Revisiting verbal recognition memory in obsessive-compulsive disorder: a computational approach

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Abstract

Deficits in primary recognition memory and confidence have previously been tested as potential contributors to excessive checking behavior in obsessive-compulsive disorder. Studies have tested both recognition for actions and, hypothesizing that recognition may be disrupted more generally across content domains, verbal recognition memory. However, studies of verbal recognition memory have yielded mixed results. We revisited this work with the benefit of hindsight, running two new experiments with larger samples, the manipulation of recognition difficulty, and a computational model-based approach to data analysis. In both datasets, we found that discriminability, defined as the difference in drift rate for old versus new stimuli in the drift-diffusion model, was reduced as a function of subclinical OCD symptoms in the general population. Paralleling work on drift rate deficits in perceptual decision making in OCD, these reductions were larger for easier recognition decisions. We also asked participants about their confidence in each recognition decision and parcellated confidence into bias, or the difference in overall confidence, and sensitivity, which represents the ability to appropriately map confidence to objective accuracy. We found no consistent evidence of a relationship between OCD symptoms and either quantity.

Keywords: obsessive-compulsive disorder, recognition memory, computational modeling, drift-diffusion model, confidence, metacognition

Revisiting verbal recognition memory in obsessive-compulsive disorder: a computational approach

Excessive checking is a prominent feature of obsessive-compulsive disorder (American Psychiatric Association, 2013; Radomsky, Shafran, Coughtrey, & Rachman, 2010; Toffolo, van den Hout, Hooge, Engelhard, & Cath, 2013). For example, individuals may be concerned with whether they locked their front door, turned off their stove, or even whether they struck someone while driving. These questions can naturally be framed as problems of recognition memory: did an event really occur, or not? From this perspective, excessive checking may be caused or exacerbated by impairments in recognition memory, doubts in one's ability to make recognition decisions (Fleming & Lau, 2014), or both. If such primary or secondary performance deficits do exist, an additional question concerns whether they are specific to particular domains such as performing actions or processing visual information, or if they are more general and include domains which are not commonly thought of as problematic for individuals with OCD, like verbal processing.

Studies have looked for evidence of impairments in verbal recognition memory both in patients and as a function of subclinical self-reported symptoms in the general population, with inconclusive results (Foa, Amir, Gershuny, Molnar, & Kozak, 1997; Macdonald, Antony, Macleod, & Richter, 1997; Rubenstein, Peynircioglu, Chambless, & Pigott, 1993; Tuna, Tekcan, & Topçuoğlu, 2005). However, this previous work is now over 15 years old and each study has one or more of several potential problems that can be identified with the advantage of hindsight. First, they employed few trials per participant (one or two lists of items to study) and relatively few participants, resulting in low overall power. Second, they did not attempt to test performance at different levels of difficulty, which is now known to interact with information processing differences in OCD in other domains, as we outline below. Third, they focused on global measures of performance such as accuracy, rather than asking more specific questions about components of information processing that can be identified and isolated using computational models of memory retrieval. Not only do model-based approaches allow us to ask more precise questions, but they also increase statistical power, and allow for the detection of differences that may be undetectable even with large sample sizes (Banca et al., 2015; Lerche & Voss, 2020; White, Ratcliff, Vasey, & McKoon, 2010). The latter feature is a result of the fact that different information processing components can push global measures such as accuracy in opposite directions, making differences difficult to detect if both components are impacted, and impossible to interpret.

Studies which have looked at confidence specifically for recognition memory have also produced mixed results (Foa et al., 1997; Macdonald et al., 1997). Moreover, confidence is likewise not a singular construct and may be parcellated into at least two different components: bias and sensitivity (Fleming & Lau, 2014). The former is a measure of the general propensity to assign lower or higher confidence to all responses, while the latter is a measure of how well an individual maps confidence to objective accuracy — that is, whether responses that are objectively correct are assigned a higher confidence on average. In addition, sensitivity is correlated with overall performance independent of other individual differences (Fleming & Lau, 2014), and it is important to control for this fact.

In the present work, we revisited whether symptoms of OCD, here measured in the general population on a continuum, were related to differences in recognition and metacognitive assessment of recognition decisions. Our approach in asking these questions borrowed from recent studies demonstrating OCD-related impairments in a different domain — perceptual decision making — both in patients and in subclinical individuals in the general population high on the OCD spectrum (Banca et al., 2015; Erhan et al., 2017; Hauser, Allen, Rees, & Dolan, 2017; Marton et al., 2019). In this previous work, participants completed the well-studied dot motion task in which they had to judge the average direction of a noisy moving dot array (Ratcliff & McKoon, 2008). Data from this task can be explained using the drift-diffusion model, a successful computational model that describes performance across different cognitive domains, including both perceptual decision making and recognition memory (Ratcliff, 1978; Ratcliff & McKoon, 2008; Ratcliff, Thapar, & McKoon, 2004). The model applies to decisions with two options, for example, deciding between motion being left or rightward, or between a stimulus being new or old as in the case of recognition memory. Fig. 1 displays a schematic illustration of the model. The state of the decision, representing the moment-by-moment preference during deliberation, follows a noisy trajectory with a mean velocity, called drift rate, which is corrupted by Gaussian noise. This velocity is a free parameter that can be inferred from an individual's choices and reaction times. Intuitively, it represents the amount of signal per unit time in favor of one option versus the other. The model makes a decision when the relative preference exceeds a threshold, hitting one of two response boundaries which represent the two options under consideration (Fig. 1). The separation between these boundaries is also a free parameter, which measures impulsivity: boundaries which are closer together result in decisions that are faster but also less accurate, because they are more dominated by noise. Other free parameters include the starting bias or preference, which can be closer to one or the other response boundary, and the non-decision time, which captures the time taken for initial processing and motor execution.

