Metacognitive antecedents to states of mental ill-health: Drops in confidence precede symptoms of OCD

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Metacognitive antecedents to states of mental ill-health: Drops in confidence precede symptoms of OCD

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Abstract

Mental health symptoms, like those in obsessive-compulsive disorder (OCD), show pronounced fluctuations over time. However, little is known about the underlying factors driving these fluctuations. Whilst theoretical accounts propose that cognitive processes drive symptom variability, cross-sectional work is unable to effectively probe these mechanisms. Based on prevailing notions of doubt and underconfidence being cognitive hallmarks of OCD, we investigated whether metacognitive processes correspond to OCD symptoms. We employed a novel smartphone-based momentary assessment design wherein participants with OCD (N = 137) logged instances of experiencing OCD symptoms across 2-weeks. Participants also completed daily scheduled assessments, and played a perceptual metacognitive task every two days. Our results showcase the validity of our novel approach and, importantly, reveal that metacognition drives OCD symptoms. Concretely, we found directional effects whereby reductions in both self-confidence and task-based metacognition preceded occurrences of OCD symptom logs, but not vice versa. Thus, our novel micro-longitudinal study design provides compelling evidence for cognitive distortions (both self-reported and task-based) preceding symptom escalations, signifying the potential for designing novel, just-in-time interventions.

Introduction

Variability is a fundamental aspect of human nature. Our moods, feelings, as well as cognitive attitudes fluctuate along different timescales, from minutes[1] to hours[2] to days and months[3]. This is also apparent in mental illnesses, where symptoms and their severity wax and wane seemingly unpredictably. Obsessive-compulsive disorder (OCD), for example, is known to show symptom fluctuations even within a single day[4]. Yet, the factors influencing these fluctuations remain unclear. This is a crucial challenge to be addressed, because pinpointing when symptoms are likely to get worse is essential for providing just-in-time support.

A prominent account potentially explaining symptom fluctuations stems from cognitive behavioural therapy[5], where it is believed that symptoms arise (or fluctuate) due to biased cognitive patterns. This suggests that a worsening in cognitive biases precedes and drives mental illness symptoms – a notion that has led to extensive research investment into characterising cognitive mechanisms underlying the disorder[6–8]. However, little is known about whether these cognitive mechanisms underlie more rapid fluctuations in symptoms on a day-to-day basis.

In this study, we put this hypothesis to the test by investigating fluctuations in OCD symptoms. To this end, we focused on metacognition as a candidate cognitive predictor. Metacognition refers to introspection into and confidence over our thoughts and/or cognitive processes[9,10] and has been linked to ensuing moods and feelings[11]. Importantly, metacognition is believed to be altered in OCD[12–14], which is thought to drive intrusive thoughts and compulsions. Empirically, lowered confidence is correlated with dysfunctional and elevated levels of checking (a form of compulsive behaviour) in clinical OCD[15]. Based on these cross-sectional and group-level findings, it is imperative to further investigate how metacognitive fluctuations correspond meaningfully to variance and severity in OCD symptoms

In the current study, we investigated whether rapid fluctuations in metacognition (i.e. changes within a few hours) were associated with ebbs and flows in OCD symptoms. To do so, we have built on our recently established ecological momentary cognitive testing (EMCT) approach[2], where we trace state fluctuations in feelings, symptoms and cognition by repeatedly sampling participants' behaviours and experiences in real-world settings.

To capture OCD symptoms in this study, we evaluated instances where participants with OCD self-reported experiencing symptoms using a 2-week smartphone protocol. We show that these daily "symptom logs" are substantively associated with relevant states and external contexts. Further, to address an ongoing discussion over the best metrics for assessing metacognition[16], we evaluated metacognition using multiple methods, including self-reported confidence and task-based judgements. In our micro-

longitudinal smartphone-based design in 137 participants, we find that both measures of metacognition are indeed related to OCD symptoms. Moreover, we demonstrate a clear directional effect, wherein drops in metacognition precede OCD symptoms. Our findings thus provide direct evidence for fluctuations in (meta-)cognition driving mental health symptoms, therefore constituting a promising avenue for predicting symptom trajectories and delivering just-in-time interventions.

Results

We conducted a microlongitudinal study in 137 participants investigating how fluctuations in metacognition were driving day-to-day OCD symptoms. Participants (76.6% female, 21.2% male, 2.2% non-binary; Age: mean [M] = 32.8 years ± 8.22 [standard deviation]) were recruited via an online worker platform and were included based on a self-declared diagnosis of OCD and a score of ≥ 21 (the traditional cut-off for clinically significant OCD) on the obsessive-compulsive inventory-revised (OCI-R[17]; M = 48.04 ± 11.43 – Figure 1).

After an initial baseline assessment, participants followed a 14-day procedure in which they were instructed to log any symptoms of OCD (defined as any instances of intrusive thoughts or compulsive behaviour) by tapping on a button on the home screen of the study app (see Figure 1a). This self-initiated 'symptom logging' was used to capture instances of OCD episodes independent of scheduled notification periods (see below). This has been successfully adopted in prior work to assess emotional states following specific events, for instance after non-suicidal self-injury[18,19] but, until now, not in OCD.

In total, 118 participants logged a total of 1862 symptoms (median logs = 6, interquartile range = 15) throughout the study period. Alongside symptom logging, participants were repeatedly notified to report on their subjective states (4 times a day), including subjective self-confidence (Figure 1b), and play a perceptual metacognitive task (once every other day) (Figure 1c-d). The combination of symptom logs with state notification reports provided enhanced insight into the drivers of OCD symptoms, allowing us to measure instances of symptom logs close in time to state confidence. Nineteen participants did not log any symptoms throughout the testing period, although they did complete the state notified assessments.

Participants reported a total of 6389 states across the 14 days (mean notification completion rate [proportion]: M = 0.82 ± 0.13; mean total number of notifications completed per person: M = 46.6 ± 7.79) and completed a total of 922 cognitive games (M = 7.4 ± 2.7). See Figure 1f and Methods for details of data and participant exclusion criteria.

To validate our novel symptom logging approach, we also assessed OCD severity during state notifications by asking participants to rate their symptoms, as is standard in other momentary sampling studies[20]. To better understand factors relating to, and fluctuating with, confidence and OCD symptoms, we also asked participants other questions related to mental health (e.g., current anxiety, mood, sleep quality – see Methods).

