

Not Just Habits: How Feedback Sensitivity and Belief Updating Shape OCD

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Abstract

OCD research has undergone several paradigmatic shifts – from cognitivism that emphasizes cognitive biases and threat-reducing function of compulsions, to the dual-process paradigm that views compulsions as habits. In our study, we build on recent ideas that focus on the relationship between aberrant feedback processing, model-based learning and OCD. Using a probabilistic contingency reversal task on two large online samples and computational modelling, we show that OCD is associated with diminished processing of certain types of feedback (i.e., rewards and valid feedback) and ability to distinguish valid from noise feedback, inflated mental model volatility and excessive epistemic uncertainty. Our results implicate the involvement of biased goal-directed mechanisms in OCD, challenging the habitual view. In future, we want to expand our ideas by investigating the neural correlates of these mechanisms.

Keywords: OCD, reinforcement learning, goal-directed behavior, computational modelling

Introduction

In the last 40 years, research on obsessive-compulsive disorder (OCD) has been subjected to several paradigmatic shifts. Cognitive theories (Clark & Purdon, 1993; Salkovskis & Kirk, 1997; Rachman, 1997) that emerged in the 1980s converge on the idea that cognitive biases, which induce excessive threat appraisal and/or inflated agency and responsibility are the main source of obsessions. Compulsions are seen as goal-directed strategies that aim to reduce these threats and/or ensuing fear. While, the cognitive view dominated research and clinical practice for many years, a shift began to appear around 2010. The diversion was based on (a) neuroimaging findings that showed aberrant activity in brain areas involved in goal-directed behavioral control and (b) the suspicion that the cognitive theories cannot explain a phenomenon frequently

observed in OCD: ego-dystonia. It was proposed that an imbalance between the goal-directed and habitual system, in which habits dominate, may be the root cause of the disorder (Gillan et al., 2016). In this view, compulsions are no longer goal-directed behaviors, but rather automated uninhibited reactions to stimuli. Evidence for this idea came from reinforcement learning studies, in which participants learn response-outcome contingencies and adapt to changes in these contingencies. Although individuals with OCD seemed to have shown no deficit in the initial learning, they exhibited difficulties in adapting to contingency changes (Gillan et al., 2011, 2014, 2015).

However, several empirical findings are hard to integrate with the habitual view of OCD. For instance, neuroimaging studies showed no abnormalities in habit-related areas (Gillan et al., 2015), while a meta-analysis observed no reliable evidence for cognitive inflexibility in OCD after controlling for cognitive capacity (Fradkin et al., 2018).

More recently, new ideas focusing on how individuals employ feedback to construct mental models, have emerged. Here, studies found OCD to be related to increased state-transition uncertainty (Fradkin et al., 2021), abnormal state-transition learning rates (Sharp et al., 2023) and abnormal reactivity to prediction errors (Hoven et al., 2023; Vaghi et al., 2017). These results all indicate an inability of sufficient use of feedback signals in building mental models of the environment.

We build on and complement these proposals with our theoretical view, in which biased goal-directed processes play the central role. We propose that learning biases – how outcome feedback is (mis)interpreted – affect individual's mental representation of their environment, which can subsequently lead to obsessions and compulsions. Specifically, we hypothesize that discrepancy detection, the first step in a goal-directed cycle (Moors et al., 2017), is distorted by a combination of punishment hypersensitivity and reward hyposensitivity. In a probabilistic environment, where feedback signals differ not only in their valence (rewards vs. punishments) but also informativeness (valid vs. noise) this distortion affects the individual's

ability to distinguish between informative and uninformative feedback signals. This leads to instability in constructing mental models and inflated epistemic uncertainty.

Methods

To test our hypotheses, we employed two versions of a probabilistic contingency reversal task (Buabang et al., 2023) on two large, heterogenous online samples ($N = 273 \times 2$) and examined how patterns of behavior and mental model building vary with OCD symptom severity. Participants had to learn a probabilistic link between a response (pressing left or right arrow) and an outcome (a diamond/reward, or a rock/punishment) for various stimuli (doors of different colors), which was subjected to an unannounced reversal. We measured participants' behavioral patterns (i.e., the rate of optimal decisions and alternation between different response options) and the process of mental model formation via computational modelling. Psychopathology was assessed with OCI-R (Foa et al., 2002), DASS-21 (Lovibond & Lovibond, 1995) and OBQ-9 (Gagne et al., 2018) questionnaires.