Using the drift-diffusion model, previous work reported lower drift rates in the dot motion task both in OCD patients and as a function of subclinical symptom severity in the general population (Banca et al., 2015; Erhan et al., 2017; Hauser et al., 2017; Marton et al., 2019). Moreover, these deficits were larger for easier trials. Contrary to expectation, these studies did not report consistent differences in boundary separation (e.g. that individuals with more severe OCD symptoms placed their decision boundaries further apart, as intuition might suggest), a point we return to later in the context of our results. In addition, Hauser et al. (2017) separated the effects of confidence bias and sensitivity in the dot motion task and found that more severe OCD symptoms were associated with decreased sensitivity, but no change in bias.

We collected two sizable datasets on verbal recognition memory where, similar to the dot motion experiments, we modulated performance difficulty and tested whether recognition ability as defined by the drift-diffusion model was related to symptoms of OCD in the general population. Here recognition ability or discriminability is defined as the difference in drift rate between true old and true new stimuli, i.e. how well one is able to tell the two apart (White et al., 2010). We expected discriminability to be reduced as a function of OCD symptoms, and potentially similar to the perceptual domain, for this deficit to be larger for easier recognition decisions. We made use of the drift-diffusion model for two reasons. First, as already mentioned, it is a standard model of recognition memory (e.g. Ratcliff, 1978; Ratcliff et al., 2004). Second, it allowed us to test the auxiliary implicit hypothesis that OCD symptoms are related to shared computational deficits across different cognitive domains.

In addition, we collected confidence data to ask whether there were differences in the metacognitive assessment of recognition decisions. There are several models of metacognitive decision making (Fleming & Lau, 2014; Pleskac & Busemeyer, 2010; Ratcliff & Starns, 2013), although there is not an accepted general purpose standard like the drift-diffusion model for us to apply here. We took a somewhat agnostic approach and modeled confidence using ordered probit regression, a purely statistical rather than cognitive model with few assumptions. Prior work reported possibly lowered recognition confidence as a function of OCD symptoms, although this work did not explicitly separate out bias and sensitivity and results were mixed (Foa et al., 1997; Macdonald et al., 1997). On the other hand, work on perceptual decision making that did separate these effects reported reduced sensitivity, but no difference in bias (Hauser et al., 2017). Our hypotheses regarding metacognition were thus less constrained, and we expected possible differences in either bias or sensitivity.

Methods

Participants

All experimental procedures were approved by the Institutional Review Board at the University of Maryland-College Park. Electronic informed consent was obtained in accordance with the approved procedures. Data were collected on Amazon Mechanical Turk. Participants were not pre-screened based on symptom scores, and data were collected from everyone except those failing a task comprehension check. After being presented with instructions and two short study-test list pairs as practice, participants completed a multiple choice quiz to gauge their understanding of the task. Those that failed to answer these questions were not able to continue. Test words with reaction times faster than 250ms or slower than 10s were excluded. Participants that did not have at least 25 trials remaining for each of the five conditions (0H, 0V, 1H, 1V, and 3V; explained below) were excluded in their entirety. This left 206 participants for analysis in dataset 1 and 215 participants in dataset 2.

Verbal recognition memory task

We collected two separate data sets with nearly identical experimental parameters, as described below. Words were chosen from the Kucera, Kučera, and Francis (1967) word pool in accordance with prior work (Ratcliff et al., 2004). In line with this work, we used a subset of words that had usage frequencies of 78 to 10,600 per million, labeled "high frequency" (H), and a subset of words with usage frequencies of 0 or 1 per million, labeled "very low frequency" (V). Each study list consisted of seven high frequency words, seven very low frequency words repeated once, and another seven very low frequency words that were repeated three times, for a total of 35 study items (7 + 7 + 21). This combination of usage frequency and repetition was chosen based on prior work in order to span a range of difficulty levels (Ratcliff et al., 2004), a feature which we successfully replicated (see *Results*). Study items were randomly shuffled in the study list. Each word was presented for 1000ms, followed by the next word. The test list immediately followed each study list and consisted of 42 items, the 21 unique words from the study list and 21 new words. To match the words in the study list, there were 7 new high frequency words and 14 new very low frequency words. In all, five conditions made up the test list based on the number of times a word appeared in the study list and its usage frequency: 0H, 0V, 1H, 1V, and 3V. These abbreviations for the conditions are used throughout the paper to make the presentation more compact. Participants also gave confidence ratings simultaneously with their old/new judgments on a scale of 1-3 with the following levels: Somewhat Certain, Certain, and Very Certain. Following a response, feedback in the form of the word "CORRECT" or "ERROR!" appeared for 300ms, and the next word appeared after a 250ms gap. Participants completed six study-test list pairs.

OCD questionnaire

OCD symptoms were measured using the Padua Inventory (Burns, Keortge, Formea, & Sternberger, 1996). Items on this scale are typically endorsed on a five point scale with levels: "Not at all", "A little", "Quite a lot", "A lot", and "Very much". Due to a coding bug, participants in the first experiment completed the questionnaire on a four point scale with the "A lot" level missing. This was corrected in the second experiment. Because the error was minor, rather than discarding this dataset, we report its results and use it as an opportunity to test the replicability of our findings. Padua scores for both experiments were z-scored in all analyses, putting the regression weights on similar scales for comparison.