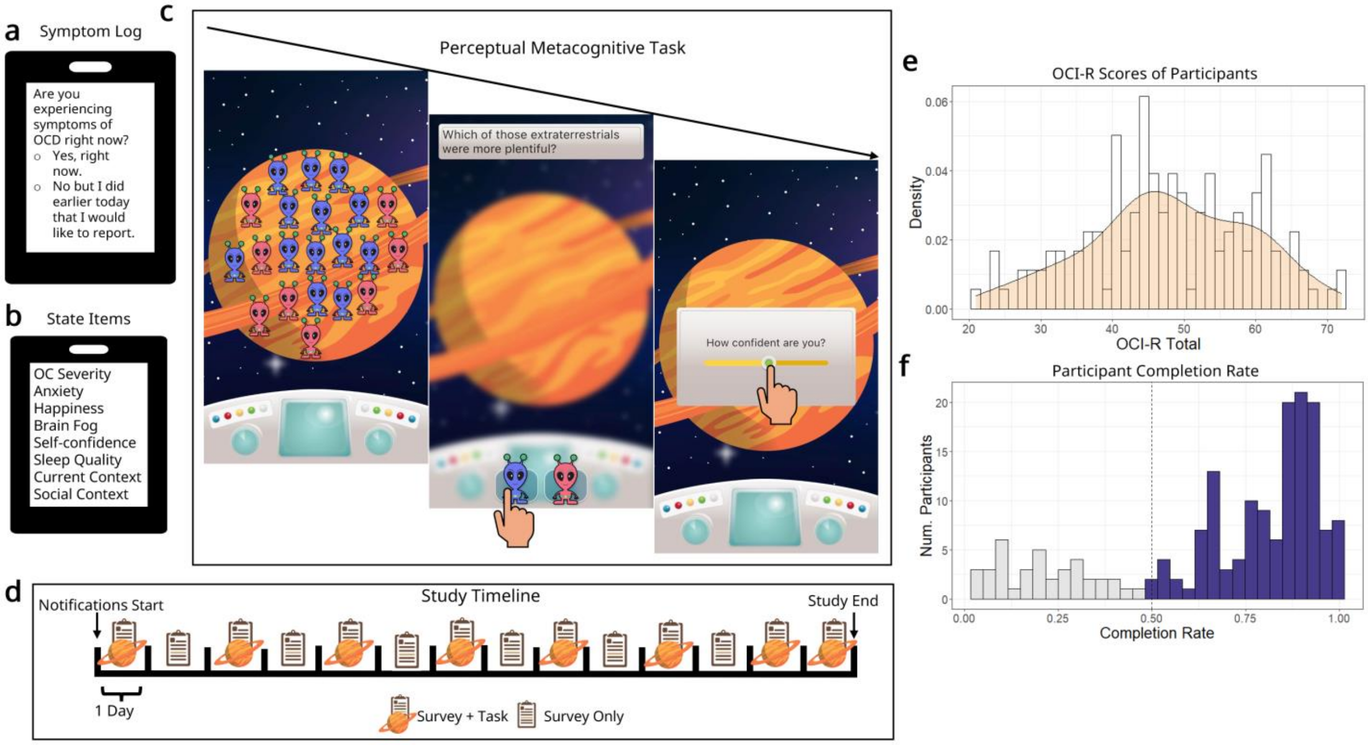

Figure 1: Microlongitudinal study design to determine the link between real-world fluctuating symptoms of OCD, self-confidence, and metacognition during decision making. ***a.*** *Participants were asked to log in the app whenever they experienced episodes of OCD. They could press 'Yes, right now' if current experiencing symptoms, or otherwise 'No' to retrospectively log symptom that happened earlier that day.* ***b.*** *Participants answered a survey probing states 4 times a day (with a minimum of 2 hours between notifications) that probed the listed constructs.* ***c.*** *On alternate days (8 total), participants completed a perceptual metacognitive task at the same time as 1 of the 4 state notifications. Trials begin with participants viewing a total of 64 aliens mixed of two different colours on a planet for 250 milliseconds. They are asked to select which alien is more abundant on the planet and then rate their confidence in their decision on a sliding bar. The task lasted 80 trials each play (40 trials per block) ~ roughly 5 minutes per play.* ***d.*** *Study timeline depicting the ecological momentary cognitive testing (EMCT) design over 14 days.* ***e.*** *All participants scored highly on an obsessive-compulsive scale (OCI-R, ≥ 21 being the traditional cut-off for OCD).* ***f.*** *Participants' data were used in the analysis if they completed at least 50% of all notifications. We excluded 38/175 people for not meeting this criterion.*

Frequency of self-initiated OCD symptom logging is linked to other state measures and external contexts

First, as a validity check, we investigated whether self-initiated OCD symptom log frequency was associated with well-established measures (e.g., OCD severity and mood) (Figure 2a). We quantified symptom logging frequency as the mean time difference between symptom logs (inter-symptom interval) in hours per participant (the lower the time, the greater density). We implemented this instead of simple counts of symptom logs which is more susceptible to compliance to the study protocol, while averaged time-between-logs better reflect intensity of symptoms (i.e., greater intensity when logs are closer in time)[21]. We found that people who had a smaller inter-symptom interval also overall reported increased state anxiety (*rho* = -0.25, *p-FDR* [false discovery rate corrected] = .02; Figure 2d) and an increase in averaged state OCD severity ratings (*rho* = -0.19, *p-FDR*= .077, *p-uncorrected* = .05), albeit the latter association did not reach corrected statistical significance. Conversely, the inter-symptom interval was linked to a reduced averaged state confidence (*rho* = 0.30, *p-FDR* = .007; Figure 2b) and happiness (*rho* = 0.32, *p-FDR*= .007; Figure 2c). These relationships align with findings from prior trait work reporting that OCD symptomatology is tied to constructs of mood, anxiety, and confidence[12,22,23] and thus provides evidence that our OCD symptom log data captured meaningful variation in behaviour.

