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The ease and sureness of a decision: evidence accumulation of conflict and uncertainty

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See Evans and Wagenmakers (doi:10.1093/brain/awz073) for a scientific commentary on this article.

The likelihood of an outcome (uncertainty or sureness) and the similarity between choices (conflict or ease of a decision) are often critical to decision-making. We often ask ourselves: how likely are we to win or lose? And how different is this option's likelihood from the other? Uncertainty is a characteristic of the stimulus and conflict between stimuli, but these dissociable processes are often confounded. Here, applying a novel hierarchical drift diffusion approach, we study their interaction using a sequential learning task in healthy volunteers and pathological groups characterized by compulsive behaviours, by posing it as an evidence accumulation problem. The variables, Conflict (difficult or easy; difference between reward probabilities of the stimuli) and Uncertainty (low, medium or high; inverse U-shaped probability-uncertainty function) were then used to extract threshold ('*a*', amount of evidence accumulated before making a decision) and drift rate ('*v*', information processing speed) parameters. Critically, when a decision was both difficult (high conflict) and uncertain, relative to other conditions, healthy volunteers unexpectedly accumulated less evidence with lower decision thresholds and accuracy rates at chance levels. In contrast, patients with obsessive-compulsive disorder had slower processing speeds during these difficult uncertain decisions; yet, despite this more cautious approach, performed suboptimally with poorer accuracy relative to healthy volunteers below that of chance level. Thus, faced with a difficult uncertain decision, healthy controls are capable of rapid possibly random decisions, displaying almost a willingness to 'walk away', whereas those with obsessive compulsive disorder become more deliberative and cautious but despite appearing to learn the differential contingencies, still perform poorly. These observations might underlie disordered behaviours characterized by pathological uncertainty or doubt despite compulsive checking with impaired performance. In contrast, alcohol-dependent subjects show a different pattern relative to healthy controls with difficulties in adjusting their behavioural patterns with slower drift rates or processing speed despite decisions being easy or low conflict. We emphasize the multidimensional nature of compulsive behaviours and the utility of computational models in detecting subtle underlying processes relative to behavioural measures. These observations have implications for targeted behavioural interventions for specific cognitive impairments across psychiatric disorders.

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Abbreviations: BF = Bayes factor; HCHU = high conflict high uncertainty; HCLU = high conflict low uncertainty; HDDM = hierarchical drift diffusion model; LCLU = low conflict low uncertainty; LCMU = low conflict medium uncertainty; OCD = obsessive-compulsive disorder

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Introduction

Uncertainty and conflict are intrinsic to our daily decisions. Uncertainty is related to the likelihood of an outcome (sureness) and conflict (ease) to the degree of similarity between choices. The constructs are commonly related and often conflated, but can be dissociated experimentally (Volz *et al.*, 2003, 2004). How we accumulate and evaluate the evidence prior to making a decision in the context of conflict or uncertainty is relevant both to our daily decision-making and disorders of pathology characterized by impulsive or compulsive behaviours (Voon *et al.*, 2016, 2017). The effect of evidence accumulation on decision-making behaviours exist as a continuum contributing to either decisional impulsivity on one end characterized by rapid poorly considered decisions (FitzGerald *et al.*, 2015; Forstmann *et al.*, 2016) and on the other, may lead to repeated compulsive checking behaviour with doubt, overestimation and indecisiveness (Sarig *et al.*, 2012; Newark, 2014; Nestadt *et al.*, 2016). Why evidence accumulation is impaired is mechanistically critical and is dependent on the context. Here we consider conflict and uncertainty, two constructs influencing evidence accumulation.

Uncertainty can be quantified as the variance of a probability distribution (Schultz *et al.*, 2008) following an inverted U-shaped curve across probabilities (P): the lower the variance, the closer to certainty (e.g. P closer to either 0 or 1) and the higher the variance, the closer to uncertainty (e.g. $P = 0.5$) or randomness (Schultz *et al.*, 2008). Conflict can arise in multiple scenarios that enable us to classify it as an easy or difficult decision. Conflict can be perceptual (e.g. random kinetic dots in which subjects decide the direction of moving dots with varying likelihood) (Banca *et al.*, 2015), probabilistic (e.g. choosing between two options with different reward probabilities) (Frank *et al.*, 2007), or prepotent response-based (e.g. the Flanker or Stroop task where a prepotent response must be suppressed) (Banca *et al.*, 2015). In tasks involving perceptual conflict such as the random dots kinetic task, objective uncertainty cannot be dissociated from conflict.

The role of uncertainty and conflict in disorders of repetitive pathological behaviours such as obsessive-compulsive disorder (OCD) and alcohol dependence remains unclear. OCD is characterized by repetitive intrusive thoughts or obsessions and repetitive actions or compulsions to alleviate the anxiety related to the obsession. The symptoms of OCD have been suggested to be rooted in uncertainty in which obsessions reflect pathological doubt and compulsive choices potentially worsening the doubt (van den Hout and Kindt, 2003*a*, *b*; Hermans *et al.*, 2008) and the associated level of confidence (Dar, 2004). The repetitive 'checking' behaviour intended to decrease the doubt associated with an action or state paradoxically only worsens the subjective uncertainty (Dar, 2004; van den Hout and Kindt, 2004). Using an implicit zero uncertain condition in a probabilistic deck drawing paradigm (Stern *et al.*, 2010) in which the subjects identified the card deck from which the four cards were drawn and rated the certainty of their decision, OCD patients were shown to experience higher subjective uncertainty with no differences in objective uncertainty compared to healthy volunteers (Stern *et al.*, 2013). However, not all studies support this theory of uncertainty intolerance in OCD (Sarawgi *et al.*, 2013; Toffolo *et al.*, 2014; Pushkarskaya *et al.*, 2015).

Similarly, the role of conflict in OCD is not completely clear with mixed results reported. Studies show either greater sensitivity with reaction time (Banca *et al.*, 2015) or no differences in accuracy (Banca *et al.*, 2015) in Stroop and probabilistic reward learning tasks (Frank *et al.*, 2007; Banca *et al.*, 2015) compared to healthy volunteers. Studies commonly show mixed or no behavioural differences in conflict-based measures but more consistently demonstrate neurophysiological differences with event-related potential (N2) and task-based functional MRI show dysfunctional hyperactive monitoring irrespective of the conflict level (Riesel *et al.*, 2017). Furthermore, impaired conflict-based error monitoring has been suggested as an underlying neurocognitive endophenotype with greater dorsal cingulate activity (Agam *et al.*, 2014) in OCD patients (Ursu *et al.*, 2003; Endrass *et al.*, 2008) and their unaffected family members (Riesel *et al.*, 2011; Carrasco *et al.*, 2013). The rationale for this current study was motivated by our previous study in OCD addressing behavioural differences as a function of conflict and uncertainty. We did not show any differences as a function of conflict in either a Stroop or probabilistic reward learning task but demonstrated using a random dot motion task both increased response times and a heightened decision threshold to greater randomness compared to healthy volunteers (Banca *et al.*, 2015). In the random dot motion task, subjects make a decision whether moving dots with differing degrees of coherence appear to be moving right or left. We had interpreted the findings as secondary to uncertainty given that there were no differences as a function of conflict in the other two tasks; however, notably the task is unable to dissociate perceptual uncertainty and conflict. Thus, this current study attempts to dissociate the role of conflict and uncertainty in OCD.