Model fitting

The retrieval/decision model and the metacognitive regression model were fit using a multi-level Bayesian framework implemented in Stan (Stan Development Team). Inference was performed via Markov chain Monte Carlo using the No-U-Turn sampler. The Gelman-Rubin $\hat{R}$ statistic was less than 1.01 (1/100th) for all variables. We ran 4 chains with 8,000 samples each, using the first 1,000 as warmup.

The memory retrieval/decision was modeled using a Wiener process with drift, with across-trial variability in drift rate and starting bias. Drift rate for subject s, condition c (one of the five conditions described above), and trial t was defined as:

$$drift_{s,c,t} = drift_c + drift_s + drift_{c,padua} \cdot padua_s + \sigma_{drift,trial} \cdot \epsilon_t.$$

Here $drift_c$, $drift_s$, $drift_{c,padua}$, and $\sigma_{drift,trial}$ are free parameters, $padua_s$ is the subject's z-scored Padua Inventory score, and ϵ_t is a random variable with a $N(0, 1)$ prior modeling across-trial variability in drift rate. The boundary separation and starting bias were similarly defined, with minor modifications. First, the starting bias did not differ by condition because it represents bias before seeing the stimulus. The starting bias was also transformed using a logistic function to the 0 (lower boundary) to 1 (upper boundary) range so that it could be defined independent of boundary separation. Second, the boundary separation did not vary across trials, only across subjects, as is customary in the drift-diffusion model. Broad weakly informative priors were used for all parameters, detailed in the Supplement. Overall discriminability was defined as the difference between the corresponding $drift_c$ parameters, and the relationship between OCD score and discriminability was defined as the difference between the corresponding $drift_{c,padua}$ parameters.

We used ordered probit regression to model the confidence data. This regression technique allows modeling an ordered categorical dependent variable such as the 3-level confidence response in our experiment. It is assumed that there is a latent variable, y^*, which represents the true response on a continuous scale corrupted by Gaussian noise. This variable is censored and we observe only whether it is between particular cutpoints. With three levels, we have two cutpoints: values of y^* below the first cutpoint represent the first level ("Somewhat Certain), values of y^* between the two cutpoints represent the second level ("Certain"), and values of y^* above the second cutpoint represent the third level ("Very Certain").

In our model, the latent response variable, y^*, consisted of the following regression terms for subject s, condition c, and trial t:

$$
\begin{aligned}
y^*_{s,c,t} =& \beta_{c,performance} \cdot performance_{s,c} + \beta_{c,padua} \cdot padua_s \\
& (\beta_{c,correct} + \beta_{s,correct}) \cdot correct_{s,c,t} + \\
& \beta_{c,performance,correct} \cdot performance_{s,c} \cdot correct_{s,c,t} + \\
& \beta_{c,padua,correct} \cdot padua_s \cdot correct_{s,c,t}.
\end{aligned}
$$

Here $performance_{s,c}$ is the z-scored (separately for each condition) average overall accuracy for a particular subject and condition, and $correct_{s,c,t}$ is a binary 1/0 variable representing whether a trial was correct or not. Intuitively, $beta_{c,correct}$ measures average overall sensitivity (i.e. how much being objectively correct increases confidence), $\beta_{c,performance,correct}$ measures additional changes in sensitivity due to differences in overall performance, $\beta_{c,padua,correct}$ measures additional changes in sensitivity due to OCD symptoms, and $\beta_{c,padua}$ measures changes in bias due to OCD symptoms.

The first cutpoint was defined for subject s and condition c as:

$$cutpoint^1_{s,c} = cutpoint^1_s + cutpoint^1_c,$$

and the second cutpoint was defined as:

$$cutpoint^2_{s,c} = cutpoint^1_{s,c} + exp(cutpoint^2_s + cutpoint^2_c).$$

The exponential function was used to enforce the constraint that the second cutpoint had to be greater than or equal to the first cutpoint. The first cutpoint represented the boundary between “Somewhat Certain” and “Certain”, and the second cutpoint represented the boundary between “Certain” and “Very Certain”.

Results

Basic check of difficulty manipulation

As a basic check of the difficulty manipulation and general performance, Fig. 2 displays the mean accuracy and reaction time for each experiment and condition. 1V (medium difficulty) responses were more accurate than 1H (hard) responses (dataset 1: $t(205) = 22.01, p = 6.73 \times 10^{-56}$; dataset 2: $t(214) = 16.37, p = 1.32 \times 10^{-39}$) and 3V (easy) responses were in turn more accurate than 1V (medium) responses (dataset 1: $t(205) = 23.24, p = 2.33 \times 10^{-59}$; dataset 2: $t(214) = 20.39, p = 4.67 \times 10^{-52}$). Likewise, 1V responses were faster than 1H responses (dataset 1: $t(205) = -8.52, p = 3.38 \times 10^{-15}$; dataset 2: $t(214) = -3.31, p = 0.001\,11$) and 3V responses were in turn faster than 1V responses (dataset 1: $t(205) = -7.64, p = 8.23 \times 10^{-13}$; dataset 2: $t(214) = -8.85, p = 3.38 \times 10^{-16}$). These results demonstrate that our difficulty manipulations were successful. Accuracy and reaction time for classifying new words were similar across the two frequency conditions (0H and 0V), with accuracy comparable to the 1V condition and reaction time comparable to the slowest condition (1H).

