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Compulsiveness drives evidence accumulation during ambiguity

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Abstract

Doubt can modulate our decision-making process. Although conceptually different, conflict (choice similarity: *difficult or easy*) and uncertainty (individual reward-likelihoods: *uncertain or certain*) are commonly related and often conflated. By posing as an evidence-accumulation problem, we assessed doubt, dissociating contextual conflict, and uncertainty and showed obsessive-compulsive disorder patients have specific impairments while processing *difficult-uncertain* contexts. It remains unclear whether this deficit is disorder-specific or a reflection of broader mental-health dimension. Multi-dimensional trans-diagnostic approaches help to tease out the mechanistic nature (specific *or* usual) of clinical observations and their validity in sub-clinical populations. Here, we first aimed to validate our conflict-uncertainty analysis approach in a larger non-clinical cohort ($n > 1300$). Second, we assessed the relationship between decisional-parameters of *difficult-uncertain* contexts and a trans-diagnostic factor capturing individual differences in ‘compulsive-behavior and intrusive-thoughts’. We replicate our previous findings in a large, general population sample and highlight that the amount of evidence accumulated in *difficult-uncertain* scenarios increases functionally with compulsive-behavior and intrusive-thought emphasizing greater cautiousness. We further show that those with high social-withdrawal tendencies gather less evidence irrespective of context reflecting a ‘jumping to conclusions’ tendency in judgment. We attempt to bridge the gap between behavior and psychological markers by integrating trans-diagnostic and computational methods.

Introduction

Doubt can influence our decisions from the mundane: ‘did I turn off the stove?’ to the consequential: ‘Should I change my job?’, or ‘Should I go to the pub at the end of lockdown?’ Obsessive-compulsive disorder (OCD) ¹⁻³ has been postulated to be characterized by impairments in doubt, potentially triggering pathological symptoms such as checking or washing, which, following the execution of repeated actions ⁴⁻⁶ further increases the doubt ¹.

How doubt drives ‘how’ or ‘what’ we decide depends on context. Here we focus on contextual uncertainty and conflict. Individual features of choices such as value and the reward-likelihood form the basis for constructs such as conflict (based on similarity between choices: difficult vs easy), and uncertainty (based on individual likelihoods of obtaining a reward: uncertain vs certain). Though commonly related and often conflated, conflict and uncertainty are dissociable experimentally ^{7,8} and aid to capture the aberrant functioning of the underlying neural structures relevant to the disorder ^{1,9-13}.

Uncertainty processing has specific relevance to OCD ^{1,14-18}, with ‘doubt’ being one of the central features thought to drive symptoms¹. OCD patients experience higher subjective uncertainty, despite no differences in objective uncertainty ¹⁷. This increased subjective-uncertainty might reflect in repetitive behavior ^{19,20} particularly while processing ambiguous (where the probability of choices are unknown) rather than risky choices (where the probabilities are known) ^{14,21}. Concerning conflict, behaviourally, no differences in response time and accuracy were observed between OCD and healthy controls in a random motion kinetic dots task. But computational parameters estimated using a hierarchical drift-diffusion model (HDDM) showed an increase in the threshold parameter (which indicates the amount of evidence accumulated before a choice is selected) in OCD patients when the randomness of the dots increased ⁹. OCD patients with higher doubt scores had low drift rates and lower certainty in their decisions ². Hauser and colleagues show increased thresholds ^{22,23} and decreased drift rates along with meta-cognitive deficits in individuals with higher compulsive traits ²⁴. In contrast, OCD patients show mixed findings with conflict monitoring ^{10,25,26}.

We devised a novel analysis to dissociate conflict and uncertainty using a sequential learning task ¹¹. Conflict reflects the difference between reward probabilities of the stimuli pairs and depends on the relationship between them whereas uncertainty reflects the variance in the

probability of a single stimulus and is independent of the other. In healthy controls, we first showed that *difficult-uncertain* (where choices are similar and their individual likelihoods being uncertain) scenarios were associated with lower evidence accumulation. In contrast, OCD patients accumulated evidence (drift rate- v) more slowly in *difficult-uncertain* contexts with a generalized increase in the amount of evidence accumulated (threshold- a)¹¹.

