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Does cognitive-behavioral therapy affect goal-directed planning in obsessive-compulsive disorder?

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ABSTRACT

Cross-sectional studies have reported failures in goal-directed planning in obsessive-compulsive disorder (OCD). It remains unclear whether these deficits confer vulnerability to developing OCD, or are a consequence of symptoms. The present study examined goal-directed learning before and after cognitive behavioral therapy (CBT), using treatment as a tool to reduce symptoms. Eighteen adult OCD patients undergoing 17 sessions of CBT completed an established task of model-based (i.e., goal directed) versus model-free planning as well as measures of OCD and depression before and after treatment. We thus tested whether improvements in goal-directed performance accompany improvements in OCD symptoms or if instead task performance remains stable despite symptom improvement. Results showed prior to treatment, higher OCD severity was associated with greater deficits in model-based planning. OCD severity scores significantly improved from pre- to post-treatment. Inconsistent with the state-view, OCD symptom improvement was not accompanied by improvements in model-based performance. At post-treatment, OCD severity scores were no longer correlated with model-based performance. Together, these data suggest that reducing OCD symptoms with CBT does not affect goal-directed planning. This supports a trait model of the relationship between goal-directed planning and OCD symptoms, such that problems in goal-directed planning may be an OCD risk factor.

1. Introduction

Obsessive-compulsive disorder is estimated to affect up to 2% of the population and can be disabling when severe (Ruscio et al., 2010). OCD symptoms typically begin by adolescence and run a chronic course when not treated (Rasmussen and Eisen, 1994). What causes OCD remains unclear. A recent approach conceptualizes OCD as the result of an imbalance between the goal-directed and habitual systems (for review see Gillan, 2017), two parallel systems that guide instrumental behavior (Dolan and Dayan, 2013). Under goal-directed control, behaviors are selected based on the outcomes they are likely to produce. This requires individuals to have a prospective model of the environment in terms of how actions are causally related to future consequences. In contrast, when behavior is under habitual control, actions are executed based on their history of reinforcement (i.e., the extent to which those actions were previously rewarded in similar situations). Habits are efficient, as they do not require us to consult internal maps or models before making decisions, but they are also rigidly-expressed, leading us to make errors when our environment changes and demands flexibility ('slips of action', de Wit and Dickenson, 2009). Based on parallels seen with the rigid and repetitive nature of compulsive behavior in OCD, some have suggested that OCD may derive from dysfunction in goal-directed control and over-reliance on the habit system (Gillan, 2017). Consistent with this model, the neurobiological circuits supporting the balance between goals and habits overlap with those thought to play a crucial role in OCD pathophysiology (namely those involving orbito-frontal cortex and striatum, de Wit et al., 2012; Gillan et al., 2015a,b; Graybiel and Rauch, 2000).

In line with this account of OCD, adults with OCD have been found to engage in more habitual responses (slips of action towards behavioral responses that are no longer valued; de Wit et al., 2014) in learning paradigms that involve subjects engaging in repetitive responding for both positive (Gillan et al., 2011) and negative (Gillan et al., 2014) reinforcement. These kind of tasks, although an

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illuminating starting-point, have been unable to derive separate estimates of these respective cognitive processes. This is because repetitive habitual responding in these tasks may arise as a result of deficits in goal-directed control (i.e., relying on habits due to weakness in goal-directed planning, Gillan et al., 2015a,b) or theoretically, an enhanced ability to form habits themselves (i.e., to develop rigid stimulus-response links). To address this, recent research in this area has employed a task that can probe goal-directed learning without invoking the habit system at all (Daw et al., 2011).