Drift-diffusion modeling

We used a multi-level Bayesian modeling framework to fit the drift-diffusion model to the data from each experiment. In the following, we plotted the full marginal posterior probability distributions for each parameter of interest to display the entire (un)certainty in the estimates. We also display the median estimate and the central 95% credible interval, and treat a result as significant if the CI excludes the critical value of interest (e.g. 0). All of the statistics appear in the plots for easy access and to make the presentation compact.

Fig. 3 displays the drift rate and boundary separation for each condition, and Fig. 4 displays differences in drift rate between conditions. Replicating previous work, drift rate was higher for 1V (medium) trials compared to 1H (hard) trials, and for 3V (easy) trials compared to 1V (medium) trials (shown here in Fig.3; Ratcliff et al., 2004). Note that we treat the upper boundary as “old” and the lower boundary as “new”, thus larger positive drift rates represent more evidence per unit time for “old” responses, and more negative drift rates represent more evidence per unit time for “new” responses. Discriminability was positive for all conditions (Fig. 4). SI Fig. S1 displays the starting bias before the stimulus was seen. Because this bias is thought to impact the decision before the stimulus appears, we fit a single bias parameter across all five conditions. There was a slight but statistically significant bias towards responding “old” on average.

Our primary hypothesis regarding individual differences in memory retrieval was that discriminability would be reduced as a function of OCD score. Fig. 5 displays the effect of OCD score on discriminability for each difficulty condition, as well as the differences between conditions. Discriminability was reduced in all difficulty conditions in both datasets (Fig. 5A). Moreover, similar to previous work on perceptual decision making, this effect was larger in easier conditions (Fig. 5B). To test whether these effects were driven by differences for “old” stimuli, differences for “new” stimuli, or both, we conducted a secondary analysis looking at the effect of OCD score on drift rate separately for each stimulus class. These results are plotted in Fig. 6. Recall that because we treat the upper boundary as “old”, more negative drift rates for old stimuli and more positive drift rates for new stimuli represent impairments. Results here were less consistent than for our primary hypothesis. Clear impairments in drift rate were seen in the 0H and 0V conditions, as well as the 3V condition. Significant impairments were also seen in 1V in one dataset, and were borderline in the other dataset. More curiously however, there was evidence that performance in the hardest condition, 1H, was actually slightly enhanced, although only by a minute amount. We also tested for differences in boundary separation and starting bias as a function of OCD score (SI Fig. S2). Previous work did not suggest we should expect to see a relationship with boundary separation, and indeed we did not find evidence of such a relationship. The starting preference was biased slightly towards “new” responses as a function of OCD score in both datasets, although the effects were small.

Differences in metacognition

We modeled recognition confidence using ordered probit regression. This approach does not assume a specific process model, given the lack of consensus on how to properly model metacognitive processes (Fleming & Lau, 2014; Pleskac & Busemeyer, 2010; Ratcliff & Starns, 2013), but it does allow us to separate out the effects of confidence bias and sensitivity. Modeling details are provided in *Methods*. We regressed the latent response variable in the model onto: (1) a binary variable representing whether each trial was correct or not, with the regression coefficient here representing overall sensitivity, (2) mean overall performance and the interaction of (1) with mean overall performance, given prior work demonstrating that sensitivity is larger when overall performance is better (Fleming & Lau, 2014), (3) the interaction between (1) and OCD score, with the regression coefficient here measuring the relationship between OCD score and sensitivity, and (4) OCD score, with the regression coefficient measuring changes in confidence bias as a function of OCD symptoms. The results are displayed in Fig. 7. As a basic sanity check, overall sensitivity was positive in both datasets for all conditions (Fig. 7A). That is, on average participants could reliably distinguish correct and error responses, and assigned higher confidence to responses that turned out to be correct. In line with prior work, we found that sensitivity increased with mean overall performance (Fig. 7B). However, turning to individual differences, there was no consistent relationship between OCD and either sensitivity (Fig. 7C) or bias in confidence (Fig. 7D).

Discussion

We investigated differences in verbal recognition memory as a function of OCD symptoms in two samples. Previous work reported conflicting results regarding impairments in this domain, but had a number of methodological shortcomings which have been significantly better understood in subsequent years (Foa et al., 1997; Macdonald et al., 1997; Rubenstein et al., 1993; Tuna et al., 2005). We found in both datasets that discriminability was reduced as a function of OCD symptoms, and that the degree of impairment was larger for easier recognition decisions, providing a parallel to the computationally defined deficits found in perceptual decision making (Banca et al., 2015;

Erhan et al., 2017; Hauser et al., 2017; Marton et al., 2019). Secondary analysis revealed that this was due to a reduction in drift rate for "new" items, and possibly to a reduction in drift rate for "old" items, although the latter finding was not consistent and seen only in the easiest conditions: 3V, and to a much lesser extent, 1V. Drift rate for the 1H condition was actually slightly enhanced. Interestingly, of the two previous studies which reported recognition memory differences, the study which tested differences separately for old and new items also reported enhancements for recognizing old items (Rubenstein et al., 1993). This study used long lists and single repetitions, and although word usage frequency was not reported the examples suggest common words, which are all features shared by the 1H condition.