Computational models included block-wise fitting an adapted Incremental State-Transition Learning model (ISTL, Sharp et al., 2023) and an adapted Bayesian Change-Point model (Fradkin et al., 2020) at the individual participant and stimulus level. ISTL model learns through reinforcement based on state-prediction errors (Equation 1), while the BCP model involves Bayesian belief updates based on assessed reliability of the feedback (Equation 2). In both models, we measured; (1) the weight participants give different types of feedback (learning rates for rewards vs. punishments and valid vs. noise feedback), (2) belief volatility (belief-reset probability or hazard rate), (3) difference between epistemic (individual) and aleatoric (environmental) uncertainty, and (4) value-based decision determinism (inverse temperature in SoftMax). We then regressed these parameters against OCD severity, while controlling for depression, anxiety, stress, age and gender.

$$T[a, s]_{t+1} \leftarrow h \cdot 0.5 + (1 - h) \cdot [T[a, s]_t + \gamma \cdot (1 - T[a, s]_t)] \quad (1)$$

$$Belief_{t+1} \leftarrow h \cdot 0.5 + (1 - h) \cdot \frac{P(Feedback|Belief_t) \cdot Belief_t}{P(Feedback)} \quad (2)$$

Results

Our behavioral results show that OCD symptoms are associated with decreased probability of optimal responding ($\beta = -.22$, $p < .001$), and increased probability of response switching, especially after rewards ($\beta = .27$, $p < .001$). Computationally, we observed deflated weighting of rewards and valid feedback signals (γ in Fig. 1), indicating decreased use of these types of feedback and inflated belief volatility (h in Fig. 1), indicating instability in mental model building. OCD symptoms were also associated with diminished ability to distinguish noise from valid feedback (η in Fig. 1) and excessive epistemic uncertainty ($\sigma_e - \sigma_a$ in Fig. 1). Lastly, we observed less value-based decision determinism (β in Fig. 1), which indicates a tendency towards exploration rather than exploitative response selection.

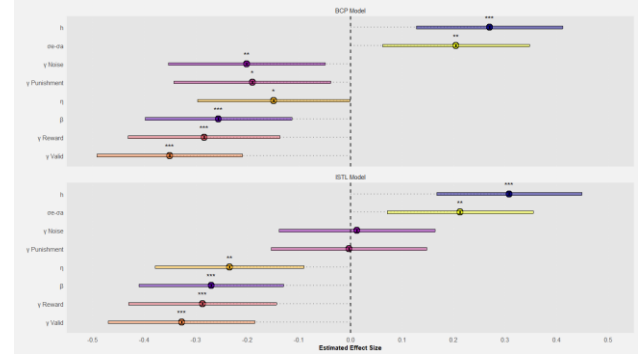


Figure 1. Regression coefficients for OCI-R scores as predictors of various computational parameters in the ISTL and BCP model in the second experiment. h – hazard rate; $\sigma_e - \sigma_a$ – calibration between epistemic and aleatoric uncertainty; γ – learning rates for different types of feedback; η – difference between γ valid and γ noise; β – inverse temperature. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Conclusions

Our study provides further evidence that OCD is associated with malfunctions in feedback processing and mental model building rather than habitual rigidity. The increased instability of beliefs and excessive uncertainty in individuals with a higher degree of OCD symptoms might stem from their inability to use rewards and valid feedback adequately. In this view compulsions serve as goal-directed information seeking strategies, which aim at resolving the excessive epistemic uncertainty. In our future research, we plan to examine how the computational parameters of interest correlate with brain signals, especially those in areas related to feedback processing (e.g., ACC).