Voon et al. (2015) took this approach, utilizing a two-step reinforcement learning task that assessed goal-directed planning in isolation (here termed "model-based learning" referring to whether participants developed a model of the task as described in detail below) and demonstrated that OCD patients indeed had significant impairments in goal-directed learning compared to healthy controls. Moreover, they showed that these deficits extended to other disorders of compulsivity, such as binge eating disorder and methamphetamine addiction. A subsequent study replicated and extended these findings in a general population sample (Gillan et al., 2016) by demonstrating a significant negative correlation between OC symptom severity and goal-directed performance (i.e., model-based performance on the task), that also applied to compulsive aspects of eating disorders and addiction. The authors used factor analysis to show that a trans-diagnostic dimension 'compulsive behavior and intrusive thoughts' had more explanatory power with respect to goal-directed deficits than symptoms based on classic DSM distinctions. These findings have been used to suggest that deficits in goal-directed behavioral control confer risk for developing the clinically relevant compulsive behaviors seen in many psychiatric disorders, consistent with the notion of a trait or even of a neurobiological 'endophenotype' (Gottesman and Gould, 2003).

However, a major caveat to this interpretation is that all of the studies conducted to date have been cross-sectional in nature. Indeed, it remains quite possible that disruptions in goal-directed task performance may be state-dependent, present only during, and perhaps resulting from, the presence of acute OCD symptoms (i.e., an "epiphenomenon," Kalanthroff et al., 2016). This study is the first to address this issue directly using a longitudinal design. Specifically, we administered a previously validated task of model-based (goal-directed) learning in convenience sample of adult OCD patients prior to, and directly following manualized cognitive-behavioral therapy (CBT) consisting of exposure and response prevention (EX/RP). As EX/RP is an efficacious short-term intervention (Öst et al., 2015; Skapinakis et al., 2016), this design allowed us to use treatment as a tool to manipulate acute OCD symptom severity. The trait view would suggest that goal-directed control deficits would not improve in this sample of adult OCD patients following EX/RP, despite patients achieving a significant reduction of symptoms. However, given the lack of previous longitudinal research in OCD, our examination represents an initial exploratory analysis of whether the trait or state view will hold.

2. Method

2.1. Overview

Data were collected in a specialty OCD research clinic in New York City. Subjects were recruited for the present study (under separate a protocol) from those who were participating in a multi-site longitudinal clinical trial (R01MH045436), which was examining whether OCD patients on stable doses of serotonin reuptake inhibitors (SRIs) who attain wellness after augmentation with EX/RP treatment (Phase 1) can then retain wellness if they then discontinue their SRIs (Phase 2). Those who entered Phase 1 at the New York site between 9/24/2014 and 8/10/2017 were invited to participate in this separate study, and the model-based reinforcement learning task was administered by the first author before and after participants received 17 sessions of EX/RP. Task data were collected only at the New York site where the additional research protocol was run, but the two sites did not differ in terms of treatment procedures. The Institutional Review Board (IRB) reviewed and approved the study protocol and all participants provided written informed consent.

2.2. Participants

Data were collected from 19 adults with a principal diagnosis of OCD as determined by the Structured Clinical Interview for DSM-IV (SCID; First et al., 1996) and who remained symptomatic (YBOCS ≥ 20) despite receiving an SRI at a maximally tolerated dose for 12 weeks or more. All remained on the same dose of their SRI during this study. None had any of the following: (1) a diagnosis of bipolar or psychotic disorder; (2) substance abuse or dependence in the past 3 months; (3) clinically significant suicidal ideation; (4) severe depression (≥20 on the 17-item Hamilton Depression Rating Scale [HDRS; Hamilton, 1960]); (5) primary hoarding symptoms; or (6) recent trial of EX/RP (≥8 sessions over 2 months) while taking an SRI.

One subject withdrew before completing all 17 sessions of EX/RP. Thus, data from 18 patients were analyzed. This final sample included 12 (67%) Females and 6 Males (33%), with a mean age of 26.22 years (SD = 7.99, minimum = 18, Maximum = 45).

2.3. Procedures

2.3.1. Clinical assessment

Psychiatric diagnoses and eligibility for the parent study were determined via clinical interview, conducted by trained clinicians (psychologists or psychiatrists) with expertise in anxiety, OCD, and related disorders, using the SCID. Independent evaluators (blinded to treatment status) assessed patients' OCD symptoms at baseline (week 0) and post-treatment (week 8). Evaluators rated OCD severity using the Yale-Brown Obsessive Compulsive Scale (YBOCS; Goodman et al., 1989a,b), the "gold-standard" measure of OCD symptom severity. Depression severity was rated with the Hamilton Depression Rating Scale (HDRS; Hamilton, 1960). In addition, at baseline participants completed the Spielberger State-Trait Anxiety Inventory (STAI-T; Spielberger et al., 2010) to rate trait anxiety (though data were missing for three participants).