The current work focused on verbal recognition memory, but at least anecdotal accounts of checking behavior suggest that it may be more commonly related to recognition for actions. Here again we point to examples such as doubting whether a door was locked, a stove was turned off, or a pedestrian was struck while driving. Recognition for actions has been investigated in previous work, although more commonly this work focused on recognizing whether actions were real or imagined rather than old or new (e.g. Hermans, Martens, De Cort, Pieters, & Eelen, 2003; Rubenstein et al., 1993). Unfortunately that work also shares many of the shortcomings possessed by previous work on verbal recognition memory, including one or more of the following: relatively small sample sizes, lack of a difficulty manipulation, and/or a focus on raw performance measures rather than individual components of information processing. In addition, there is some reason to doubt the ecological validity of testing recognition of imagined versus experienced events instead of new versus old events. In the case of the former, the implicit assumption is that occasionally sometime in the past, individuals imagine an action such as turning off their stove instead of actually performing it, and they have to later remember whether an action was real or imagined — something which appears rather unlikely. Instead, it is more likely that individuals simply fail to perform a required action on occasion, and they have to later properly recognize whether an action was performed or not. It would be of interest to apply the same model-based analysis to the recognition of old versus new actions. Regardless however, our results suggest that recognition memory may be more generally impaired in OCD across more than one content domain.

We also tested whether OCD symptom score covaried with confidence bias and sensitivity. We found positive average sensitivity in all conditions, and in line with previous work, a positive relationship between mean overall performance and sensitivity (Fleming & Lau, 2014). However, we did not find evidence of a consistent relationship between OCD score and either sensitivity or bias. Looking at individual conditions, sensitivity was reduced specifically for both “new” conditions (0H and 0V) similar to the drift rate impairments seen there. In addition, sensitivity appeared slightly increased in the 1H condition, similar to the drift rate enhancements seen in that condition. We are reluctant to draw strong conclusions given the absence of a similar relationship in the 3V and 1V conditions, and a lack of any a priori theory to explain this particular pattern of results, but the parallels between individual differences in sensitivity and drift rate are worth exploring in future work.

Another compelling direction for future work, which could also help align traditional lab-based studies with self-report measures (Nedeljkovic & Kyrios, 2007), is to understand how OCD symptoms vary with aspects of *global* confidence (Liberman, 2004; Rouault, Dayan, & Fleming, 2019). Whereas local confidence refers to confidence for individual memory retrieval episodes or decisions, global confidence refers to judgments about overall performance. Although these two aspects of metacognition are clearly tightly coupled, a computational understanding of how one is related to the other is only beginning to form (Rouault et al., 2019). An interesting possibility is that OCD is more closely associated with differences in global confidence, or the mapping from local to global confidence, than with local confidence.

Whether recognition itself and/or the metacognitive assessment of recognition decisions are related to symptoms of OCD has obvious important implications for guiding treatment. Metacognitive differences more generally have been shown to be important in OCD, and treatment focused on metacognitive beliefs has been suggested to be effective (e.g. Fisher & Wells, 2005, 2008; Solem, Håland, Vogel, Hansen, & Wells, 2009). While we do not argue against the importance of a metacognitive perspective more generally, our results also suggest the existence of primary performance differences in recognition memory specifically. Thus, treatment aimed at improving recognition memory could potentially be beneficial. Further research is necessary to understand why performance is disrupted. For example, this could be due to differences in attention, more fundamental failures in storage, maintenance, and/or retrieval, or perhaps it is that symptoms of OCD themselves cause this disruption in addition to or instead of the other way around.

The Supplement includes further discussion, including contextualization of our analysis of boundary separation, the specificity of our results, and other limitations.

Acknowledgments

The authors wish to thank Bingxin Song for help running the experiments.

Funding

This work was funded by the University of Maryland-College Park.

Conflict of interest

Declarations of interest: none.

Data

Experimental data is available at `https://osf.io/vs8pk/`.

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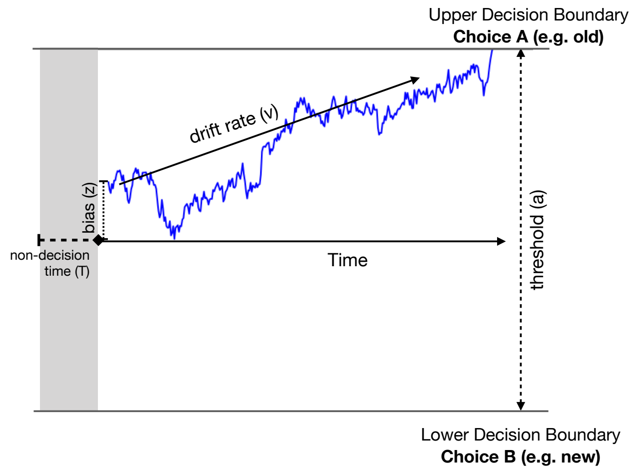

Figure 1. An illustration of the drift-diffusion model, which is able to account for data on decision making and memory retrieval in a number of different contexts. The state of the memory retrieval, which here results in labeling a test word as “old” or “new”, is represented by a point particle with an average velocity called drift rate (a free parameter), but which is also corrupted by noise. The blue line is an example of one such possible trajectory. The two options are represented by decision boundaries, and retrieval ends and a decision is made when the particle reaches one of the boundaries. This amounts to reaching a threshold amount of evidence for one option versus the other. The distance between the boundaries is a free parameter which measures impulsivity. Other free parameters include the starting preference of the point particle, which can start closer to one response or the other, and the non-retrieval time, which captures residual reaction time not due to the retrieval.