Similarly, the context of uncertainty and conflict are also highly relevant in alcohol dependence with slower response times, higher interference scores (Goudriaan *et al.*, 2006) and lower accuracy rates in the incongruent high conflict condition of the Stroop task (Dao-Castellana *et al.*, 1998; Pitel *et al.*, 2007) and show higher uncertainty tolerance (Lawrence *et al.*, 2009*a*, *b*). However, given previous experimental designs, the effect of conflict is difficult to dissociate from the influence of uncertainty; thus, whether subjects with OCD and alcohol dependence have impairment in conflict or uncertainty remains unclear (Schlösser *et al.*, 2010; van Ravenzwaaij *et al.*, 2012).

Here, we leverage the two-step sequential learning task (Daw *et al.*, 2011) originally designed to dissociate model-based goal-directed from model-free habit control (Daw

et al., 2011; Voon *et al.*, 2015) to assess evidence accumulation dissociating the concepts of conflict and uncertainty (Fig. 1A). We used a novel approach using the second stage stimulus-pair reward probabilities of the task (Fig. 1A) and the hierarchical drift diffusion model (HDDM) (Wiecki *et al.*, 2013), a Bayesian-based drift diffusion model. HDDM is considered to be one of the best methods to analyse two-choice tasks (Voss *et al.*, 2013; Forstmann *et al.*, 2016) with the estimated parameters directly mapping on to psychological constructs (Voss *et al.*, 2013). HDDM's hierarchical nature has the advantage of simultaneously estimating multiple group distributions (healthy volunteers, OCD and alcohol dependence) and inter-subject differences within each group (Wiecki *et al.*, 2013). The study focuses on the second stage reward probabilities alone and, with respect to this particular analysis, can be viewed as a value learning task.

We first show that conflict and uncertainty are potentially dissociable. We then analysed the responses of OCD and alcohol-dependent patients with the aim to identify their sensitivity towards conflict and uncertainty when compared to healthy participants. We hypothesized that OCD subjects would show greater behavioural impairments in the context of uncertainty and that subjects with alcohol dependence would show impairments across both conflict and uncertainty.

Materials and methods

Participants

A total of 243 participants (173 healthy volunteers, 32 OCD and 38 alcohol-dependent subjects) were recruited and have been described previously (Voon *et al.*, 2015). Subjects were included if they were above 18 years of age. For healthy volunteers, the exclusion criteria were any serious medical, neurological or psychiatric illnesses, or head injury or the use of psychotropic medications. For OCD and alcohol dependence, the exclusion criteria were similar except a current mild depression was allowed, as was antidepressant use. Subjects were screened using a structured clinical interview (Mini International Neuropsychiatric Inventory) (Amorim *et al.*, 1998). All participants completed the Beck Depression Inventory (Beck and Steer, 1987); and the State and Trait Anxiety Inventory (Spielberger, 1985). The study was approved by the University of Cambridge Research Ethics Committee and written informed consent was obtained before the start of the experiment. Participants completed the behavioural task and were compensated for their time and performance.

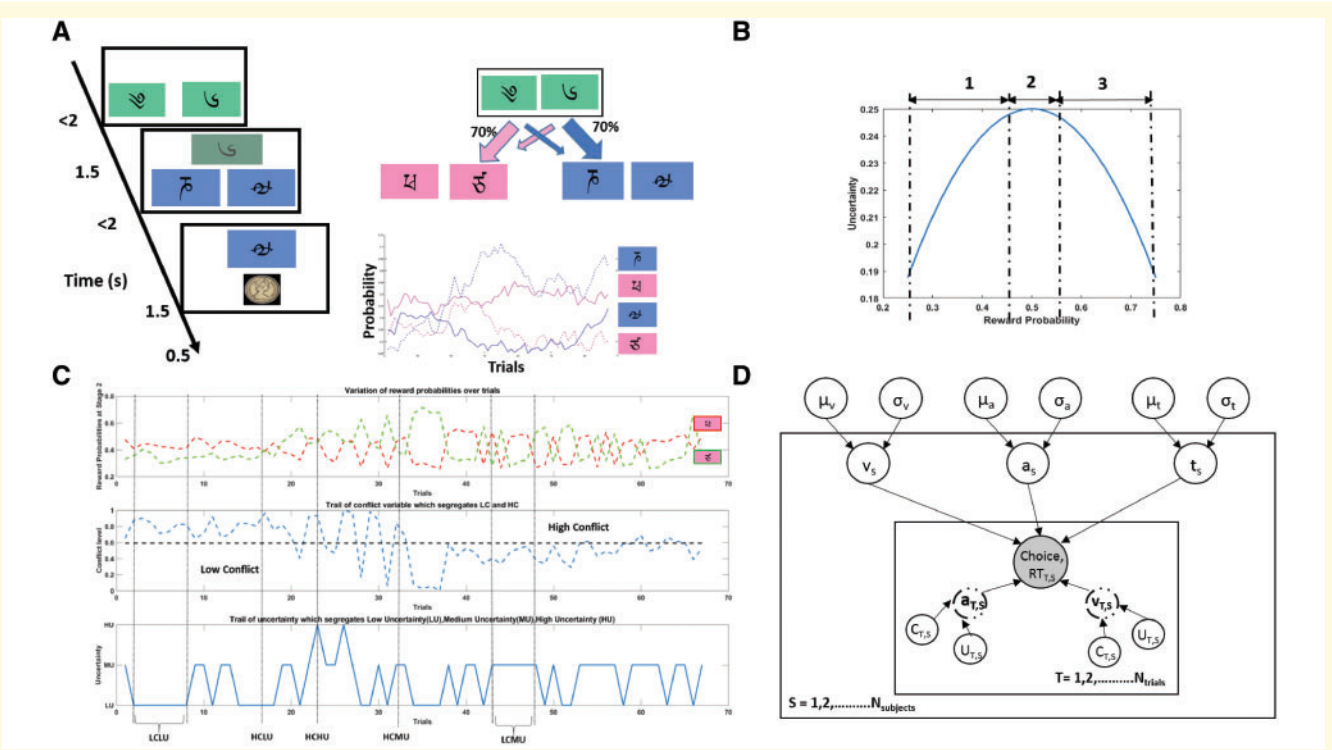

Figure 1 Schematic of the sequential learning task with examples of conflict and uncertainty trials and HDDM. (**A**) A graphical representation of the two-step task and its stages including the transition durations. Subjects choose between a stimulus pair at the first stage which transitions with fixed probability to one of two stimulus pairs at the second stage. The graph shows the gradually changing probability of reward of the second stage stimuli based on a random Gaussian walk. (**B**) Uncertainty as a function of reward probability (stage 2). (**C**) An example across one block of each trial of reward probabilities (*top*), conflict based on Equation 1 (*middle*); and uncertainty based on Equation 2 (*bottom*). (**D**) Pictorial representation of the HDDM where *a* (threshold) and *v* (drift rate) vary as a function of conflict (*C*) and uncertainty (*U*) for subject (S), with the total number of trials ('T') per subject for each experimental group.