2.3.2. Treatment

EX/RP sessions were 90 minutes long and comprised of two introductory sessions followed by 15 exposure sessions, daily homework assignments (self-directed exposures and response prevention), and phone check-ins between each session (Foa et al., 2012). EX/RP was delivered by doctoral-level clinicians (PhD), who participated in weekly group supervision to standardize treatment delivery.

2.3.3. Reinforcement learning task

We used a two-step reinforcement-learning task (Daw et al., 2011) that separates "model-based" learning (a proxy for goal-directed behavior) from a simpler form of learning that relies only on past experience ("model-free") (Fig. 1). This is a sequential decision making task, in which participants make choices at two stages. In the first stage, subjects are presented with a choice between two fractals (presented on a black background). Each fractal commonly (i.e., 70% of the time) leads to a particular second stage state (orange or blue background screen). On the remaining 30% of 'rare' trials, the transition takes participants to the other second stage state. If one wanted to transition to the blue state, for example, then they should choose the fractal on the left of Fig. 1, which has a 70% (common transition) probability of going to the blue background. At the second stage (blue or orange screen), subjects are presented with another two fractal stimuli that they must choose between. These second stage fractals each have a specific probability of being rewarded with a coin, which changes slowly over the course of the task (according to a Gaussian random walk). This

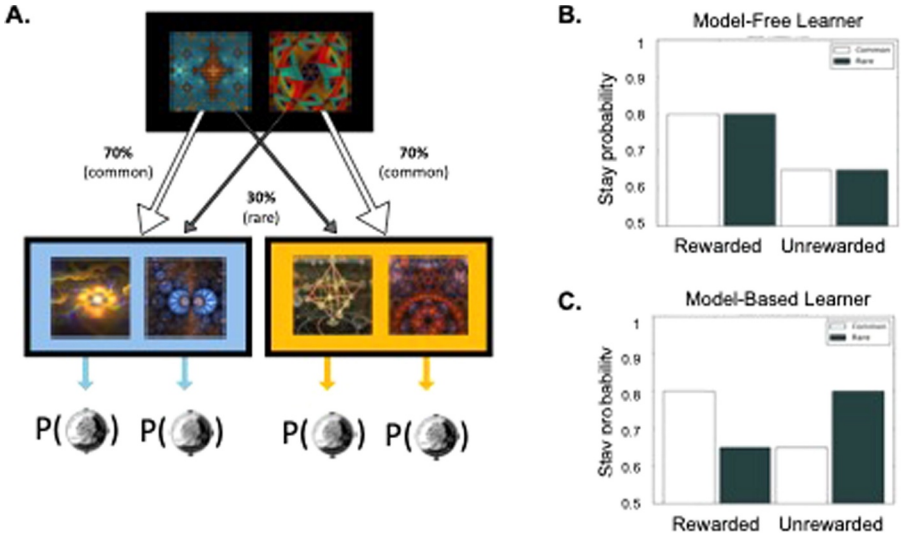

Fig. 1. *Model-based planning task*. A. Schematic of the sequential learning task. On each trial, the first-stage choice involved choosing between two fractal images presented on a black background; this choice determined what participants saw next. In the second stage, participants chose between new fractal pairs, presented on colored backgrounds (Blue versus Orange). One of the first stage choices led more frequently to the blue screen (70% versus 30%), while the other led more frequently to the orange screen (70% versus 30%). These transition probabilities ("Common" versus "rare") were fixed throughout the task. In the second stage decision, each fractal choice was associated with a probability of being rewarded that drifted slowly throughout the game. Subjects thus had to dynamically keep track of which second stage fractals were currently most likely to lead to reward. B. Schematic depicting an idealized model-free learner. Repeating the previous choice ("Stay") vs. choosing the alternative ("Switch") behavior is solely predicted by reinforcement history (i.e., whether or not a choice was rewarded or unrewarded on the prior trial). C. Schematic depicting an idealized model-based learner. Here, behavior is predicted by an interaction between Reward (Rewarded, Unrewarded) and Transition (Common, Rare).