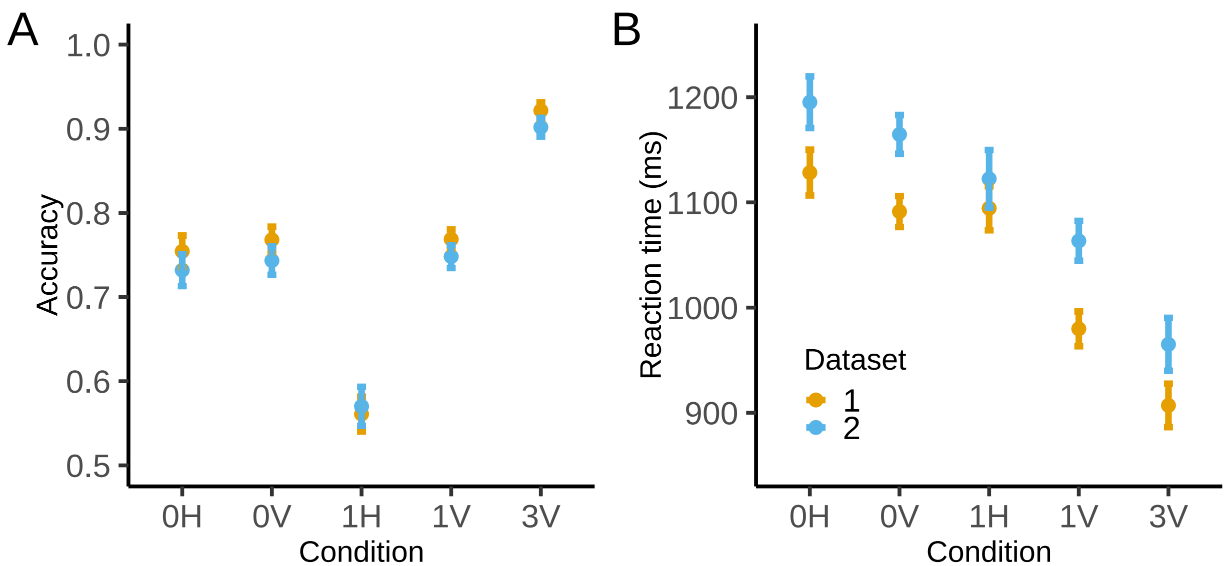

Figure 2. Raw accuracy and reaction time data for both datasets. 0H: new high frequency words, 0V: new very low frequency words, 1H: old high frequency words (hard), 1V: old very low frequency words (medium), 3V: old very low frequency words repeated 3x in the study list (easy).

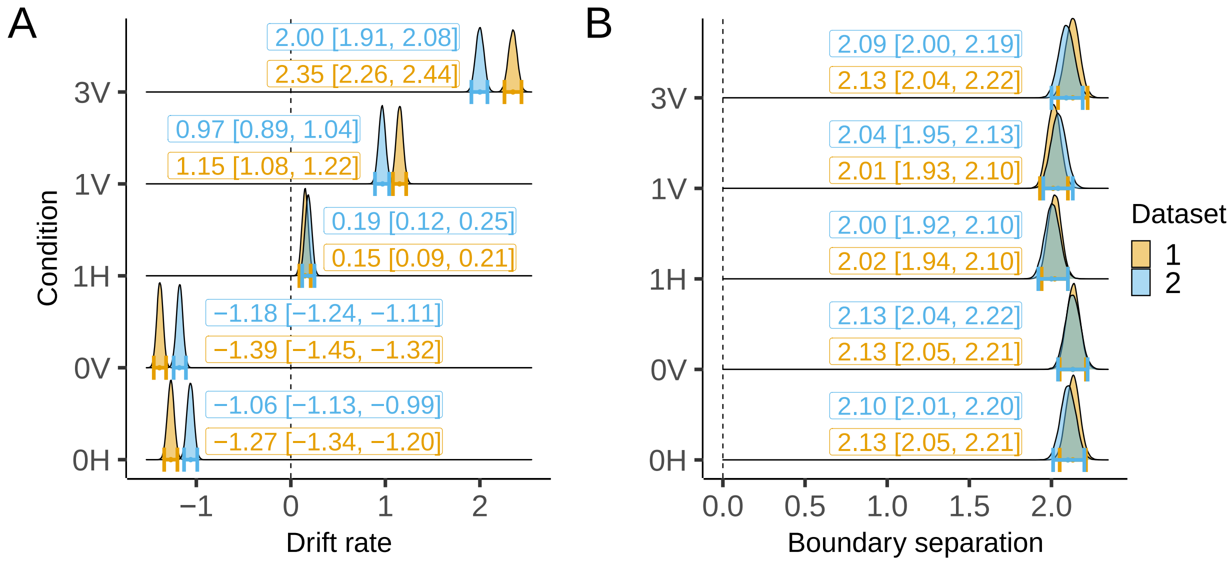

Figure 3. Drift rate and boundary separation for each condition for both datasets. We treated the upper boundary as "old" and the lower boundary as "new", thus more positive drift rates represented more evidence for "old" stimuli and more negative drift rates represented more evidence for "new" stimuli. Plots are density plots of the marginal posterior distribution for each parameter, with the median and central 95% credible interval marked. 0H: new high frequency words, 0V: new very low frequency words, 1H: old high frequency words (hard), 1V: old very low frequency words (medium), 3V: old very low frequency words repeated 3x in the study list (easy).