The sequential learning task

The sequential learning task (Daw *et al.*, 2011) consisted of two stages. At stage 1, subjects chose between a stimulus-pair, which led to one of two stimuli pairs with a fixed probability ($P = 0.70$ or 0.30). Choice of a stimulus at stage 2 led to a reward (£1 or no reward) with probability gradually shifting based on a random Gaussian walk ($P = 0.25$ to 0.75, Fig. 1A). Subjects were allowed a decision time of 2 s at each stage, 1.5 s transition time between stages and observed the outcome for 1 s. Participants underwent a computerized self-paced training lasting 15–20 min and all completed three sessions.

Conflict and uncertainty

The reward probabilities of the stage 2 stimuli were used to calculate a measure of conflict per trial. The conflict variable (C) was based on the degree of similarity or dissimilarity between reward probabilities for each stimulus pair (Fig. 1C) e.g. low conflict (LC): $P_1 = 0.75$; $P_2 = 0.25$; high conflict (HC): $P_1 = 0.65$; $P_2 = 0.55$ and was calculated as:

$$C_j^i = 1 - \frac{|P_{1j}^i - P_{2j}^i|}{max(|P_{1j}^i - P_{2j}^i|)} \quad (1)$$

Where C_j^i is the conflict variable, P_{1j}^i and P_{2j}^i are the reward probabilities of the transitioned stimuli 1 and 2 at stage 2 for trial i and subject j.

The conflict variable was normalized such that a low value of C (=0.1) would indicate a low conflict trial and a higher value (=0.9) a high conflict trial. Each trial i for subject j is classified as either low or high conflict (LC or HC) based on the median of the calculated conflict (Equation 1) for all trials in each of all three sessions. For ease of understanding, we refer to high conflict as difficult and low conflict as easy trials in subsequent sections.

Uncertainty was based on the variance of the reward probability distribution (Fig. 1B) of each stimulus (Schultz *et al.*, 2008).

$$U_{x,j}^i = P_{x,j}^i(1 - P_{x,j}^i) \quad (2)$$

Where $U_{x,j}^i$ is the uncertainty variable, $P_{x,j}^i$ is the reward probability of the transitioned stimulus 'x' at stage 2 for trial i and subject j. The probabilities for each stimulus ranged between 0.25 and 0.75 varying as a slow Gaussian walk across the trials. We then defined three ranges of probabilities (G1: $P = 0.25$–0.45, G2: $P = 0.46$–0.55 and G3: $P = 0.56$–0.75) (Table 1) to categorize the levels of uncertainty. For a given instance, the trial was classified as either low (both stimuli come under G1/G3 or their combination); medium (one stimulus falls under G1 or G3 and the other under G2) or high (both stimuli fall under G2).

Each of the difficult high conflict trials were further categorized into low (HCLU), medium (HCMU) or high uncertainty (HCHU) and easy low conflict only into either low (LCLU) or medium (LCMU) (Fig. 1B). For example, in trial i, the probabilities associated with the stimuli are both low ($P_A = 0.25$; $P_B = 0.30$, Table 1); although the probabilities are low, the certainty with which the subject could estimate the reward outcome is high, thereby defining the trial as a difficult-certain one (HCLU, Fig. 1C). Because of the task design, the participants do not experience any trials with easy low conflict high uncertainty (LCHU) condition. This categorical approach of dividing the uncertainty is just a discretized version of the sum of individual uncertainties (Supplementary Fig. 7), which provides an opportunity to study the psychological processes when the two options are both low or high uncertainty or a combination of high and low uncertainties.

To summarize, conflict reflects the difference in the reward probabilities between stimulus pairs and depends on the relationship between the two stimuli, whereas uncertainty reflects the variance in the probability of a single stimulus and is independent of the other stimulus, making them conceptually different.

Table 1 The probability range of the two choices and their combinations to form each of the uncertainty conditions

Stimulus reward probability	Group
0.25–0.45	1
0.45–0.55	2
0.55–0.75	3
Group combination	**Uncertainty condition**
(1,1) or (3,3) or (1,3) or (3,1)	LU
(1,2) or (2,3) or (3,2) or (2,1)	MU
(2,2)	HU

HU = high uncertainty; LU = low uncertainty; MU = medium uncertainty.

Hierarchical drift diffusion model

HDDM falls under the class of sequential sampling methods, which use Bayesian methods to estimate the drift diffusion model parameters such as the threshold (a) and the drift rate (v), starting bias (z) and non-decision time (t). We focus our analysis on the parameters a (threshold at which an action is taken) and drift rate v (cognitive/perceptual information processing speed) (Voss *et al.*, 2013; Forstmann *et al.*, 2016) because of their importance in earlier conflict-uncertainty studies (Frank, 2006; van Ravenzwaaij *et al.*, 2012; Banca *et al.*, 2015). The Bayesian-based HDDM estimates a and v parameters as posterior probability distributions with the mean of the distribution representing the group's average. The model utilizes the Markov Chain Monte Carlo sampling method to estimate the distributions. The prior distribution for each parameter was based on 23 studies that reported the best fitting drift diffusion model parameters for multiple cognitive tasks (Matzke and Wagenmakers, 2009; Wiecki *et al.*, 2013). The pre-analysis code was written in MATLAB version 2017a and the built-in HDDM python package by Wiecki *et al.* (2013) was used for the parameter estimation.

The HDDM package can use explicitly defined variables such as the categorical conflict (low or high conflict)/uncertainty (all five categories) to influence the estimation of the parameters. These conflict and uncertainty inputs to the HDDM model are categorical variables rather than their numerical values. We used a total of three models to analyse the task data independently. The first two models allowed either conflict (C) or uncertainty (U) to influence the sampling and estimation and the third model used both C and U (Fig. 1C). Another popular approach (Frank *et al.*, 2015) where a single threshold and drift rate are estimated, which would reflect the

regression with degree of conflict, was not used in this study. This is mainly because of two reasons: (i) it would have been very complicated to study the interaction with uncertainty given that uncertainty was set up as a non-linear categorical one; and (ii) the approach we followed allowed us to estimate the parameters based on the trial type (e.g. easy versus difficult in conflict), which addresses the primary objective of the study.

Because of the randomness in the experimental design, only 155 of 173 healthy volunteers, 30 of 31 the subjects with OCD, and 37 of 38 alcohol-dependent subjects experienced all the conflict-uncertainty conditions and were included for analysis in this last model. The trials with response times below 50 ms or no response were excluded from the analysis to ensure model convergence and to constrain the data to realistic response times. The parameters were estimated by drawing 20 000 samples, with the first 1000 samples being discarded as burn-in. The convergence of the model was assessed by both visual inspection of the chains and computation of the Gelman-Rubin statistic, which indicated convergence ($\hat{R} < 1.1$) (Krypotos *et al.*, 2015). We also calculated the deviance information criterion (DIC), which evaluates a model's goodness-of-fit while accounting for model complexity (i.e. number of free parameters), with lower DIC values indicating a better model fit (Spiegelhalter *et al.*, 2002).