means that fractals that were frequently rewarded at the beginning of the task, might slowly lose their value over time (probability ranging between 0.25–0.75). Changing reward probabilities encourages participants to explore different choices over time to maximize rewards. Subjects completed 200 trials. Responses were indicated using the left ('E') and right ('I') keys and had 2.5 seconds to make their choices. Subjects completed this task at two time-points, pre- and post-EX/RP. Fractal images were unique to each session to minimize carry-over effects and the order of fractal sets was counterbalanced across subjects.

Model-based learning involves integrating the causal structure of the task (the choice-dependent transitions from state to state) with slowly acquired estimates of what second stage stimuli are currently the most rewarding. This kind of learning has been previously shown to protect against forming habits tested using devaluation, and model-based learning during the task is thus considered an apt formalization of goal-directed behavior (Gillan et al., 2015a,b). Model-free learning, on the other hand, relies *only* on these slowly acquired estimates – causing someone who relies exclusively on this strategy to repeat start stage actions that were previously rewarded, even though this is sometimes suboptimal. For example, when a first stage choice is followed by a rare (30%) transition and a reward ultimately follows in stage 2, a model-based learner would take into account state-transition structure (common vs. rare transitions) and would be likely to switch their first stage choice in order to get the same reward on the next trial. In contrast, a model-free learner would instead repeat the original choice at the first stage, which would more commonly lead to the opposite second stage state.

2.3.4. Data analysis

Data were analyzed using mixed-effects logistic regression. Specifically, we tested the extent to which stay/switch patterns (coded as switch: 0; stay: 1, relative to the most recent choice) were influenced by Reward (coded as rewarded: 1; unrewarded: −1), Transition (coded as common: 1, rare: −1), and their interaction, on the preceding trial. A main effect of reward indicates that there is a significant contribution of model-free learning to choice behavior. An interaction between Reward and Transition indicates that there is a significant contribution of model-based learning to choice behavior. These analyses were implemented with the *lme4* package in the R programming language, version 3.1.1 (http://cran.us.r-project.org). Within-subject factors (the intercept, main effects of reward and transition, and their interaction) were taken as random effects (i.e., allowed to vary across subjects). We used Bound Optimization by Quadratic Approximation (bobyqa) with 1e5 functional evaluations. The basic model was specified in the syntax of R as follows: Stay ~ Reward × Transition + (Reward × Transition + 1 | Subject)

3. Results

3.1. Treatment effects

Among the 18 participants who completed EX/RP in this study, the mean reduction in YBOCS from pre-treatment to post-treatment was significant, $t(17) = 9.52$, $p < 0.001$ (mean difference in YBOCS: 14.44, standard deviation(SD) = 6.4, range: 2–24). Expressed as percent change, symptoms were on average reduced by 54% (SD = 0.23). Remission (YBOCS ≤ 12; Farris et al. 2013) was achieved in 12/18 of patients, corresponding to 66.67% of the sample. There was a trend for depression symptoms to also reduce following treatment, but this effect was marginal, $t(17) = 1.98$, $p = 0.06$.

3.2. Model-based planning, pre-treatment

Prior to treatment, there was a significant main effect of Reward on stay/switch behavior ($\beta = 0.5$ (0.14), $Z = 3.6$, $p < 0.0001$), providing evidence for model-free learning in this sample. The intercept was also significant, indicating that on average subjects have a tendency to repeat previously executed choices ($\beta = 2.02$ (0.30), $Z = 6.71$, $p < 0.001$) as in prior studies using this task (Daw et al., 2011; Otto et al., 2013a,b). Evidence for model-based planning in this patient sample, however, was not statistically significant (Reward × Transition interaction, $\beta = 0.19$ (0.11), $Z = 1.76$, $p = 0.08$) (Fig. 2**A**).

