Simulated performance, using mean parameter estimates from computational modeling, is shown in Supplementary Figure 1.

Supplementary Table 1. Partial Spearman correlations between experimental and clinical variables, controlling for IQ.

Abbreviations: Sx, Symptoms; Func, Functioning. ** = p < 0.05; + = p < 0.10.

Supplementary Table 2. Comparison of non-psychotic participants taking antipsychotic medications and not, on clinical and experimental variables.

Notes: $a = t$ -test; $b = z$ of Mann-Whitney U-test. Abbreviations: APD, Antipsychotic Drug; WASI, Wechsler Abbreviated Scale of Intelligence; Sx, Symptoms; Func, Functioning; Avg, Average.

Supplementary Table 3. Comparison of non-psychotic participants taking stimulant medications and not, on clinical and experimental variables.

Notes: ^a = t-test; ^b = z of Mann-Whitney U-test. Significant between-group differences in **boldface**. Abbreviations: WASI, Wechsler Abbreviated Scale of Intelligence; Sx, Symptoms; Func, Functioning; Avg, Average.

Abbreviations: beta_alphaG, inverse temperature * learning rate for gains; beta_alphaL, inverse temperature * learning rate for losses; alphaG, learning rate for gains; alphaL, learning rate for losses; LLE, final log likelihood estimate; LLE0, initial log likelihood estimate; LLE - LLE0, change in log likelihood estimate, as a consequence of fitting; AIC - AIC0, change in Akaike's Information Criterion, as a consequence of fitting; Chance Perf, subject was deemed to exhibit chance performance.

Supplementary Table 5. Mean estimates of model parameters in participants showing betterthan-chance behavior and in participants showing at-chance behavior.

Abbreviations: α_G, Learning rate for gains (Go-learning); α_L, Learning rate for losses (NoGo-learning); AIC = Akaike's Information
Criterion. (AIC - AIC₀) and Pseudo-R² are both measures of model fit. Significant

Supplementary Table 6. Comparison of participants showing better-than-chance behavior and not, on clinical and experimental variables.

Notes: $a = t$ -test; $b = z$ of Mann-Whitney U-test. Abbreviations: WASI, Wechsler Abbreviated Scale of Intelligence; Sx, Symptoms; Func, Functioning; Avg, Average. Significant between-group differences are **bolded**.

Supplementary Table 7. Spearman correlations between clinical variables and modeling parameters from individual participants.

Abbreviations: α_G, Learning rate for gains (Go-learning); α_L, Learning rate for losses (NoGo-learning); Sx, Symptoms; Func, Functioning. $* = p < 0.05$.

Supplementary Figure 1. Simulations of participant behavior across first two Acquisition blocks (first 120 Acquisition trials) using parameters estimated from computational modeling. (A) Comparison of actual and simulated performance of all 70 participants, including those exhibiting at-chance behavior, on all three Acquisition pairs (AB = 80%/20%; CD = 70%/30%; EF = 60%/40%). Actual performance plotted using solid lines; simulated performance plotted using dashed lines. "Correct Percentage" = proportion of choices of more-frequently-rewarded stimulus. Each Bin represents 12 trials. (B) Comparison of actual and simulated performance of 57 participants showing better-than-chance performance (excluding those exhibiting at-chance behavior), on all three Acquisition pairs.

References

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