Statistical analyses

In line with the HDDM estimation of a and v, we used Bayesian methods as implemented in JASP (Team, 2017) for statistical analysis. Bayesian repeated measures ANOVA was used to test the significance across groups, conditions and their interactions and, if significant, *post hoc* Bayesian paired and independent *t*-tests were used to assess the mean difference. Evidence for hypothesis testing was inferred from the Bayes factors (BF_{10}), with a $BF_{10} > 3$ indicating moderate evidence and >10 strong evidence in support of the alternate hypothesis (Krypotos *et al.*, 2015). The Bayes factor used to report the evidence for (or against) a hypothesis was obtained from JASP, which is based on the algorithm described (Team, 2017; Wagenmakers *et al.*, 2018*a*, *b*). The behavioural (response time and accuracy) and demographic measures were analysed using frequentist repeated measures ANOVA and *post hoc* Bonferroni corrected independent paired and sample *t*-tests using SPSS version25.

The HDDM estimates—threshold (a) and drift rate (v) from the conflict alone model (easy versus difficult)—were analysed using Bayesian paired-sample *t*-test to assess the effect of conflict. We then analysed the relationship between HDDM estimates without conflict or uncertainty as dependents and reinforcement learning parameters (Daw *et al.*, 2011), model-based and model-free behavioural measures, working memory, age and gender to assess any possible relationships. Next, we addressed the main hypotheses of differences between healthy and patient population using repeated measures ANOVA followed by *post hoc* tests for the estimated HDDM values.

Since the DIC value for the combined conflict and uncertainty model was the lowest compared to the conflict or uncertainty alone model, the thresholds and drift rates across groups and multiple conditions of the conflict-uncertainty model was further studied.

Data availability

Supporting data will be made available on request.

Results

Demographics

The groups did not differ by gender (% male: healthy volunteers = 46.8%; OCD = 43.8%; alcohol dependence = 60.5%) [$\chi^2(2,N = 243) = 2.68$, P = not significant (ns)] but differed by age [$F(2,242) = 12.04$, $P < 0.001$], with alcohol-dependent subjects [mean = 43.68, standard deviation (SD) = 12.27] older than healthy volunteers (mean = 32.44, SD = 12.79) [$t(209) = 4.94$, $P < 0.001$] and subjects with OCD (mean = 34.66, SD = 13.40) [$t(68) = 2.94$, $P < 0.01$]. Age did not differ between subjects with OCD and healthy volunteers [$t(203) = 0.89$, P = ns].

Behavioural measures: accuracy and response times

Effect of conflict

Two separate mixed measures ANOVAs, including group as a between-subject variable and conflict (difficult and easy) as a within-subject variable, were conducted. In terms of response times, the main effect of conflict was significant [$F(1,240) = 5.86$, $P < 0.05$], indicating slower response times during high conflict (reported as mean ± SD 816 ± 175 ms) than low conflict (798 ± 175 ms), with no group × conflict interaction [$F(2,240) = 2.25$, P = ns] or group effect [$F(2,240) = 0.65$, P = ns]. In terms of accuracy, there was no main effect of conflict [$F(2,240) = 0.02$, P = ns], group × conflict interaction [$F(2,240) = 0.10$, P = ns], or group effect [$F(2,240) = 0.10$, P = ns].

Effect of conflict-uncertainty

Two separate mixed measures ANOVAs were conducted including group as a between-subject variable and conflict-uncertainty (HCHU, HCMU, HCLU, LCMU and LCLU) as a within-subject variable. In terms of response times, there was no main effect of conflict-uncertainty [$F(2,218) = 1.92$, P = ns], but showed group × conflict-uncertainty interaction [$F(2,218) = 4.09$, $P < 0.001$], with OCD patients taking longer to respond in LCMU [$t(183) = 3.37$, $P < 0.01$; OCD: 821 ± 167 ms; healthy volunteers: 740 ± 110 ms] and alcohol dependents in HCLU [$t(189) = 2.59$, $P < 0.05$; alcohol dependence: 814 ± 161 ms; healthy volunteers: 756 ± 111 ms] and LCMU [$t(189) = 2.63$, $P < 0.05$; alcohol dependence: 801 ± 180 ms; healthy volunteers:740 ± 110 ms] conditions than healthy volunteers.

In terms of accuracy, there was a main effect of conflict-uncertainty [$F(2,218) = 48.706$, $P < 0.001$] and group × conflict-uncertainty interaction [$F(2,218) = 8.07$, $P < 0.001$] effect. The OCD patients performed poorly

relative to healthy volunteers [$t(183) = -4.69$, $P < 0.01$; A_{OCD}: 0.36 ± 0.15, A_{HV}: 0.49 ± 0.14] and alcohol dependents [$t(64) = -2.84$, $P < 0.05$; A_{AD}: 0.48 ± 0.2] in the HCHU (difficult-uncertain) condition and better relative to alcohol dependents [$t(64) = 3.17$, $P = 0.01$; A_{OCD}: 0.61 ± 0.12, A_{AD}: 0.53 ± 0.1] in the LCMU condition. Patients with alcohol dependence relative to healthy volunteers were worse only in the LCMU [$t(189) = -4.29$, $P < 0.01$; A_{AD}: 0.53 ± 0.1, A_{HV}: 0.6 ± 0.09] condition.

Threshold and drift rates as function of conflict

Conflict-based HDDM estimates in healthy volunteers

To confirm the validity of our approach, we compared the estimates for difficult relative to easy choices (high conflict versus low conflict) in healthy volunteers using a Bayesian paired-sample *t*-test, demonstrating, as expected, strong evidence for slower drift rates (99.99% of $v_{LC} > v_{HC}$ with $BF_{10} = 2.7 \times 10^{20}$) and moderate evidence for higher thresholds (76% of $a_{HC} > a_{LC}$ with $BF_{10} = 3.2$) (Fig. 2).

We assessed the HDDM estimates for correlations with reinforcement learning parameters (Daw *et al.*, 2011 and Supplementary material), age, gender, and working memory. The HDDM estimates (a and v) showed moderate to strong evidence for lack of correlation with reinforcement learning parameters (Supplementary Table 1) [randomness (β_1 and β_2), learning rate (η_1 and η_2), preservation (ps) and model free-model based weight (w) (Voon *et al.*, 2015), and behavioural model-based and model-free measures] except for β_2. Lower drift rates (v) (slower rate of processing) were associated (Supplementary Fig. 1) with higher choice randomness or exploration at the second stage (β_2: $r = 0.28$, $BF_{10} = 115.6$). There was also strong evidence for a lack of correlation with age and moderate evidence for a lack of correlation with working memory and no variation with gender (Supplementary Table 1).

Conflict-based HDDM results between groups

We then analysed the HDDM results of threshold and drift rate separately as a function of group and conflict using two mixed measures Bayesian ANOVAs with group as a between-subjects factor and conflict as a within-subjects factor.