Next, to further assess symptom log validity, we confirmed that symptom logs were significantly associated with moment-to-moment state OCD severity ratings (see Supplementary for detailed analyses on OCD severity ratings and other state and trait scores) during notification periods. Indeed, current OCD severity ratings were positively associated with past (β = 0.149, 95% CI [0.06 0.22], $p < .001$) and future symptom logs (β = 0.234, 95% CI [0.15 0.31], $p < .001$) within a 4 hour-window (Figure 2e), indicating that our novel symptom log measure is temporally linked to (more traditionally implemented) ecological momentary assessment (EMA)-based OCD severity ratings[20].

Additionally, we confirmed that symptom logs were meaningfully capturing external events (i.e., whether probability of a symptom log varied based on current activities and social contexts) and explored how symptom log occurrence fluctuated by the time-of-day and the day-of-week (see Supplementary).

Our findings support the ecological validity of this logging approach allowing us to further investigate the relationship between symptom logs and its drivers.

<u>Self-confidence linked to self-esteem and perceived cognitive impairment</u>

Because our momentary assessment of self-confidence (probed using the question 'How confident do you feel right now?' – see Methods) was not used in this context before, we assessed whether it is associated with well-established trait measures. Indeed, participants with greater trait self-esteem (measured with the Rosenberg self-esteem scale[24]) also reported increased mean state self-confidence (*rho* = 0.49, *p-FDR* < .001; Figure 2f), thus confirming the construct validity of our state self-confidence question. Additionally, more (averaged state) self-confident participants reported lower perceived cognitive impairment related to OCD (*rho* = -0.38, *p-FDR* < .001, Figure 2g; measured using the Cognitive Assessment Instrument of Obsessions and Compulsions-13[25]; example item: "Do you doubt having done things properly?"), suggesting that self-reported confidence is also linked to OCD-related metacognition.

These trait-state relationships were maintained even when accounting for other state measures (mean anxiety, happiness, sleep quality, and brain fog) using partial Spearman correlations (see Supplementary). Further analyses on links between self-confidence and external contexts, the time-of-day, and the day-of-week can be found in the Supplementary Material.

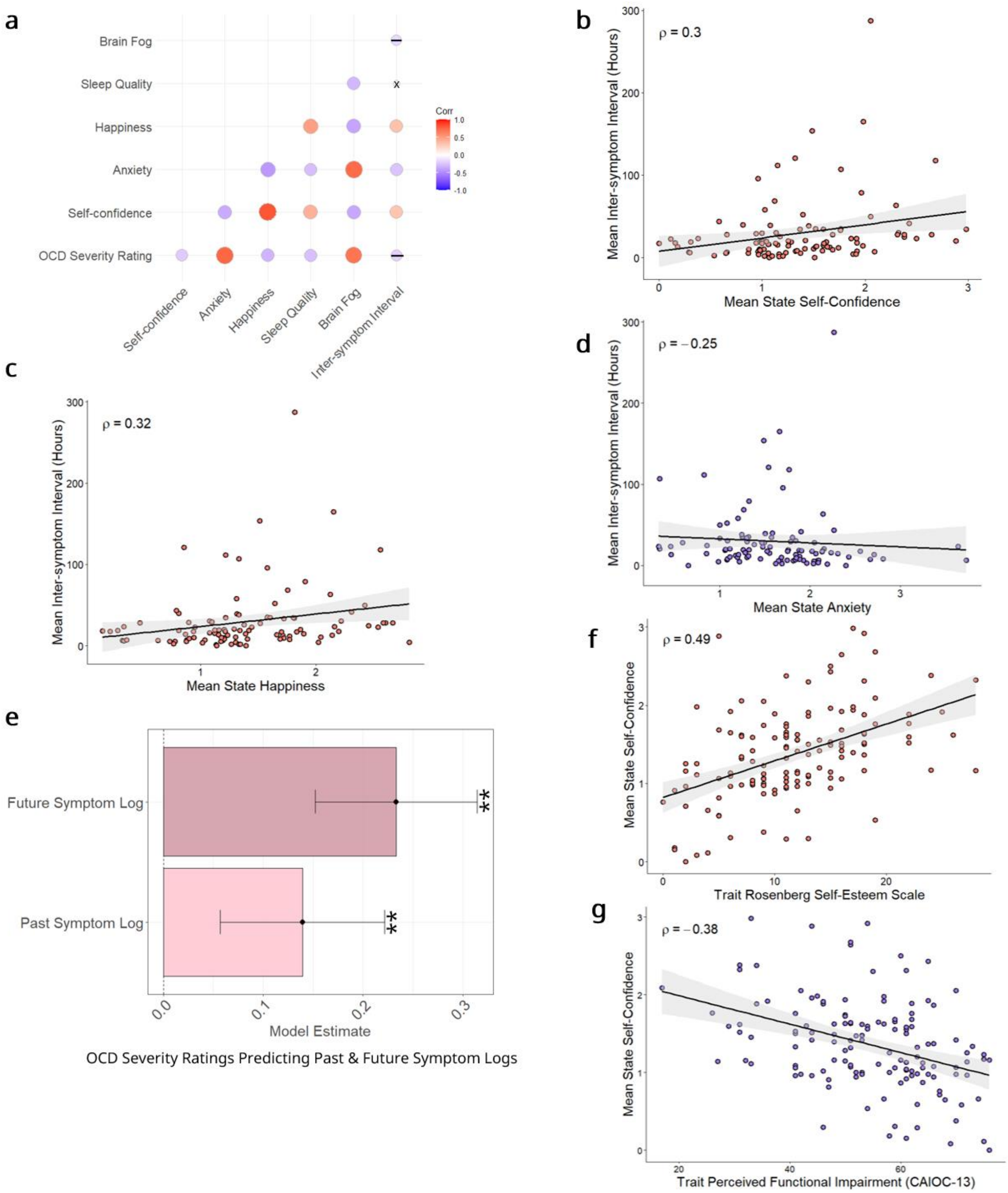

Figure 2: Identifying correlations between trait- and state-measures, with a focus on OCD symptoms and self-confidence. ***a.*** *Correlation matrix showing Spearman relationships between averaged state measures. 'X' indicates correlation is not statistically significant, while a '-' indicates marginal significance (p-FDR < .1)* ***b – d****. Scatterplots depicting key relationships between averaged states and symptom log frequency (quantified as mean time difference between logs). State measures are always displayed on the x-axis. Spearman's Rho (ρ) displayed top left of each plot. Higher averaged time between symptom logs (inter-symptom interval) was significantly correlated with averaged self-confidence (b) and happiness (c), but inversely related to averaged anxiety (d).* ***e.*** *OCD severity ratings during notifications are significantly linked to past and future OCD symptom logs within a 4-hour window. *p< .05, **p<.01, Error bars = 95% confidence intervals.* ***f-g.*** *Scatterplots depicting correlations between averaged self-confidence and*

self-esteem (f) and between averaged self-confidence and perceived functional impairment related to OCD (g). Across all subplots, purple colours indicate significant negative relationships while red indicates significant positive relationships.