Adding YBOCS scores to our regression analysis, we found a significant interaction between Reward, Transition and Baseline YBOCS scores, $\beta = -0.27$ (0.07), $Z = -3.697$, $p < 0.001$, such that higher OCD scores were related to poorer model-based planning (Fig. 2**C**). The magnitude of the effect was such that 1 standard deviation increase in YBOCS scores was associated with a complete elimination of any model-based planning. This relationship was specific; we did not find associations between YBOCS severity and model-free learning ($\beta = 0.20$ (0.09), $Z = 1.17$, $p = 0.24$) or subjects tendency to repeat previously executed actions, (i.e., perseveration), $\beta = 0.01$ (0.29), $Z = 0.03$, $p = 0.98$. Failures in model-based planning were not associated with depression $\beta = 0.037$ (0.1), $Z = 0.37$, $p = 0.71$ or trait anxiety,

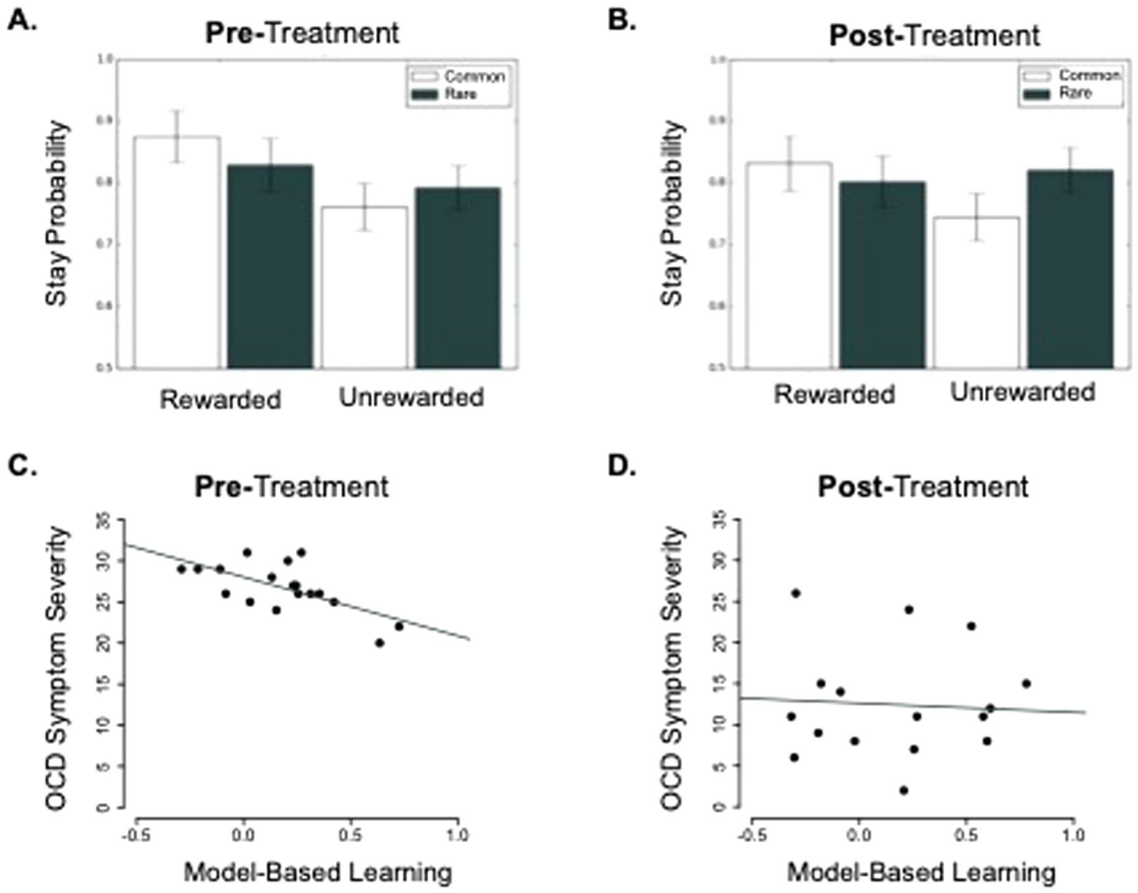

Fig. 2. *Pre- and Post-Treatment Task Performance*. A. Task performance in OCD patients at baseline (pre-treatment) showed characteristic signatures of model-free planning, such that subjects were more likely to repeat previously made choices (i.e., "stay probability") that were rewarded compared to those that were unrewarded. Evidence of model-based planning in this sample was limited, with the interaction between reward (rewarded, unrewarded) and transition (common, rare) failing to reach significance. B. Task performance in OCD patients post-treatment. Neither model-based ($p = 0.57$) nor model-free ($p = 0.33$) behavior was significantly improved following treatment. Model-free planning remained significant, and model-based planning failed to reach significance. C. The pre-treatment association between model-based learning and OCD symptoms was significant ($p < 0.001$). The most severe patients had the greatest deficits in model-based planning. D. The post-treatment association between model-based learning and OCD symptoms was not significant ($p = 0.78$).

$\beta = 0.02$ (0.1), $Z = 0.27$, $p = 0.79$.

3.2. Model-based planning following treatment

Following EX/RP, model-free learning (main effect of Reward, $\beta = 0.036$ (0.12), $Z = 3.10$, $p = 0.002$) and the intercept (i.e., tendency toward perseveration) ($\beta = 1.98$ (0.33), $Z = 6.00$, $p < 0.001$) were both significant, but once again we failed to find evidence of statistically significant model-based planning in this sample (Reward × Transition interaction, $\beta = 0.32$ (0.17), $Z = 1.90$, $p = 0.06$) (Fig. 2**B**). To test whether goal-directed planning deficits are state-dependent (i.e., ameliorated when acute symptoms improve), we examined whether model-based planning at