With respect to threshold 'a' we found strong evidence for a group effect ($BF_{10} = 9911$) and moderate evidence for no group × conflict interaction ($BF_{01} = 5.6$). On *post hoc* testing, the Bayesian independent sample *t*-test showed strong evidence for both patient groups to have higher thresholds (Fig. 3) than healthy volunteers (HV) for both low and high conflict conditions [alcohol dependence (AD)-HC: 99.68% of $a_{AD} > a_{HV}$ with $BF_{10} = 89.81$; AD-LC: 99.88% of $a_{AD} > a_{HV}$ with $BF_{10} = 232.28$; OCD-HC: 99.1% of $a_{HV} < a_{OCD}$ with $BF_{10} = 2209$; OCD-LC: 99.4% of $a_{HV} < a_{OCD}$ with $BF_{10} = 7628$].

With respect to drift rates 'v', we showed strong evidence for a conflict effect ($BF_{10} = 6.14 \times 10^{25}$) and very weak evidence for a group effect ($BF_{10} = 2.5$). Here although we showed strong evidence for a conflict × group interaction ($BF_{10} = 56.68$), the Bayesian independent sample *t*-test showed strong to moderate evidence for alcohol dependents to have slower drift rates compared to healthy volunteers (99.5% of $v_{AD} < v_{HV}$ with $BF_{10} = 113.9$) and to OCD (81.9% $v_{AD} < v_{OCD}$ with $BF_{10} = 3.6$) during easy (low conflict) but not difficult (high conflict) decisions (Supplementary Table 2). However, there was no evidence for difference in drift rates ($BF_{10} = 1.4$, $v_{HC} \neq v_{LC}$) in alcohol-dependent patients as a function of conflict. This indicates that the conflict level in a given trial failed to modulate the drift rates (Supplementary Fig. 2) in alcohol-dependent subjects when compared to patients with OCD ($BF_{10} = 6827$, $v_{HC} \neq v_{LC}$) or healthy volunteers.

Put together, alcohol dependents were slower to process evidence (lower drift rates) during easy-low conflict relative to both OCD subjects and healthy volunteers. Both alcohol dependent and OCD subjects accumulated more evidence (higher thresholds) relative to healthy volunteers, but not as a function of conflict.

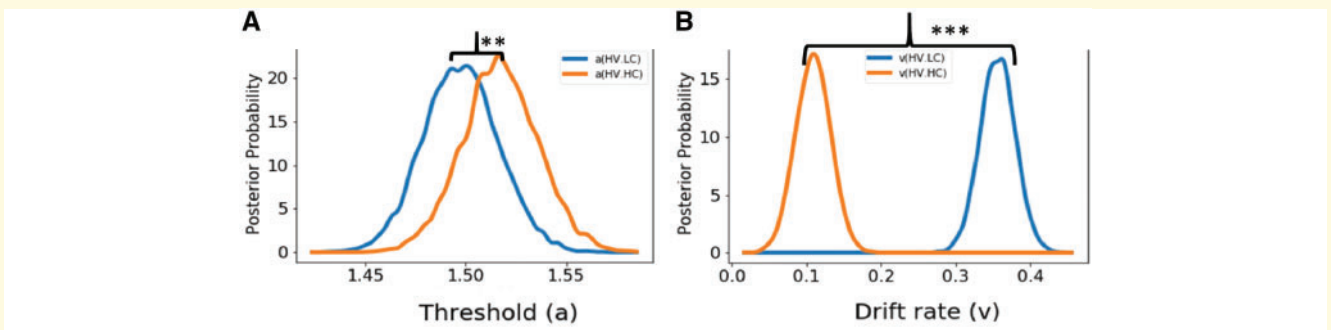

Figure 2 Conflict-based HDDM estimates across healthy volunteers. Plot of the posterior distributions of (**A**) threshold and (**B**) drift rate for healthy volunteers ($n = 173$ subjects), in easy (low conflict, LC) and difficult (high conflict, HC) decisions. **$BF_{10} > 3$, ***$BF_{10} > 10$. HV = healthy volunteers.

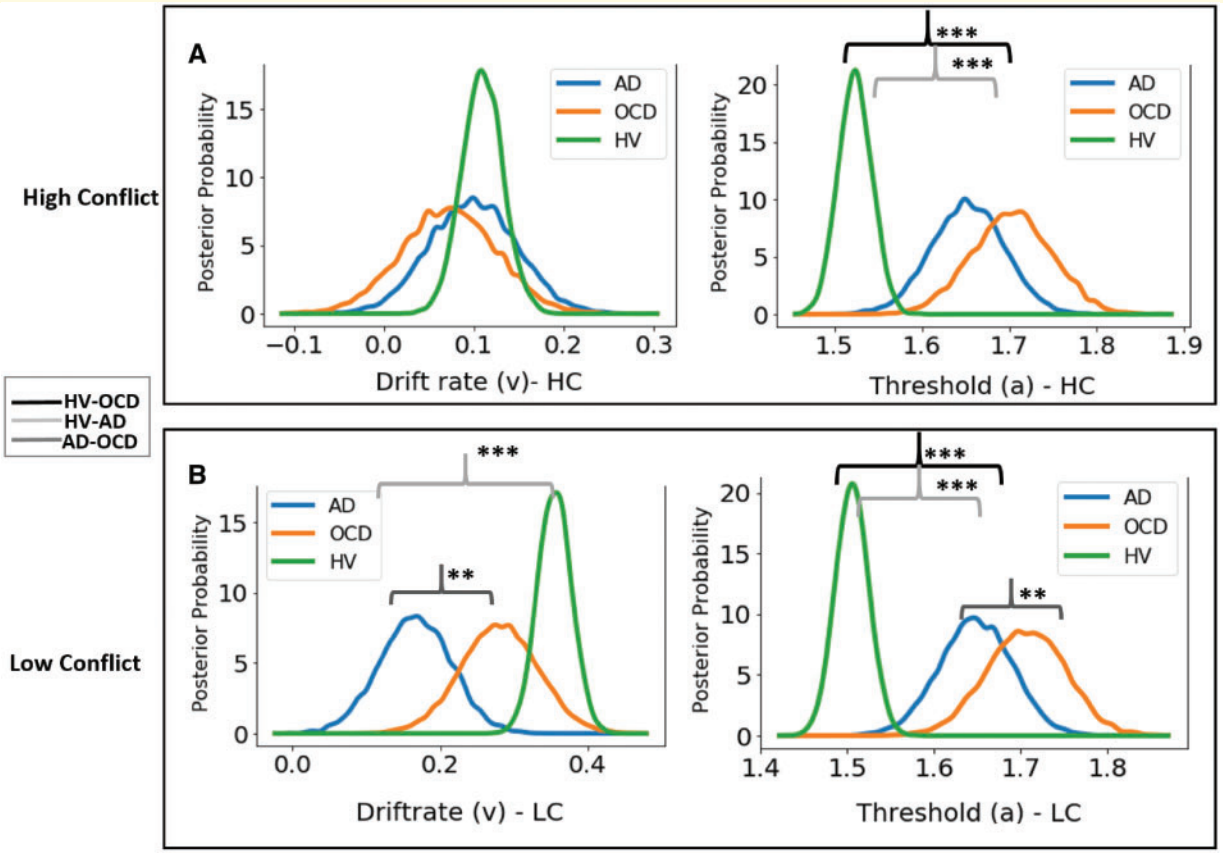

Figure 3 Group level posterior distributions. (**A**) Drift rate (v) and (**B**) threshold (a) for difficult (high conflict, HC) and easy (low conflict, LC) decisions for healthy volunteers (HV), patients with OCD and subjects with alcohol dependence (AD). The evidence for differences between the groups was calculated using BF_{10} (Supplementary Table 3). **$BF_{10} > 3$, ***$BF_{10} > 10$.