Reduced self-confidence predicts future OCD symptom logs

Our main question in this study was to assess whether and how fluctuations in momentary confidence contributed to the emergence of OCD symptoms. We therefore leveraged our temporally fine-grained assessments to not only investigate associations, but also directionality of these effects. To do this, we used logistic mixed effects models, with state measures predicting whether a symptom was logged within 4 hours of completing a state questionnaire. We found that above other state measures (anxiety, brain fog, happiness, and sleep quality), a future symptom log was best predicted by reduced self-confidence (Odds Ratio = 0.72, $\beta = -0.33$, $p = .005$), as well as increased OCD severity ratings (Odds Ratio = 1.32, $\beta = 0.28$, $p = .012$) - Figure 3a. These significant effects were maintained even when subsequently controlling for activities people reported they were currently doing. The association with OCD severity ratings supports the notion that symptom logging in this study reflects *genuine* OCD ratings, while the association with self-confidence expands current understanding of how confidence contributes to OCD symptoms. These results held even when testing shorter time windows between symptom logs and state questionnaires (i.e., within 3 hours, 2 hours, and 1 hour; see Supplementary). This means that drops in self-confidence were meaningfully associated with OCD symptoms.

Next, we were interested in the directionality of these effects, i.e. whether drops in self-confidence preceded increased OCD severity or vice versa. To this end, we tested whether self-confidence was more related to past (OCD_{t-1}; suggesting OCD affects future confidence) or future OCD logs (OCD_{t+1}; confidence affecting OCD). We uncovered that the relationship between self-confidence and the likelihood of logging a symptom was unidirectional: in a linear mixed-effects model current self-confidence was significantly associated with a future symptom log ($\beta = -0.18$, 95% CI [-0.26 -0.10], $p < .001$; Figure 3b) but not the other way around ($\beta = 0.007$, 95% CI [-0.08 0.09], $p = .88$). These findings were maintained even when using past, current, and future OCD severity ratings during timed notifications to predict self-confidence – see Supplementary. This means that drops in self-confidence precede OCD symptoms, but OCD symptoms do not precede drops in self-confidence.

Task-derived metacognitive bias is coupled with self-confidence

Next, we were interested in whether metacognition influencing symptom occurrence was specific to self-reported self-confidence, or whether it generalised to other metacognitive measures, such as task-related confidence. To this end we asked participants to play a smartphone-compatible gamified perceptual metacognition task

(8 times total throughout the EMCT period; Figure 1b) with staircased performance[26], an essential component for computational metacognition research.

To further study the construct validity of these different measures, we investigated whether self-confidence was linked to task metacognitive measures. From the metacognition task, we derived two commonly studied measures: (i) metacognitive bias (essentially the mean confidence rating), where low bias indicates underconfidence while high bias indicates overconfidence and (ii) metacognitive efficiency (meta-d'/d'), derived using signal-detection theoretic computational models[27], which quantifies whether task confidence ratings are sensitive to correct and error trials while controlling for performance (d'). We utilised these task measures based on existing literature; where some reports indicate that obsessive-compulsivity is associated with biased (e.g., too low) reporting of confidence (i.e., related to metacognitive *biases*) (see Hoven et al., 2019[12] for review) while other findings suggest compulsivity is linked to imprecise confidence judgements[13,28], manifesting as decreased sensitivity in delineating correct from incorrect choices in their confidence ratings (i.e., pertaining to metacognitive *efficiency*)[29,30].

We found a significant within-subjects correlation between metacognitive bias and self-confidence (Figure 3c; median Spearman's rho = 0.24, one-sample Wilcoxon rank-sum test: $p < .001$). Metacognitive efficiency was not significantly associated with self-confidence ($p = .27$). We formally tested the robustness of the association between self-confidence and metacognitive bias in a model controlling for other state measures (anxiety, brain fog, happiness, OCD severity rating). Indeed, only self-confidence was significantly associated with metacognitive bias ($\beta = 0.12$, 95% CI [0.04 0.20], $p = .002$). The relationship between metacognitive bias and self-confidence was maintained ($\beta = 0.12$, 95% CI [0.05 0.19], $p < .001$) even when controlling for other task measures, namely signal strength (numerical difference between task stimuli; a measure of task difficulty), choice reaction time, and staircased (i.e., adaptive; see Methods) accuracy. These findings provide strong evidence for different confidence measures measuring a common underlying metacognitive construct, even though the assessment modalities (self-report vs task) and frequency (4 times daily vs every other day) differed substantially.

<u>Metacognitive bias fluctuations drive future OCD symptom logs</u>

Lastly, we assessed whether task metacognitive bias was linked to OCD symptom logs. When inserted into a logistic mixed effects model, lower metacognitive bias (Odds ratio = 0.75, $\beta = -0.28$, $p = .022$), but not metacognitive efficiency ($\beta = 0.027$, $p = .84$), was significantly associated with a future symptom log (within a 4-hour period from completing a game).

We conducted further analyses to thoroughly assess the robustness of the relationship between metacognitive bias and symptom logs. First, controlling for other task measures in the same model still indicated that reduced metacognitive bias was significantly associated with a future symptom log (Odds Ratio = 0.78, β = -0.25, *p* = .046) – see Figure 3d. Next, the relationship was maintained (Odds Ratio = 0.60, β = -0.51, *p* = .036) when controlling for state measures (anxiety, brain fog, happiness, OCD severity rating, and sleep quality) that were close in time to the completion of the task (within at most a 4-hour period). Finally, using shorter time windows between game completion and symptom log (<4 hours) yielded similarly significant results (see Supplementary).

