



Harvard Psychiatry

Research Poster Session and Mysell Lecture

Modeling reveals slower learning
from positive but not negative
outcomes in depression

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Reduced Reward Responsiveness in Depressed Adults: An RL-DDM Analysis of the PST

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Depression has been associated with insensitivity to rewards¹.

- Supported by reduced positive learning rates in reinforcement learning models².
- Remains unclear how differences in reinforcement learning are represented in a dynamic decision-making process.
- In the present study we seek to better characterize reward-based decision-making in depression by fitting data from depressed and non-depressed individuals with the unified Reinforcement Learning Drift Diffusion Model (RL-DDM)³.

Healthy controls and MDD patients exhibited similar choice and response time behavior.

Over the course of the experiment, participants became more likely to choose the high-reward option and were faster to respond, with no meaningful group differences.

Healthy Controls

MDD Patients

RL-DDM reveals group differences in positive learning rates, suggesting group differences are centered on learning rather than the decision process.

The RL-DDM combines classic reinforcement learning with a drift diffusion model⁴ to account for reward-based decision-making as it unfolds over time.

$$Q_{s,t} = Q_{s,t-1} + \alpha(\text{Reward}_{s,t-1} - Q_{s,t-1})$$

$$v_t = (Q_{\text{upper},t} - Q_{\text{lower},t}) * \nu$$

The RL-DDM estimated reduced learning rates from rewards, but not punishments, among MDDs relative to healthy controls (probability of MDD < HC: 85.24%), with similar decision processes.

Posterior of Negative Alphas

Posterior of Positive Alphas

Probabilistic Selection Task⁴

Select:

Probabilistic Selection

Select:

Rewarded

Probabilistic Selection

Total Trials: 240
41 Control
43 MDD

References

1. Pizzagalli, D.A., et al. (2011). Anhedonic depression: A neurobiological and behavioral model. *Journal of Affective Disorders*, 133(1-3), 10-27. doi:10.1016/j.jad.2011.01.026

2. Pizzagalli, D.A., et al. (2009). Reduced reward responsiveness during anticipatory anxiety caused by depression. *Proceedings of the National Academy of Sciences*, 106(10), 4382-4387. doi:10.1073/pnas.0810149106

3. O'Neill, C.A., et al. (2021). Reduced reward responsiveness in depressed adults: An RL-DDM analysis of the PST. *Harvard Medical School*. doi:10.1101/2021.04.10.438287

4. Frank, R.C., et al. (2004). The hot/cold executive function test. *Journal of Experimental Psychology: Applied*, 10(2), 179-190. doi:10.1037/1076-898X.10.2.179

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SCIENTIFIC ABSTRACT

Background. Anhedonic depression may reflect dopaminergic abnormalities (Pizzagalli, 2014), suggesting impairments in signaling reward prediction errors (RPEs; Schultz, 1998) critical for reinforcement learning (Huys et al., 2013). Importantly, however, few prior studies have investigated how participants make decisions based on learned values, which the reinforcement learning drift diffusion model (RLDDM; Pedersen & Frank, 2020) can do. We therefore investigated the impact of depression on learning and decision-making by fitting the RLDDM to data from healthy and depressed adults.

Methods. Forty-three unmedicated adults with Major Depressive Disorder (MDD) and 41 healthy controls (HC) completed the Probabilistic Selection Task (PST; Frank et al., 2004). In the PST, participants use probabilistic feedback from 240 training trials to learn to select the more frequently rewarded symbols out of three pairs. The data were fit with the RLDDM, a Bayesian hierarchical model that uses Q-learning to model value assignment but models choice with the DDM (Ratcliff, 1978), providing a more comprehensive treatment of decision-making than the commonly used Softmax. Our implementation included parameters for positive and negative learning rates, the speed of evidence accumulation, and the width of decision thresholds.

Results. Both groups learned to quickly choose the high-reward image in each pair. The RLDDM did not reveal group differences in decision parameters, but it did estimate slower learning rates following rewards in MDD vs. HC (posterior probability of MDD < HC: 85.24%).

Conclusions. The RLDDM revealed slower learning following rewards in depressed adults vs. healthy controls. Although modest, this result supports the hypothesis that anhedonic depression may impair reinforcement learning by disrupting RPEs. Moreover, this work demonstrates that, by modeling learning and decision-making simultaneously, the RLDDM provides a sensitive assessment of the negative impact of depression on behavior. In subsequent analyses, we will integrate these modeling results with functional neuroimaging.

SEARCH POSTERS



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1:30-2:10 pm

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RESEARCH AREAS

COGNITION, COMPUTATIONAL MODELING, DECISION MAKING, DRIFT DIFFUSION MODEL, LEARNING, MOOD DISORDERS

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