The drift rate of the OCD group showed a positive correlation with β_2 alone (Supplementary Table 1). Unlike healthy volunteers and OCD patients, the alcohol dependence group's measures showed no relationship with any of the reinforcement learning parameters (Supplementary Table 1).

Threshold and drift rates as function of conflict and uncertainty

To understand the interaction between conflict and uncertainty, we then focused our main analyses on the combined conflict-uncertainty model comparing thresholds and drift rates across groups and multiple conflict and uncertainty level conditions (HCHU, HCMU, HCLU, LCMU and LCLU). The DIC analyses supported such an approach, indicating that the combined conflict-uncertainty model had the best fit (82 323.25) compared to conflict alone (89 417.19) or uncertainty alone (82 490.01) models. For uncertainty-based HDDM model estimates, see Supplementary Fig. 3.

HDDM results in healthy volunteers

First, we ran a repeated measures ANOVA of the conflict-uncertainty conditions in the healthy volunteers alone and showed a main conflict-uncertainty effect ($BF_{10} = 24.28$). The *post hoc* Bayesian paired sampled t-tests showed strong evidence for lower thresholds (Fig. 4C) for difficult-uncertain decisions (HCHU) compared to difficult-certain decisions (HCLU) (84.9% of $a_{HCHU} < a_{HCLU}$ with $BF_{10} = 182.4$) (Supplementary Table 3).

With respect to drift rates, we showed strong evidence for the main conflict uncertainty effect ($BF_{10} = 7.22 \times 10^{50}$) with independent t-tests also showing strong evidence for all combinations of uncertainty and conflict, with the lowest drift rate for difficult-uncertain (HCHU) and the highest for easy-certain (LCLU) choices (Supplementary Table 3).

HDDM results between groups

For threshold, the mixed measures ANOVA with group as a between-subjects factor and conflict-uncertainty conditions as a within-subjects factor showed strong evidence for a group effect ($BF_{10} = 13764.98$). The *post hoc* Bayesian t-test showed that both OCD (strong evidence) and alcohol dependence (moderate evidence) groups had higher thresholds than healthy volunteers across all the conflict-uncertainty conditions (Fig. 5 and Supplementary Table 4).

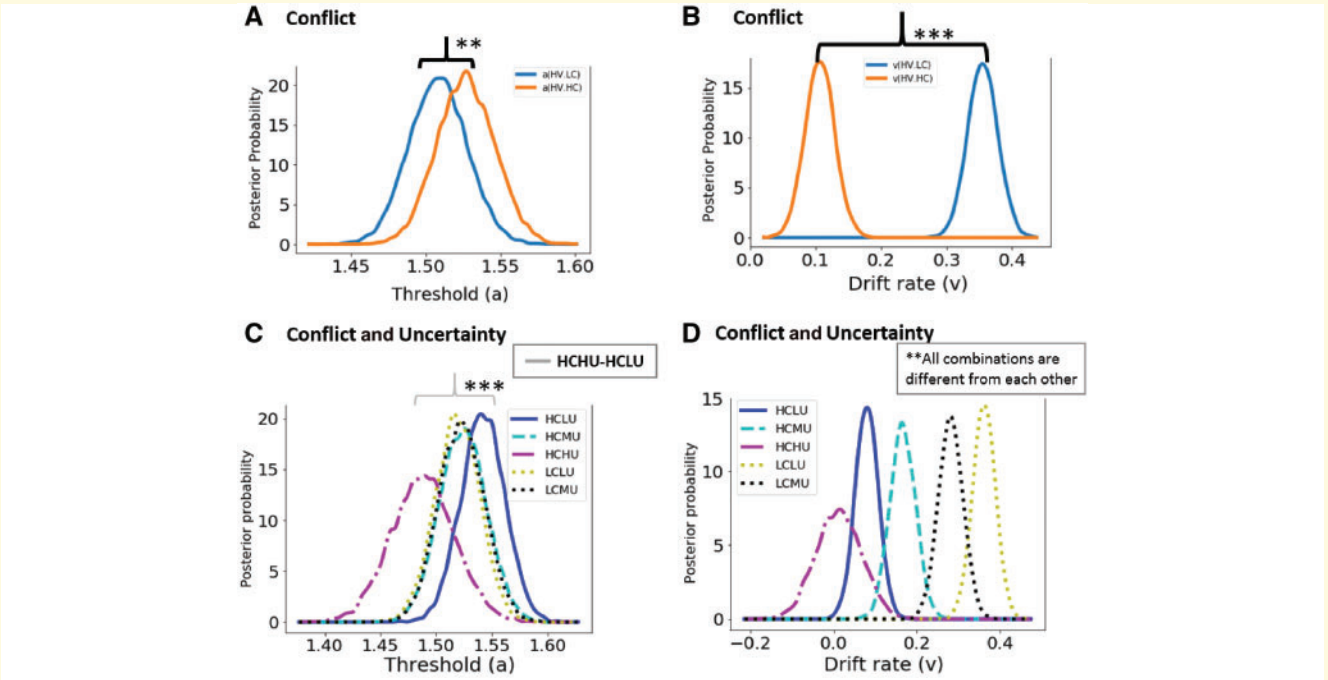

Figure 4 Posterior distribution for the conflict and conflict-uncertainty model for healthy volunteers (n = 155) for thresholds (A and C) and drift rates (B and D). The evidence for differences between the distributions is indicated by BF_{10} for difficult-uncertain (HCHU) and difficult-certain (HCLU) conditions. **$BF_{10} > 3$, ***$BF_{10} > 100$. HV = healthy volunteers.