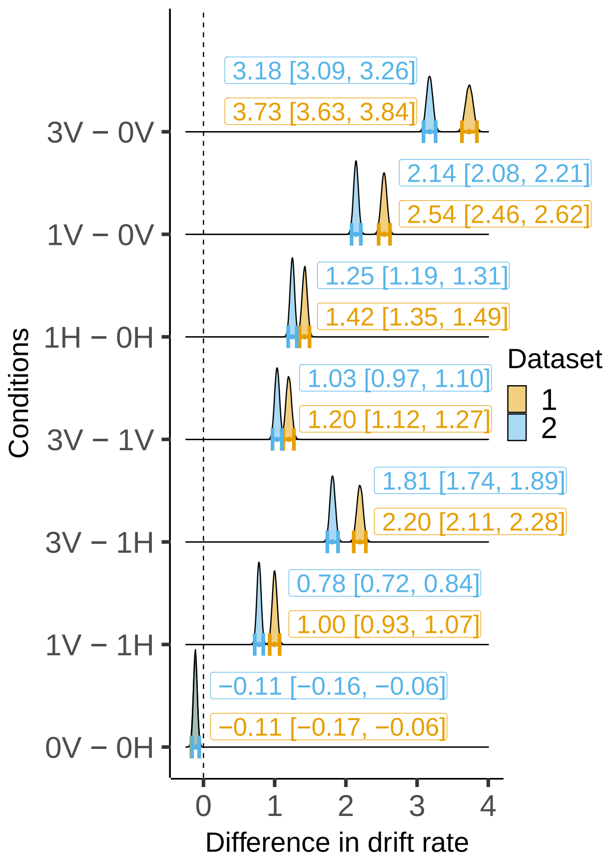

Figure 4. Differences in drift rate between conditions. The first three rows from the top represent discriminability for each corresponding condition. Plots are density plots of the marginal posterior distribution for each parameter, with the median and central 95% credible interval marked. 0H: new high frequency words, 0V: new very low frequency words, 1H: old high frequency words (hard), 1V: old very low frequency words (medium), 3V: old very low frequency words repeated 3x in the study list (easy).

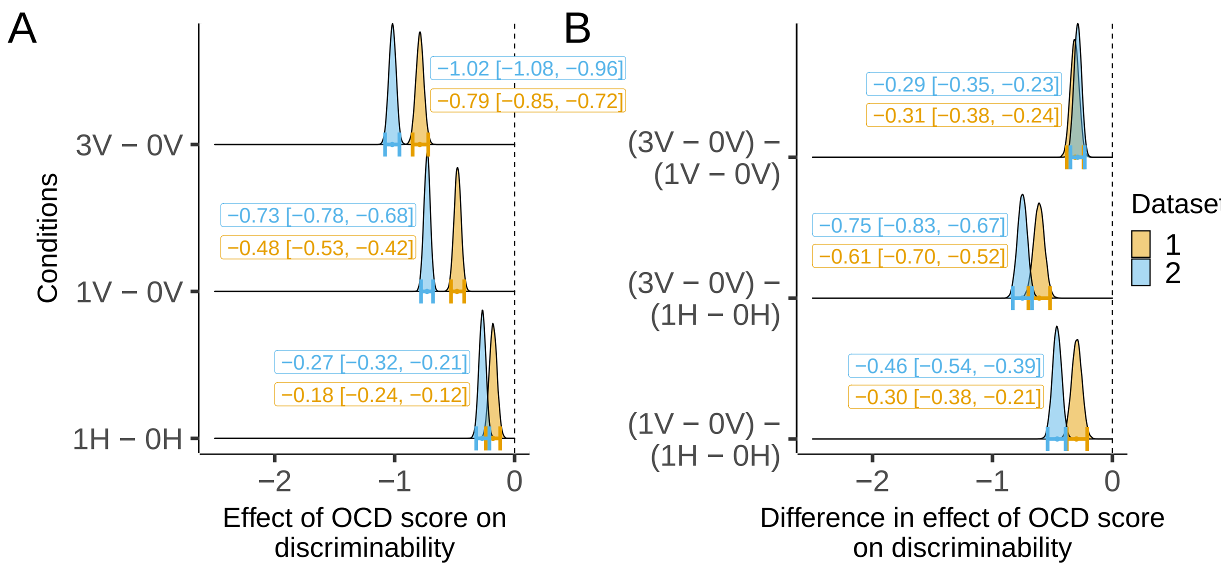

Figure 5. A. Effects of OCD score on discriminability (the difference in drift rate for old versus new items). B. Differences between the effects of OCD score on discriminability between conditions (i.e. how much worse discriminability is for easier compared to harder trials.) Plots are density plots of the marginal posterior distribution for each parameter, with the median and central 95% credible interval marked. 0H: new high frequency words, 0V: new very low frequency words, 1H: old high frequency words (hard), 1V: old very low frequency words (medium), 3V: old very low frequency words repeated 3x in the study list (easy).