post-treatment had increased from the baseline assessment by including Time as a within-subjects variable in our analysis of trial-by-trial behavior. Despite making significant therapeutic gains, we found no change in OCD patients' model-based performance following treatment (Time × Reward × Transition, $\beta = 0.05$ (0.01), $Z = 0.56$, $p = 0.57$). Consistent with this, we found that changes in YBOCS (expressed as a difference score) from pre- to post-treatment were unrelated to changes in model-based planning over the same period, $r(18) = 0.23$, $p = 0.35$. Sensitivity analyses using percent reduction in symptom instead of the change scores found the same pattern of results ($r(18) = 0.08$, $p = 0.74$). In addition, following EX/RP treatment, the previously observed association between model-based planning and OCD symptom severity was no longer present (YBOCS × Reward × Transition, $\beta = -0.04$ (0.16), $Z = -0.27$, $p = 0.78$) (Fig. 2**D**).

3.3. Exploratory treatment response prediction analysis

Given recent interest in identifying biomarkers of individual treatment response, we ran an exploratory correlational analysis testing if baseline model-based planning performance was associated with changes in YBOCS scores following EX/RP. The correlation was not only not significant ($r(18) = -0.25$, $p = 0.31$) but negative, such that the largest treatment gains were seen in those with the poorest model-based learning at baseline.

4. Discussion

OCD patients typically experience repetitive and stereotyped behaviors (i.e., compulsions). Recent work suggests that these symptoms may result from dysfunction in goal-directed control over behaviors and a consequent bias towards habit-like stimulus-driven behavior. Several reports have found deficits in goal-directed control in OCD. However, it was unclear in the extant literature whether these deficits are the consequence of acute symptoms (i.e., a state marker) or reflect disease risk (i.e., a trait marker) (Kalanthroff et al., 2016). The present study is the first to investigate these competing ideas longitudinally, using EX/RP as a tool to reduce OCD symptoms and measure what effect this has

on model-based learning (a task marker of goal-directed behavior) in a clinical population. We found that model-based learning performance remained stable in our sample of OCD patients, despite their achieving significant therapeutic gains. These findings are incompatible with the epiphenomenon account that goal-directed failures result from OCD symptoms (state view) and instead lend support for the notion that deficits in goal-directed planning may be a trait-like, stable phenomenon.