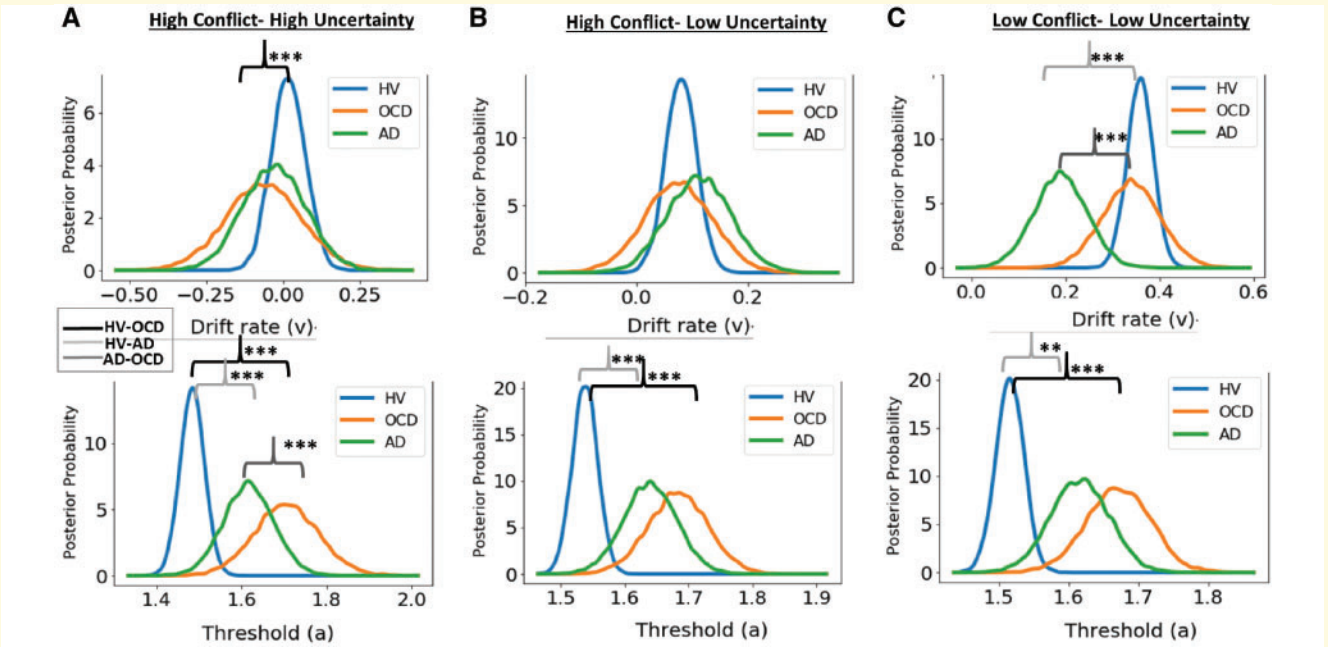

Figure 5 Mean thresholds and mean drift rates for healthy volunteers (HV), and subjects with OCD and alcohol dependence (AD) as a function of conflict-uncertainty conditions. Moderate evidence is indicated by **$BF_{10} > 3$, and strong evidence by ***$BF_{10} > 10$.

For drift rate, the mixed measures ANOVA showed moderate to strong evidence for a group effect (BF_{10} = 6.4), a conflict-uncertainty condition effect ($BF_{10} = 1.45 \times 10^{68}$) and their interaction (BF_{10} = 30.76). *Post hoc* independent *t*-tests showed these effects were driven by slower drift rates in OCD patients relative to healthy volunteers only when the trials were both difficult and uncertain (HCHU) (73.1% of $v_{OCD} < v_{HV}$ with BF_{10} = 21.7). Thus, OCD patients

appear to have slower processing speed of sensory evidence during difficult and uncertain scenarios. Similar to the results observed in the conflict alone model, alcohol dependent subjects showed slower processing speed only during easy low conflicting scenarios despite the level of uncertainty (LCMU = $v_{HV} > v_{AD}$ with $BF_{10} = 244.12$ and LCLU = $v_{HV} > v_{AD}$ with $BF_{10} = 22.46$).

These results were corroborated in *post hoc* comparisons of the patient groups: OCD patients showed strong evidence for higher thresholds relative to alcohol dependent subjects only during difficult-uncertain trials (99.6% of $a_{OCD} > a_{AD}$ with $BF_{10} = 11.2$). Similarly, OCD showed faster drift rates relative to alcohol dependence when choices were easy irrespective of uncertainty levels [LCMU (95.4% of $v_{CD} > v_{AD}$ with $BF_{10} = 12.6$) and LCLU (96.32% of $v_{OCD} > v_{AD}$ with $BF_{10} = 6.6$)] (Supplementary Table 4).

In the behavioural analysis, OCD patients showed impaired accuracy relative to healthy volunteers [$t(183) = -4.69$, $P < 0.01$; A_{OCD}: 0.36 ± 0.153, A_{HV}: 0.49 ± 0.14] and alcohol-dependent subjects [$t(64) = -2.84$, $P < 0.05$; A_{AD}: 0.48 ± 0.2] in the difficult-uncertain (HCHU) condition. There were no differences in reaction times (for more details, see 'Behavioural results' section).

Discussion

We applied a novel analysis investigating evidence accumulation of a sequential learning task dissociating conflict (as a function of the difference in probabilities between the two choices) and uncertainty (as a function of the variance in outcomes of either choice). We first validated this approach in healthy volunteers, and then compared the findings in disorders of pathology characterized by impaired decision-making.

The effects of conflict on threshold and drift rates in healthy volunteers were as expected (Frank *et al.*, 2007; Zaghloul *et al.*, 2012) thus validating our approach: the threshold or the amount of evidence accumulated is higher and drift rate or the speed of evidence accumulation is slower during difficult versus easy decisions (high conflict versus low conflict) (Frank, 2006). As the task was originally designed to investigate the relative balance of goal-directed and habitual control, we also assessed the relationship between evidence accumulation and reinforcement learning measures. There was no relationship between threshold or drift rate and goal-directed and habit control or learning parameters of the reinforcement learning algorithm parameters or behavioural model free model-based measures. However, the drift rate positively correlated with the second stage randomness parameter (β_2) in healthy volunteers. The β_2 parameter (inverse of temperature in soft-max) controls the exploitative or explorative levels during decision-making with low values corresponding to greater exploration or choice randomness (Sutton and Barto, 1998). Thus, individuals with higher exploitation, or greater tendency to stick with the choice with the highest reward probability rather than sampling alternate options, have a faster build-up of evidence prior to a decision. Those with greater exploration tendencies have a slower build-up of evidence. This relationship was also observed in OCD but not alcohol dependent subjects. Although there were no differences between alcohol dependent subjects and healthy controls in β_2 (Voon *et al.*, 2015), we have previously shown that the same alcohol dependence group have lower exploratory behaviours on a different explore-exploit task (Morris *et al.*, 2016). Although these measures differ, this observation may account for the lack of correlation between drift rate and β_2 in alcohol dependence. Further studies to clarify this observation are indicated.

We then show a critical interaction between conflict and uncertainty in healthy volunteers, where threshold was modulated not just by conflict, but also the degree of uncertainty within the choices. When choices were easy and certain (LCLU), the accumulation of evidence was lower (low threshold) and at a faster rate (high drift rate). The opposite was observed when the choices were difficult but certain; when the likelihood of an outcome is certain but choosing between two choices is difficult (HCLU); here we cautiously accumulate more evidence (high threshold) at a slower rate (low drift rate). This suggests that the degree of conflict between choices is driving the rate of evidence accumulation.

Critically, however, when we need to make decisions between choices that are difficult but uncertain [i.e. when the individual likelihood of the stimuli outcomes is uncertain or risky and closer to chance ($P \sim 0.50$) and choosing between the two choices is difficult, HCHU], we unexpectedly do the opposite: we accumulate less evidence (lower threshold) as compared to options where the return is more certain. Thus in the context of greater difficulty, the level of uncertainty appears to be a crucial factor. Unlike other conflict-uncertain scenarios where systematic evidence accumulation occurs, when faced with difficult choices with too much uncertainty, less evidence is accumulated and evaluated before making a decision.