Lastly, we also investigated the temporal succession of these effects, i.e. whether a drop in metacognition preceded or followed the emergence of OCD symptoms. In line with our self-confidence findings, we saw that reduced metacognitive bias predicted future symptom logs (β = -0.21, 95% CI [-0.40 -0.015], *p* = .035) but past symptom logs did not impact current metacognitive bias (β = 0.03, 95% CI [-0.13 0.19], *p* = .69) – Figure 3e.

In summary, both task-based (as well as self-reported) metacognition preceded the appearance of OCD symptom logs. This indicates that fluctuations in metacognition predict a likely rise in OCD symptoms within a few hours' time.

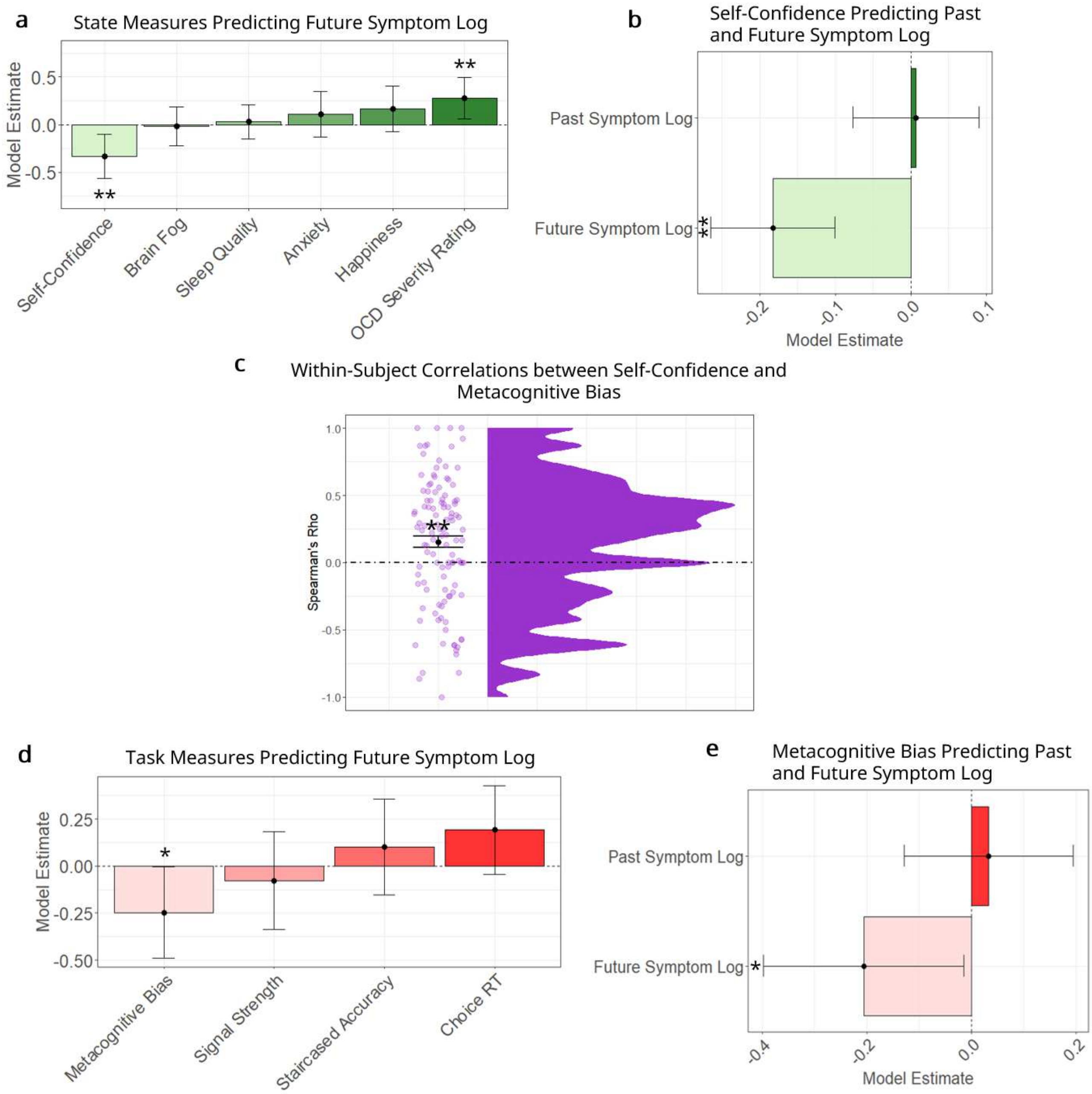

*Figure 3: Elucidating associations between OCD symptoms and metacognitive constructs. **a.** Low self-confidence and high OCD severity significantly predict the occurrence of a future OCD symptom log. **b.** The effects of confidence on symptom logs are unidirectional; high self-confidence is associated with a lower probability of a symptom being logged, but not the other way around. Past and future symptom logs (within 4 hours of answering the state questions) were used as independent variables in a logistic mixed-effects models predicting self-confidence. The bar plots depict model coefficient estimates from mixed-effects models. All model included individual random intercepts as covariates. **c.** Raincloud plot showing an overall positive within-subject correlation between metacognitive bias and self-confidence (significantly different from 0 using Wilcoxon one-sample signed rank test). Each circle represents one participant's Spearman's Rho value quantifying the correlation strength between their own self-confidence and metacognitive bias. Overall mean correlation coefficient and standard error are shown in black. **d.** Low metacognitive bias significantly predicts future symptom logs above other task measures, and **e.** the effect of metacognitive bias over symptom logs is also unidirectional (metacognitive bias predicting future symptom logs). Key: *p< .05, **p<.01, Error bars = 95% confidence intervals.*

Discussion

In this densely sampled longitudinal study, we established that fluctuations in metacognition potentially drive symptoms of OCD. During instances of reduced confidence, both in the self and in perceptual decisions, participants with self-declared OCD demonstrated a greater likelihood of logging symptoms. These effects were directional – lowered confidence preceded symptom logging, but past symptom logs were not predictive of future low confidence. Our findings thus support the notion that fluctuations in cognitive processes may predict (in a temporal sense) future mental health symptoms, and that in OCD, metacognition is a key driver.