At baseline, we found a significant negative association between OCD severity and model-based planning. This replicates findings from prior work examining continuous associations between OCD severity and goal-directed learning which show that poorer goal-directed control is correlated with more severe OC symptoms in the general population (Gillan et al., 2016; Snorrason et al., 2016). At post-treatment however, there was no significant relationship between symptom severity and task performance and crucially, there was no correlation between symptom improvement following treatment and changes in model-based learning performance. Together, these data suggest that EX/RP does not exert its therapeutic effect in OCD by improving the goal-directed processing system.

Overall, these results mirror prior results with the error-related negativity, another putative OCD trait-marker that is unchanged by successful treatment (Hajcak et al., 2008; Riesel et al., 2015) and might relate to anxiety and worry commonly seen in OCD (Gillan et al., 2017). Future research is needed to determine whether deficits in goal-directed planning are heritable and might be experienced at higher rates in unaffected family members of OCD patients at higher rates than the general population (as was shown for the ERN; Riesel et al., 2015).

Deficits in goal-directed control have been observed not only in OCD but also in other disorders, such as addictions (Sjoerds et al., 2013; Voon et al., 2015; Gillan et al., 2016) and aspects of eating disorders, such as binge eating and purging behavior (Furlong et al., 2014; Voon et al., 2015; Gillan et al., 2016). These disorders are thought to have a common compulsive element to their core symptomatology that may be explained by common deficits in goal-directed learning. Taken together with the findings of the present study, it is possible that deficits in goal-directed control might be a vulnerability factor for multiple disorders, in line with recent efforts to study transdiagnostic compulsivity as a construct (Gillan et al., 2016; Gillan et al., 2017), consistent with the NIMH Research Domain Criteria Initiative (RDoC), which aims to explore trans-diagnostic traits rather than discrete DSM diagnoses (Insel et al., 2010).

The current study is the first to apply a longitudinal methodology to the study of goal-directed planning in relation to OCD symptoms and as such improves upon the extant literature in this area, which has been entirely cross-sectional. However, several important study limitations should be noted. First, all of the patients in this study were receiving SRI pharmacotherapy at both time-points. Although this should be taken into account with respect to overall main effects, this does not confound the longitudinal analysis that is critical to this investigation (since patients were required to be stable on medications for at least 8 weeks prior to study entry, with the actual observed $M = 96.1$ weeks stable prior to entry). Second, the sample size was relatively small, which precludes us from analyzing subgroups within OCD (e.g., based on different OCD symptom dimensions), and this small sample size may have limited power to detect changes in model-based planning. Thus replication with larger samples is warranted. However, a previous study using a similar intervention-based design (within-subjects manipulation with L-Dopa) with $N = 18$ was able to detect significant differences in model-based planning (Wunderlich et al., 2012), suggesting that our study was adequately powered to detect meaningful within-subject differences in task performance. Third, this study did not employ a healthy comparison group, which limits the extent to which we can characterize baseline performance as 'deficient' in the patients studied here. However, evidence for model-based planning was not significant in our OCD sample, which taken together with prior work using this task in healthy samples (e.g. Daw et al., 2011; Otto et al., 2013a) is consistent with the interpretation that patients in the present study were impaired. This mirrors what has been seen previously in OCD patients on this task (Voon et al., 2015) and others like it (Gillan et al., 2011, 2014, 2015a,b). Finally, future research is needed to test if goal-directed planning deficits pre-date the onset of OCD symptoms. Without this, we cannot draw conclusions about whether this cognitive deficit is a 'risk factor' for OCD. Rather, these data suggest that symptoms alone do not appear to cause goal-directed planning deficits.

Notwithstanding these limitations, the present results contribute incremental new knowledge to studies of the balance between goal-directed and habitual behaviors in OCD. Our data suggest that reducing OCD symptoms with EX/RP does not affect goal-directed planning. This supports a trait model of the relationship between goal-directed planning and OCD symptoms, such that problems in goal-directed planning do not result from OCD symptoms and may in fact be a stable risk factor making some individuals more vulnerable for developing OCD.

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Conflicts of interests

In the last three years, Dr. Simpson has received research support from Biohaven Pharmaceuticals and royalties from Cambridge University Press and UpToDate, Inc.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.psychres.2018.12.079.

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