We then compared the estimates from the patient groups to healthy volunteers obtained from conflict and conflict-uncertainty models. The conflict model showed that OCD subjects modulated their drift rates but not thresholds depending on conflict level whereas patients with alcohol dependence failed to adjust with no difference as a function of conflict. Although OCD patients accumulated more evidence during either easy or difficult trials, there was no significant difference in terms of accuracy or response time relative to healthy volunteers suggesting that conflict *per se* was not an issue. However, in the context of the interaction between high conflict and high uncertainty (HCHU) conditions, OCD subjects had slower processing speed for the sensory evidence yet unexpectedly showed worse performance reflected in their low accuracy levels. Thus, we suggest that impaired evidence accumulation in OCD is not specific to either conflict or uncertainty, but rather an interaction between the two factors.

This abnormal evidence accumulation behaviour may be related to a strategy used to reduce the presumed uncertainty associated with the choices with increase in doubt (Hermans *et al.*, 2008) and may be related to their 'checking' symptomatology (van den Hout and Kindt, 2003*b*, 2004; Dar, 2004). This slower processing speed in OCD subjects appears to be specific to difficult and uncertain scenarios. This combination of slowed but suboptimal performance in OCD is intriguing. Healthy controls appear to be more impulsive and accumulate less evidence in difficult uncertain contexts and perform at chance accuracy levels, which is expected given the context ($P = 0.46$ to 0.55 for both stimuli). That the choice is more rapid relative to easier and less conflictual contexts suggests that the healthy controls are aware of the difficult or the near impossible nature of the context and hence make a rapid and perhaps more random decision consistent with the chance performance. In contrast, OCD subjects appear to be more deliberative and cautious in this context. Critically, however, OCD subjects perform suboptimally with accuracy rates much lower than chance; that they choose the wrong choice suggests that they must have learned the probabilities and are implicitly aware of the difference between choices but yet persist in poor performance. This suggests the issue is not one of learning differences in contingencies, highlighting dissociation between learning and performance.

This context of high uncertainty and conflict is an ecologically valid model in OCD. For instance, an OCD individual with cleanliness and washing compulsive behaviours needs to make a decision: 'Are my hands clean enough to stop washing?' They must decide whether their objectively clean hands are sufficiently subjectively clean to either continue or stop handwashing. The decision is highly conflictual as in a pathological state, the decision is not between dirty and clean but between the patient's highly subjective feeling or belief of being 'clean enough' or 'not clean enough'. The outcomes are also highly uncertain as neither stopping nor continuing changes the ambiguous and subjective nature of these outcomes. Subjects then deliberate further or are more cautious and accumulate more evidence but critically, despite being implicitly aware of the different choices, they perform poorly and make the wrong judgement. This is in keeping with the subjective clinical experience that the obsessions and compulsions are 'egodystonic': that they are aware that the behaviour is somehow wrong or inconsistent with their goals yet the behaviour persists. Subjects may also have difficulties in appreciating the specific contextual difference (i.e. recognizing or appreciating the impossibility of a difficult uncertain decision), have overactive performance monitoring and be overly concerned about making mistakes (have impairments in balancing cost-benefit), or have difficulties in switching between decision policies with respect to specific contextual changes (Endrass *et al.*, 2008; Riesel *et al.*, 2011; Agam *et al.*, 2014; Riesel, 2014; Weinberg *et al.*, 2015; Gillan *et al.*, 2017). These findings also might highlight why the literature on OCD is mixed with respect to sensitivity to conflict or uncertainty as the interaction is the critical issue.

In contrast, patients with alcohol dependence appear to have more specific difficulties with conflict. When compared to healthy volunteers and OCD patients, alcohol dependents showed slower processing speeds (drift rates) during low relative to high conflict. In this case, what should be an easy decision, perhaps more obvious to others, is approached in a similar way to a difficult decision. These findings are consistent with previous observations that alcohol-dependent subjects show reduced discrimination of conflict (Beylergil *et al.*, 2017) and risk levels (Zhu *et al.*, 2016) with reported conflict-related deficits in dorso-lateral prefrontal cortex (DLPFC) (Boschin *et al.*, 2016; Beylergil *et al.*, 2017). In humans, the rate of evidence accumulation or the drift rate has been linked to the fronto-parietal network (Mulder *et al.*, 2014). The impairment in ability to adjust their drift rates with respect to the conflict level maybe similarly be related to their deficits in DLPFC activity.

Both computational models captured the group differences in parameters not observed in the behavioural data. The final performance metric (accuracy or response time) is a weighted combination of multiple cognitive processes occurring simultaneously whereas the HDDM parameters represent the underlying components of this process, which may otherwise be camouflaged in behavioural metrics. These parameter estimates indicate how computational models can help identify more subtle pathological changes (e.g. decreased drift rate in alcohol dependence), which may not yet manifest behaviourally in performance.

Our study is not without limitations. The response duration for evaluating the second stage choice was limited to 2 s, which might differentially impact more difficult choices, which could be a reason that we observed moderate evidence for a higher threshold (a) during high relative to low conflict conditions. However, we show that OCD subjects differ from healthy controls in the difficult-uncertain condition, suggesting that the response duration is not a limiting factor. We have used objective reward probabilities (P) rather than learned subjective/learned probabilities in the analysis. The rewards are binary stochastic with an implicit component of uncertainty making their explicit estimation difficult. Learned probabilities are known to lag behind the objective probability and to be more imprecise. However, as the objective probabilities were binned into low, medium and high, the subject was only required to distinguish them broadly between stimuli rather than a more fine-grained difference. These arguments support our approach of using objective probabilities for this analysis. But as the rationale behind the two-step task design was neither to study conflict nor uncertainty, utilizing it to study the psychological constructs of trial-wise variations in conflict/uncertainty may require more refinement of the task structure or to analyse the learned subjective probabilities particularly if using a regressor rather than a categorical approach.

This categorical approach of defining the uncertainty using both the available options differs from methods that might take choice into account. In future studies, we would like to use the uncertainty associated with the selected choice and compare it with the manuscript's uncertainty categorization. Despite having an imbalance in the number of trials among different conflict and uncertainty conditions, the minimum number of trials required to achieve high precision in the parameter estimation was maintained in the model.

Thus, we highlight a critical role for uncertainty in the context of difficult or high conflict trials. Healthy volunteers accumulate less evidence with difficult uncertain decisions, perhaps reflecting a switch to a more random decision policy. In contrast, OCD subjects behave more cautiously, accumulating more evidence, yet perform suboptimally below chance levels. In contrast, subjects with alcohol dependence show a main impairment in conflict processing. Here we highlight the multidimensionality underlying the observation of compulsive or repeated behaviours in OCD or alcohol dependence. Although we observe impairments in evidence accumulation in both patient groups, which may be interpreted as cautiousness, indecision, or slowness, we highlight the critical differences in context. Together these observations may provide insight into therapeutic strategies targeting core cognitive deficits.

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Competing interests

The authors report no competing interests.

Supplementary material

Supplementary material is available at *Brain* online.

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