This EMCT study is the first to implement naturalistic self-initiated symptom logging throughout the assessment period, which enabled us to effectively ascertain the temporal relationship between multimodal metacognitive processes and OCD symptoms. Our work significantly extends prior cognitive OCD literature which has produced mixed accounts with regards to metacognition. To illustrate, clinical studies point to OCD being associated with reduced metacognitive bias, i.e., underconfidence, across multiple cognitive domains[12] while transdiagnostic research indicates that, in general populations, compulsivity is more associated with inflated confidence[11,14,30,31] and possibly metacognitive inefficiency[29,30]. A limitation of these cross-sectional studies is that they are unable to capture variability in these erratic processes. By contrast, our powerful EMCT design successfully enabled i) insight into how these processes interact over time while controlling for potential confounding factors, and ii) assessment of the temporal directionality between processes. Using this state fluctuation approach, we established, for the first time, that it is reductions in confidence that antecede OCD symptoms within the timescale of a few hours. Moreover, our online sample, who have self-identified as having OCD and show high obsessive-compulsive scores, may reveal metacognitive patterns (i.e., lowered bias) more akin to in-person clinical samples than to online transdiagnostic samples[31], signifying strong clinical relevance. Investigating whether clinical and subclinical/transdiagnostic populations are in alignment on these within-subject momentary associations between metacognition and OCD(-like) symptoms could shed further light on diverging cross-sectional findings thus far.

Leveraging EMCT, we further addressed how metacognitive processes from different modalities are interrelated and shape mental health. We uncovered that confidence during decision-making was significantly related to one's own self-confidence on a moment-to-moment basis. This points to metacognition being a unified psychological construct (i.e., domain-general) rather than being context specific. Moreover, our results may support the theory that metacognitive processes are organised hierarchically, an ongoing and pertinent area of study[32]. Briefly, lower levels along the hierarchy are thought to pertain to 'local' confidence (i.e., confidence in specific contexts such as in trial-by-trial decisions on a cognitive task) and higher levels represent 'global' confidence related to metrics like self-esteem. Indeed, compulsivity has been linked to specific alterations at different levels of the metacognitive hierarchy[14,33]. In the context of the present study, we demonstrate how self-beliefs generalise across different domains and that alterations in these beliefs go on to potentially drive obsessive-compulsive symptoms.

As our findings indicate that *task* metacognitive biases drive moment-to-moment symptom emergence, this could serve as a foundation for future work to incorporate mobile neuroimaging techniques with EMCT to identify the neural mechanisms underlying these fluctuations. Whilst the neural mechanisms associated with *fluctuations* in metacognition remain unknown, we speculate that connectivity between prefrontal cortices and right dorsal anterior cingulate cortex and striatal regions (bilateral putamen and right caudate) could act as drivers given their involvement both in metacognition[34,35] and OCD symptomatology[7,36].

Ultimately, this study paves the way for the design of just-in-time interventions targeting reduced confidence, to alleviate symptoms of OCD as they occur. Prior research has already established that cognitive behavioural therapy targeting meta-memory leads to immediate improvements in memory confidence, and corresponds to decreased checking symptoms over time[37] while deep brain stimulation applied to the ventral striatum leads to an immediate increase in self-confidence, coupled with improved OCD symptoms[38]. These studies collectively point to confidence as an effective intervention target while our current EMCT study unveils the promise of mobile confidence and symptom tracking to define precisely *when* interventions should be delivered (i.e., during drops in confidence) to maximise effectiveness.

In sum, our study provides empirical evidence for metacognitive processes contributing to fluctuations in symptoms of OCD. We reveal that moment-to-moment reductions in confidence across different domains (in the self and in perceptual decision-making) are associated with greater likelihood of reporting symptoms. This implies that lowered confidence can serve as a temporal marker for episodes of OCD, and further, underconfidence could be targeted with remote and/or mobile interventions to facilitate momentary alleviation of symptoms.

Methods

Participants

The study was conducted online (https://prolific.co/), following 3 distinct stages: pre-screening, baseline, EMCT. We pre-screened 290 participants (residing in the United Kingdom) who declared they had a diagnosis of OCD on Prolific. Other inclusion criteria at the pre-screening stage were as follows: aged 18-55 years, fluency in English, and smartphone ownership. During pre-screening, we selected participants who scored ≥ 21 on the OCI-R (the traditional cutoff for OCD[39]), and who did not have a history of neurological conditions or a diagnosis of Schizophrenia/psychosis. Following pre-screening, 286 participants were invited to the baseline assessment, which involved completing trait questionnaires and being briefed on the EMCT portion of the study; 201 participants completed this stage and were enrolled onto the EMCT part. After removal of dropouts and people who did not meet the completion criterion (minimum 50% EMCT notification completion), we analysed data from 137 participants (see Figure S[supplementary]1A for participants recruitment flowchart), 118 of which logged symptoms of OCD at least once throughout the study period (Figure S1B). The study was approved by the University College London Research Ethics Committee (reference: 15301/001) and all participants provided informed consent. See Figure S2 for further demographic information.

Design and Procedure

During pre-screening, participants completed the OCI-R and declared any psychiatric and/or neurological diagnoses. During baseline, participants completed demographic and trait questionnaires on REDCap (Research Electronic Data Capture). Next, EMCT was completed on participants' own smartphones within the Brain Explorer Android or iOS app (www.brainexplorer.net). EMCT began the following morning after enrolment onto the study using the app. Participants resumed their usual daily routines while responding to notifications prompting them to complete state reports and a perceptual metacognitive game over the next 14 days. Participants received 4 state notifications total per day: one every morning (between 08:30 to 11:30) and three notifications between 13:30 to 21:30. Actual notification times were spaced at least 2 hours apart from each other and were pseudorandomised. Participants knew to expect 4 notifications a day but were not informed of the exact delivery times to minimise expectation effects. We programmed notifications to be sent out this frequently (x4 a day) to rigorously capture time-of-day effects on symptom severity – as OCD symptoms are reported to fluctuate significantly within a single day[4]. The perceptual metacognitive task (see description below) was played on alternate days (8 games total). The number of games associated with state notifications in the morning, afternoon, evening, and night was counterbalanced (twice for each time of day).

Participants were reimbursed at a base rate for completing the screening and trait questionnaires (£5.25) and received additional payment at the end of the 14-day study based on the number of assessments completed (up to £20 extra).