Multi-dimensional trans-diagnostic approaches, focused on identifying common mechanistic underpinnings across various psychiatric conditions for better diagnosis and outcomes, are attaining wide attention²⁷⁻²⁹. Using an integrated factor-based trans-diagnostic approach, Gillan and colleagues studied goal-directed behavior using the 2-step sequential learning task in a large cohort ($n > 1300$)³⁰. They showed that deficits are not specific when we look at disorder-symptoms in isolation, but that specific associations were recoverable, when trans-diagnostic methods are used. Specifically, they revealed that deficits in goal-directed control were linked to a trans-diagnostic factor reflecting individual differences in ‘compulsive behaviour and intrusive thought’³¹. A recent meta-analytic study also showed that sub-clinical OCD groups display low confidence levels while performing a range of cognitive tasks³². However, these effects might be an artefact of comorbidity: when co-occurring anxiety and depression symptoms are accounted for, compulsive individuals actually exhibit *greater* confidence in their decisions^{29,33}.

Given that contradictory findings can emerge when using case-control studies versus trans-diagnostic methods, a major gap remains in our understanding of behavioural and cognitive markers of decision making under conflict and uncertainty in mental illness. Here, we aim to address this issue by first testing if our previous findings of evidence accumulation in the context of conflict and uncertainty¹¹ would generalise across a larger non-clinical sample³¹. We then examined the relationship between the computational estimates of decision making and the trans-diagnostic factors, hypothesizing that the amount of evidence accumulation in the *difficult-uncertain* context is related to individual differences in ‘compulsive behaviour and intrusive thought’. Finally, we extracted the computational estimates independent to the context of conflict or uncertainty and explored their relationship with trans-diagnostic factors.

Methods

Participants

Data were analysed from a previously collected, open-source dataset ³¹, gathered using the online platform Amazon's Mechanical Turk, where participants were paid a base rate (\$2.50) in addition to a bonus based on their earnings during the reinforcement-learning task ($M = \$0.54$, $SD = 0.04$). The participants were based in the USA (US billing address with an associated US credit card, debit card or bank account), with an age range between 18 to 76. The research team were unknown of participants' identities. Informed consent was obtained from the participants, who provided their consent online by clicking 'I Agree' after reading information on the study and consent language following procedures approved by the New York University Committee on Activities Involving Human Subjects. The study was conducted and approved in accordance with the guidelines and regulations. For further details on recruitment, inclusion, and exclusion criteria please refer to ³¹.

The sequential learning task

The task consisted of two stages (Figure 1a) ³⁰; subjects chose between a stimulus-pair (fractals) at stage 1 (display for 2.5 seconds) which led to one of two stimuli-pairs (orange or blue) with a fixed probability ($P = 0.70$ (common) or 0.30 (rare)). The choice of a stimulus at stage 2 (another set of fractals) led to a reward (25¢) or no reward) with probability gradually shifting based on a random Gaussian walk ($P = 0.25$ to 0.75 , Figure 1b). Responses were made using the left ('E') and right ('I') keys. Subjects were allowed a decision time of 2.5seconds at each stage1, 1 second at stage2, and the outcome was displayed for 1 second. The participants completed 200 trials. (See ³¹ for details).

Insert Figure 1 here

Hierarchical Drift Diffusion model (HDDM)

HDDM falls under the class of sequential sampling methods which utilize Bayesian methods to estimate the DDM 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 first three parameters as t primarily concerns motor and non-decision-making processes. The Bayesian based HDDM, estimates 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 DDM parameters for multiple cognitive tasks^{34,35}. The pre-analysis code was written in MATLAB version 2018a and the built-in HDDM python package by³⁵ was used for the parameter estimation.