- 180 **References**
- 181 Buabang, E. K., Köster, M., Boddez, Y., Van
182 Dessel, P., De Houwer, J., & Moors, A.
183 (2023). A goal-directed account of
184 action slips: The reliance on old
185 contingencies. *Journal of experimental*
186 *psychology. General*, 152(2), 496–508.
187 <https://doi.org/10.1037/xge0001280>
- 188 Clark, D. A., & Purdon, C. (1993). New
189 perspectives for a cognitive theory of
190 obsessions. *Australian Psychologist*,
191 28(3), 161–
192 167. [https://doi.org/10.1080/000500693](https://doi.org/10.1080/00050069308258896)
193 [08258896](https://doi.org/10.1080/00050069308258896)
- 194 Foa, E. B., Huppert, J. D., Leiberg, S., Langner,
195 R., Kichic, R., Hajcak, G., & Salkovskis,
196 P. M. (2002). The Obsessive-
197 Compulsive Inventory: Development
198 and validation of a short version.
199 *Psychological Assessment*, 14(4), 485–
200 495. [https://doi.org/10.1037//1040-](https://doi.org/10.1037//1040-3590.14.4.485)
201 [3590.14.4.485](https://doi.org/10.1037//1040-3590.14.4.485)
- 202 Fradkin, I., Adams, R. A., Parr, T., Roiser, J. P.,
203 & Huppert, J. D. (2018). Searching for
204 an anchor in an unpredictable world: A
205 computational model of obsessive-
206 compulsive disorder. *Psychological*
207 *Review*, 125(5), 627–648.
208 <http://dx.doi.org/10.1037/rev0000188>
- 209 Fradkin, I., Ludwig, C., Eldar, E., & Huppert, J.
210 D. (2020). Doubting what you already
211 know: Uncertainty regarding state
212 transitions is associated with obsessive
213 compulsive symptoms. *PLOS*
214 *Computational Biology*, 16, e1007634.
- 215 Gagné, J.-P., Van Kirk, N., Hernandez-Vallant,
216 A., Potluri, S., Krompinger, J. W., Cattie,
217 J. E., Garner, L. E., Crosby, J. M.,
218 Brennan, B. P., & Elias, J. A. (2018).
219 Obsessive Beliefs Questionnaire-9
220 (OBQ-9) [Database record]. APA
221 PsycTests.
222 <https://doi.org/10.1037/t70715-000>
- 223 Gillan, C. M., Apergis-Schoute, A. M., Morein-
224 Zamir, S., Urcelay, G. P., Sule, A.,
225 Fineberg, N. A., Sahakian, B. J., &
226 Robbins, T. W. (2015). Functional
227 neuroimaging of avoidance habits in
228 obsessive-compulsive disorder.
229 *American Journal of Psychiatry*, 172,
230 284–293. [https://doi.org/](https://doi.org/10.1176/appi.ajp.2014.14040525)
231 [10.1176/appi.ajp.2014.14040525](https://doi.org/10.1176/appi.ajp.2014.14040525)
- 232 Gillan, C. M., Pappmeyer, M., Morein-Zamir, S.,
233 Sahakian, B. J., Fineberg, N. A.,
234 Robbins, T. W., & de Wit, S. (2011).
235 Disruption in the balance between goal-
236 directed behavior and habit learning in
237 obsessive-compulsive disorder.
238 *American Journal of Psychiatry*, 168(7),
239 718–726.
240 [https://doi.org/10.1176/appi.ajp.2011.10](https://doi.org/10.1176/appi.ajp.2011.10071062)
241 [071062](https://doi.org/10.1176/appi.ajp.2011.10071062)
- 242 Gillan, C. M., Morein-Zamir, S., Urcelay, G. P.,
243 Sule, A., Voon, V., Apergis-Schoute, A.
244 M., Fineberg, N. A., Sahakian, B. J., &
245 Robbins, T. W. (2014). Enhanced
246 avoidance habits in obsessive-
247 compulsive disorder. *Biological*
248 *Psychiatry*, 75, 631–638. [https://doi.org/](https://doi.org/10.1016/j.biopsych.2013.02.002)
249 [10.1016/j.biopsych.2013.02.002](https://doi.org/10.1016/j.biopsych.2013.02.002)
- 250 Hoven, M., Rouault, M., van Holst, R., &
251 Luijckes, J. (2023). Differences in
252 metacognitive functioning between
253 obsessive-compulsive disorder patients
254 and highly compulsive individuals from
255 the general population. *Psychological*
256 *medicine*, 53(16), 7933–7942.
257 [https://doi.org/10.1017/S003329172300](https://doi.org/10.1017/S003329172300209X)
258 [209X](https://doi.org/10.1017/S003329172300209X)
- 259 Marzuki, A.A., Vaghi, M.M., Conway-Morris, A.,
260 Kaser, M., Sule, A., Apergis-Schoute,
261 A., Sahakian, B.J. and Robbins, T.W.
262 (2022). Atypical action updating in a
263 dynamic environment associated with
264 adolescent obsessive-compulsive
265 disorder. *J Child Psychol Psychiatr*, 63,
266 1591-1601.
267 <https://doi.org/10.1111/jcpp.13628>
- 268 Rachman, S. (1997) A Cognitive Theory of
269 Obsessions. *Behaviour Research and*
270 *Therapy*, 35, 793-802.
271 [https://doi.org/10.1016/S0005-](https://doi.org/10.1016/S0005-7967(97)00040-5)
272 [7967\(97\)00040-5](https://doi.org/10.1016/S0005-7967(97)00040-5)
- 273 Salkovskis, P. M., & Kirk, J. (1997). Obsessive-
274 compulsive disorder. In D. M. Clark & C.
275 G. Fairburn (Eds.), *Science and practice*
276 *of cognitive behaviour therapy* (pp. 179–
277 208). Oxford University Press.
- 278 Sharp, P. B., Dolan, R. J., & Eldar, E. (2023).
279 Disrupted state transition learning as a
280 computational marker of compulsivity.

281 *Psychological Medicine*, 53(5), 2095–
282 2105. doi:10.1017/S0033291721003846
283 Vaghi, M. M., Vértes, P. E., Kitzbichler, M. G.,
284 Apergis-Schoute, A. M., van der Flier, F.
285 E., Fineberg, N. A., ... & Robbins, T. W.
286 (2017). Compulsivity reveals a novel
287 dissociation between action and
288 confidence. *Neuron*, 96(2), 348–354.e4.
289 <https://doi.org/10.1016/j.neuron.2017.09>
290 .006
291 Voon, V., Derbyshire, K., Rück, C., Irvine, M.
292 A., Worbe, Y., Enander, J., ... &
293 Robbins, T. W. (2015). Disorders of
294 compulsivity: A common bias towards
295 learning habits. *Molecular Psychiatry*,
296 20(3), 345–352.
297 <https://doi.org/10.1038/mp.2014.44>
298
299