Assessments

Trait and demographic questionnaires. Participants completed the Cognitive Assessment Instrument of Obsessions and Compulsions (CAIOC-13)[25], Rosenberg Self-Esteem Scale[24], Barratt Impulsivity Scale-11 (BIS-11)[40], Intolerance of Uncertainty Scale (IUS)[41], Patient Health Questionnaire-9 (PHQ-9)[42] for depression severity, trait anxiety scale (STAI-T)[43], and the obsessive-compulsive inventory-revised (OCI-R)[39], as well as demographic questions (age, gender, ethnicity, education level, socioeconomic status).

Subjective states and momentary contexts. The state assessment included 8 items total, 7 of which occurred at every notification timepoint, while an additional sleep quality item was in the morning only (see Table S1 in Supplementary).

Previous momentary sampling studies of OCD have predominantly assessed symptoms using dimension-specific items, such as those targeting checking or cleanliness (see Braga et al., 2025, for extensive review)[44]. However, given the substantial heterogeneity in disorder presentation, we opted for a broader question probing symptom intensity based on an item successfully utilised in EMA work identifying candidate neural biomarkers (using intracranial electrophysiology) of OCD severity[20]. Past EMA research was also used to inform the self-confidence item[45].

We tested for state anxiety[45,46], and happiness/mood[45,47] because OCD has high comorbidity rates with both anxiety and depressive disorders[22], and it is thus important to control for these variables when investigating the link between OCD and confidence. Similarly, we assessed sleep quality once a day due to the disorder being associated with sleep disturbances and reduced sleep efficiency[48].

To address the potential impact of poor concentration or diminished thought clarity resulting from OCD symptoms on performance in the perceptual metacognitive task, we included a ‘brain fog’ item designed to assess difficulties with mental clarity. Evaluating this aspect was considered important, as ‘mind-blanking’ is also observed during states of anxiety[49].

To assess the external validity of our state measures, we also examined how states are influenced by current activities and social contexts. This approach was particularly relevant given that daily routines and situational factors have been shown to affect OCD symptom severity[50].

The first 6 state questionnaire items were rated on a 5-point Likert scale (not at all, a little, moderately, very, extremely), while the current activity item contained check box options (‘Work/school/studying/training’, ‘resting/relaxing’, ‘Everyday tasks/errands/shopping’, 'Inactive leisure activities (e.g., reading, surfing the net, social media, games, watching TV)', 'Active leisure activities (e.g., sports, hiking)', 'travelling (e.g., on foot, car, public transport)', 'Self-care/personal hygiene/eating/drinking') and the social context item had the options 'Alone' and 'With others'. Activity and social context options were obtained from existing items used in EMA research (German Center for Mental Health, 2024).

Symptom Log. Participants were asked to log whenever they were experiencing symptoms of OCD. This self-initiated logging enabled assessment of close-in-time associations between state and metacognitive measures used. To encourage compliance, we ensured that symptom logging required minimal effort; participants merely needed to tap on a 'Symptom Log' button on the app front page, and they would then be asked 'Are you experiencing symptoms of OCD (e.g., intrusive thoughts, compulsions) right now?'. Participants would then select 'Yes' if they were experiencing symptoms at the given moment. They were also able to retrospectively log symptoms, an option we provided to account for their symptoms of OCD interfering with their ability to log symptoms at the specific moment. To do this, in response to the question above, they would select the option 'No, but I did earlier today that I would like to report'. They would then be able to select an approximate time (in 30-minute intervals) that they last experienced symptoms. To encourage compliance further, we sent daily reminders in the evenings to notify participants to log symptoms of OCD if any symptoms occurred on the day. These notifications were pseudorandomised between 18:00 and 21:00 daily.

Perceptual Metacognitive Task[51]. The task was implemented on the Brain Explorer app on participants' mobile phones. Participants were instructed to make a perceptual decision based on an array of two different coloured aliens presented for 250 milliseconds (ms). They then had to decide which of the two aliens was more abundant by selecting the specific alien on screen. This was followed by a confidence rating in which participants had to rate their decision certainty on scale from 'totally guessing' to 'totally certain' [these labels were adopted from prior work[51]]. Participants were instructed to use the full length of the scale.

The first-time participants played the task, they completed 20 practice trials in which they only made the perceptual decision (no confidence rating) and were given feedback, where either a green tick (correct) or a red cross (incorrect) appeared on screen. The actual task consisted of 80 trials divided into 2 blocks of 40 trials each (with the option for a break in between blocks). Feedback was not provided in the actual task. A maximum of 68 aliens were displayed on screen on any given trial.

A staircase procedure was used throughout the training and task to match participants' performance[26]. Equating performance across participants in this way was done to enable observation of biases in task confidence ratings (i.e., metacognitive bias)[52]. To this end, we used a 2-up-1-down staircase procedure converging at ~70% accuracy which was initiated during the 20 practice trials to minimise burn-in period. The difference between the two-coloured aliens was initialised at 15 and then would change by +4 or -4 with every step of the staircase. We used a continuous staircase meaning that the staircasing did not reset between task plays.

Statistical Analyses

Analyses were conducted using in RStudio using R version 4.3.3. A statistical significance threshold of $p < 0.05$ was adopted and all tests reported here were two-tailed unless otherwise stated.

Data validity checks. We conducted data validity checks before running the analyses. First, there were several instances where participants bulk completed notifications in one sitting. To account for this, in the initial 175 recruited participants, we removed data points that were too close in time to each other within each participant (> 1 hour). We always retained the first data point within a given hour (e.g., if notification A was completed first, and notification B was completed 5 minutes later, we would retain data from notification A and discard B).

Next, we excluded participants (38 out of 175 recruited participants) who did not provide data ≥ 50% of the total timepoints. The final sample (N = 137) represented 78.3% of the recruited sample (see participant recruitment and exclusion flowchart in Supplementary).

Trait-State relationships. Spearman correlations were employed to correlate averaged trait scores with mean (averaged across the 14 days) state measures and between each mean state measure (see Figure S3). Benjamini-Hochberg's false discovery rate (FDR) was used to correct for resulting p-values. Additionally, we conducted partial correlations to assess robustness of key trait-state correlations (e.g., partial correlation between mean state self-confidence and trait self-esteem controlling for mean state happiness). We also observed how states are correlated within-people using within-subject Spearman correlations. We computed a Spearman correlation coefficient (rho) per subject for each pair of states (e.g., OCD severity and self-confidence; see Tables S2 – S4).