Trials with response times less than 50 ms were discarded from the analysis to ensure model convergence and to constrain the data to realistic response times. The parameters were estimated by drawing 120000 samples with the first 10000 samples being discarded as burn-in and saving only every 10th sample. The convergence of the model was assessed by visual inspections for the caterpillar type Monte-Carlo chains.

Analysis 1 – Context of Conflict and Uncertainty

We utilized our previous analysis to dissociate the concept of conflict (*difficult vs easy*) and uncertainty (*uncertain vs certain*)¹¹. The methodology of the analysis is as follows.

We first calculated a measure of conflict per trial, using the reward probabilities of the stimuli at stage 2. The conflict variable (C) indicated the degree of similarity or dissimilarity between the reward probabilities for each stimulus-pair (Figure-2c, e.g. *easy* (LC): $P_1 = 0.75$; $P_2 = 0.25$; *difficult* (HC): $P_1 = 0.65$; $P_2 = 0.55$) and was calculated as

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

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

We then calculated uncertainty, which is dependent on the variance in the probability of a single stimulus and is independent of the other stimulus (Figure-2a)³⁶ $U_{x,j}^i = P_{x,j}^i(1 - P_{x,j}^i)$

$$(2)$$

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 (Group1: $P = 0.25-0.45$, Group2: $P = 0.46-0.55$ and Group3: $P = 0.56-0.75$) (Figure 2d) to categorize the levels of uncertainty: For a given instance, the trial was classified to either low (both stimuli come under Group1/Group3 or their combination);

medium (one stimulus falls under Group1 or Group3 and the other under Group2) or high (both stimuli fall under Group2).

Based on the conflict level (*difficult vs easy*) and uncertainty (*uncertain vs certain*), each of the trials were categorised into one of the 5 categories : difficult-certain (HCLU); difficult-medium (HCMU) ;difficult-uncertain (HCHU); easy-certain (LCLU) ; easy-medium (LCMU) (Figure-2c) (See ¹¹ for further details). For example, in trial i , the probabilities associated with the stimuli are both low ($P_1 = 0.6$; $P_2 = 0.65$); the probabilities are high and the certainty with which the participant could estimate the reward outcome is also high, thereby defining the trial as a difficult-certain (HCLU, see Figure-2c). Due to the task design, the participants do not experience any trials that are easy-uncertain (LCHU). This categorical approach of dividing the uncertainty is just a discretized version of the sum of individual uncertainties (See Supp. of ¹¹ for further details), 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.

Using the accuracy (the stimulus with highest reward probability is defined as the correct choice) and reaction time information along with the trial type as the inputs to the HDDM (Figure 2b) model, we estimated threshold and drift rates across the 5 conflict-uncertainty categories.

Insert Figure 2 here

Analysis 2: HDDM estimates independent of context

In addition to conflict-uncertainty based analysis, we performed an exploratory analysis where the participant overall responses for accuracy (correct vs incorrect) and risk (risky vs non-risky) with response time individually, were used to estimate the threshold (a) and drift rate (v) individually.

For the accuracy based estimate, the individual conflict-uncertainty categories were collapsed and a single value of threshold and drift rate was estimated using choice (correct vs incorrect) and response time.

We also labelled the participant's response to be either risky vs non-risky. To mark whether the choice selected was risky or not, we applied the variance expression (eqn. 2 (Figure 2e))

^{36,37} on the stimuli presented at each trial. The riskiest or uncertain choice was the stimulus whose reward probability was at chance level ($P = 0.5$), i.e., associated with the greatest variance in outcomes, and the least risky or certain choice was associated with either $P = 0.25$ or $P = 0.75$ with a greater likelihood of either winning or not winning and hence greater certainty or lower uncertainty. This information about the choice was then compared with the participant's selected choice in a given trial, to classify it to be either a risky or a non-risky one. This was repeated for all the trials and subjects and used as input to the HDDM model (Figure 2f). For this category alone, we estimated response bias (z) in addition to ' a ' & ' v '.