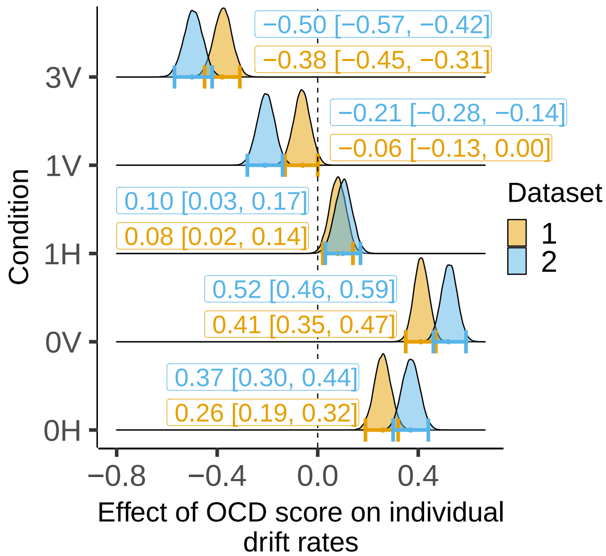

Figure 6. Effects of OCD score on individual drift rates. We treated the upper boundary as “old” and the lower boundary as “new”, thus more positive drift rates represented more evidence for “old” stimuli and more negative drift rates represented more evidence for “new” stimuli. Plots are density plots of the marginal posterior distribution for each parameter, with the median and central 95% credible interval marked. 0H: new high frequency words, 0V: new very low frequency words, 1H: old high frequency words (hard), 1V: old very low frequency words (medium), 3V: old very low frequency words repeated 3x in the study list (easy).

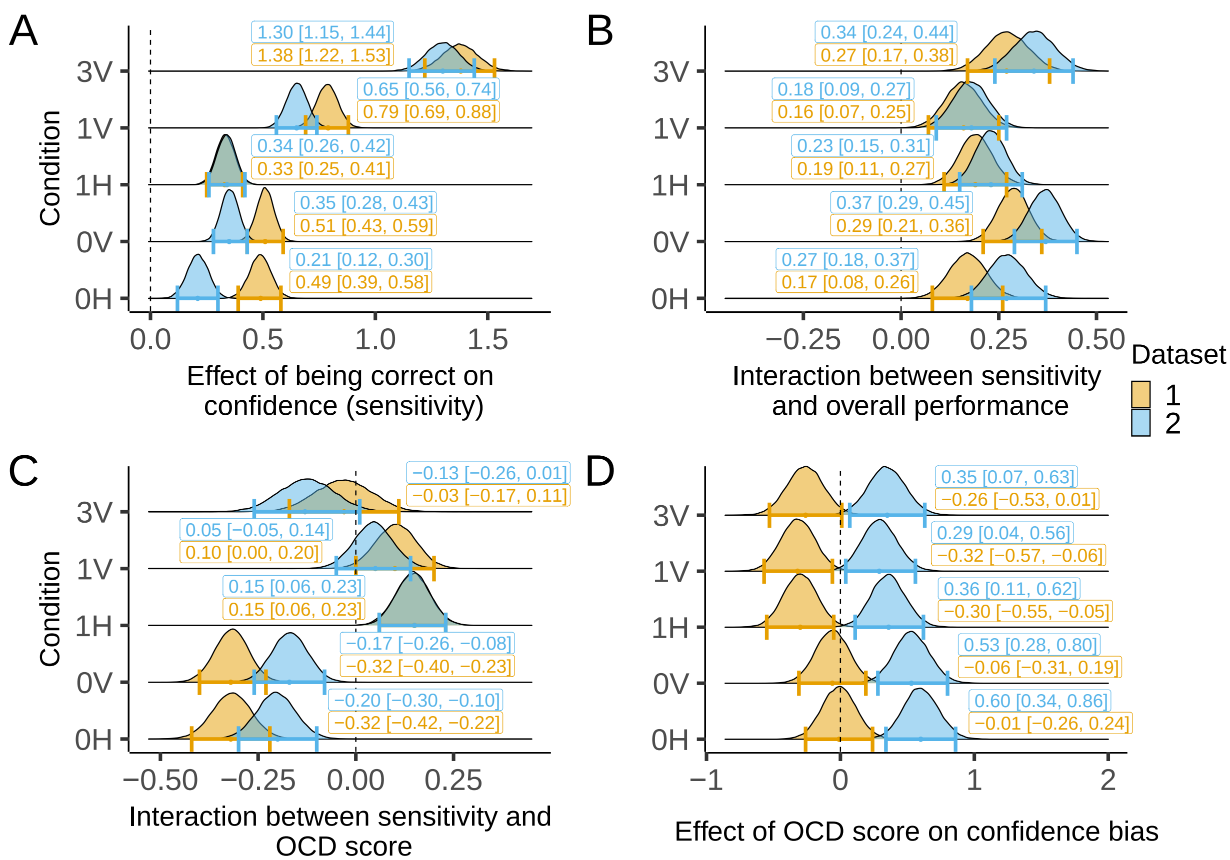

Figure 7. Effects on confidence in the ordered probit regression model. A. Overall sensitivity, i.e. the effect of a trial being objectively correct. B. Additional changes in sensitivity due to differences in overall accuracy across trials. C. Additional changes in sensitivity due to differences in OCD symptoms. D. Changes to bias in confidence due to OCD symptoms. Plots are density plots of the marginal posterior distribution for each parameter, with the median and central 95% credible interval marked. 0H: new high frequency words, 0V: new very low frequency words, 1H: old high frequency words (hard), 1V: old very low frequency words (medium), 3V: old very low frequency words repeated 3x in the study list (easy).