Regression analyses. To formally deduce factors impacting moment-to-moment OCD symptoms, we employed various regression analyses. All continuous state and task measures were within-person centred (z-scored) before being inserted into the regressions. Linear models were used when all predictor and dependent variables were within-person centred (e.g., OCD severity, self-confidence). Linear mixed effect models (see Equation 1) containing random intercepts per participant were used when either predictor or dependent variables (or both) could not be within-person centred (e.g., time-of-day).

$$stateY_{i,t} \sim stateX1_{i,t} + stateX2_{i,t} \ldots + stateXn_{i,t} + (1 \mid i) - Equation\ 1$$

$$i = individual, t = time\ point, n = number\ of\ states\ used\ as\ predictors\ in\ model$$

Logistic mixed effect models with random intercepts (see Equation 2) were used when 'symptom log' (presence [1] or absence [0] within a 4-hour time window from the completion of a state or task notification) was inserted as the dependent variable. These models were fitted using the *glmer* function from the R *lme4*[53] package. To obtain accurate maximum likelihood estimates, we used adaptive Gauss-Hermite quadrature with 10 points (nAGQ = 10). The BOBYQA optimizer was specified via glmerControl(optimizer = "bobyqa"). The model was specified with a binomial (logit) link function.

$$SymptomLog_{i,t} \in \{0,1\} \sim stateX1_{i,t} + stateX2_{i,t} \ldots + stateXn_{i,t} + (1 \mid i) - Equation\ 2$$

$$i = individual, t = time\ point, n = number\ of\ states\ used\ as\ predictors\ in\ model$$

For cross-correlation analyses (e.g., to check how self-confidence affects past and future OCD), we created lagged and leading versions of the symptom log variables (Equation 3). Lagged and leading symptom log variables were inserted in the same logistic mixed effect model predicting 1) self-confidence and 2) metacognitive bias.

$$stateY_{i,t} \sim SymptomLog_{i,t+1} \in \{0,1\} + SymptomLog_{i,t-1} \in \{0,1\} + (1 \mid i) - Equation\ 3$$

$$i = individual, t = time\ point$$

To corroborate our results showing reduced self-confidence is associated with future symptom logs**,** we also assessed the effects of self-confidence over OCD severity ratings during timed notifications using regression techniques above (see Figure S6).

Robustness Tests. We conducted several robustness tests to ensure reliability of results. **1)** We checked if study compliance (operationalised as proportion of notifications answered by each participant) impacted our findings. To do this, we inspected whether compliance correlated with any averaged state and task measures, and if so we repeated our regression analyses controlling for compliance (operationalised as number of notifications answered throughout assessment period). Next, **2)** we repeated models accounting for different slopes per subject although several models did not reach convergence. Results were maintained for majority of models when per-subject slopes were included. Additionally, **3)** we reran our models controlling for age (z-scored) and gender ('Female' or not) and found that all significant results were maintained. **4)** We found that time-of-day, day-of-week, and current context (i.e., current activities) variables were significantly associated with OCD severity ratings, self-confidence, and symptom logging (for current context only, see Figures S4 – S5), we also repeated relevant models controlling for these elements. Lastly, **5)** to assess robustness of the symptom log results, we repeated our analyses using different symptom log time windows (i.e., within 3 hours, 2 hours, and 1 hour of a state/task notification). See Supplementary Tables S5 – S6 for results of all robustness tests.

Linear model validity was determined through inspection of approximate normality of residuals and assessing collinearity of predictors (variance inflation factor > 5). We checked for under- or over-dispersion of residuals when fitting logistic models using the *blmeco*[54] R package.

As metacognitive bias emerged as the strongest task predictor of symptom logs, we checked the reliability of this measure by calculating the intraclass correlation coefficient between each pair of games (e.g., 1 and 2, 2 and 8 etc) and computed the average per pair across all subjects (see Figure S7).

Modelling metacognitive sensitivity. We estimated metacognitive sensitivity, meta-*d'*[55] based on Signal Detection Theory[27], using the *cpm* toolbox (Dome et al. in-preparation)[56]. For full model description, see Maniscalco & Lau (2012)[55]. Briefly, the model is designed to quantify how well people differentiate between correct and incorrect decisions as indexed by the confidence attributed to choices. This is captured by the model parameter, meta-*d'*, where larger values correspond to better differentiation, and smaller values correspond to worse differentiation. Metacognitive efficiency (meta-d'/d'), used in our analysis, is simply the ratio of meta-d' to d' (perceptual sensitivity) which enables comparisons across participants with different d' values. The model used also specifies other parameters, collectively called meta-c_2, which are a set of response thresholds the model uses in combination with meta-*d* to provide confidence ratings. These thresholds essentially determine the propensity to endorse judgements with a certain degree of confidence by the model.

Exclusions from modelling. Estimating meta-*d'* requires the discretisation of continuous confidence ratings that underlies our meta-c_2 estimates. In our case, this meant binning the confidence ratings of each completed session into four distinct bins. This comes with a caveat that if participants had too many extreme values in both the lowest and highest bins, we could not estimate meta-*d'*. Hence, we excluded each session where the 10th and 25th percentile being equal coincided with the 75th and 90th percentile being equal for the confidence bins. Furthermore, we excluded participant's session if their confidence rating for a given session had a very low variance (SD < 5) or extreme mean (M < 5 or M > 95). Overall, this resulted in the exclusion of 162 sessions (including the complete data set of 4 participants).

Fitting procedure. Following previous work[55], for the current parameter estimation, we adjusted the model parameters to minimise the difference between human confidence ratings and the probability of those ratings as output by the model, quantified via the negative log-likelihood. This was done for each session the participants completed. We searched for the best-fitting model parameters via Trust-Region Methods[57], which is an iterative algorithm that finds the parameter values with the lowest negative log-likelihood, the one best approximating human responses.

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Competing Interest:
TUH consults for limbic ltd and holds shares in the company, which is unrelated to the current project. The other authors declare no conflicts of interest.

Data Availability Statement
The data that support the findings of this study are available at https://osf.io/x7h5k/. All analysis scripts are available under https://github.com/aleyaamarzuki/EMCT-OCD.

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