Trans-diagnostic factors

Using factor analysis on 209 question items drawn from a set of 9 psychological questionnaires, Gillan et al (2016) extracted 3 factors that corresponded to dimensions of anxious-depression (factor 1), compulsive behaviour and intrusive thought (factor 2), and social withdrawal (factor 3) (See ³¹ for details). We tested for associations between individual differences in scores on each of these 3 factors and the computational (conflict-uncertainty and context independent) estimates from the HDDM model.

Statistical Analyses

In line with the HDDM estimation of a and v , we used Bayesian methods as implemented in JASP for statistical analysis. Bayesian repeated measures ANOVA was used to test the significance, across the conditions 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 > 100 strong evidence in support of the alternate hypothesis ³⁸. The Bayes Factor used to report the evidence for a hypothesis was obtained from JASP which is based on the algorithm described in ³⁹⁻⁴¹.

Repeated measures ANOVA was used to test the significance in the accuracy levels and response time across the different conflict-uncertainty categories, which was greenhouse-geisser corrected for sphericity violation. A non-parametric spearman correlation was used as the trans-diagnostic factors did not obey normality. This was performed in SPSS version 27.

Results

Demographics: A total of 1413 participants completed a single session of the sequential learning task consisting of 200 trials. Within this cohort, a sub-sample of 1387 (806 Female) participants with mean (\pm SD) age (32.96 ± 10.78) and IQ (97.99 ± 9.56), who received adequate number of trials across all the five conflict-uncertainty conditions were used for further analyses.

Analysis 1 – Context of Conflict and Uncertainty

Behavioural measures: A repeated measures ANOVA shows a main effect of conflict-uncertainty (greenhouse-geisser corrected) on the accuracy levels ($F(2.25, 3120.74) = 98.98, p < 0.001$) and response time ($F(2.19, 3047.27) = 37.03, p < 0.001$) with means and standard deviations reported in Table 1. The participants performed at chance level in the *difficult-uncertain* (HCHU) when the choices were similar and the uncertainty associated with each of the choices was at chance ($P \sim 0.5$) and the highest accuracy was recorded for *easy-certain* (LCLU) scenario. Similarly, for response time, the participants were slower when the choices were certain and easy suggesting a systematic evaluation compared to when the uncertainty was high.

Table 1 lists the mean (\pm SD) values of accuracy, response time (seconds), threshold (a) and drift rate (v) for each of the conflict and uncertainty conditions

Condition	Accuracy	Response time (seconds)	Threshold (a)	Drift rate (v)
difficult-uncertain	0.5 ± 0.28	0.58 ± 0.26	1.37 ± 0.11	0.02 ± 0.08
difficult-medium	0.54 ± 0.11	0.59 ± 0.19	1.4 ± 0.18	0.15 ± 0.2
difficult-certain	0.53 ± 0.08	0.61 ± 0.19	1.43 ± 0.19	0.11 ± 0.17
easy-medium	0.55 ± 0.2	0.61 ± 0.21	1.42 ± 0.14	0.16 ± 0.16
easy-certain	0.62 ± 0.1	0.62 ± 0.19	1.45 ± 0.19	0.38 ± 0.25

HDDM estimates in the context of conflict and uncertainty: Using the choice, response time, and the type of conflict-uncertainty category (difficult-certain (HCLU); difficult-medium (HCMU); difficult-uncertain (HCHU); easy-certain (LCLU); easy-medium (LCMU)) from 1387 participants, as inputs to the HDDM, the threshold (a) and drift rate (v) were estimated.

For threshold, a repeated measures Bayesian ANOVA shows very strong evidence (Figure 3a) for a difference in the values for each of the conflict-uncertainty categories ($BF_{10} = 8.47 \times 10^{108}$) with individual means listed in Table 1. A post-hoc analysis for individual differences shows strong evidence across each of the conditions except difficult-certain and easy-medium conditions (See Supp. Table S1).

Insert Figure 3 here

For drift rate, a repeated measures Bayesian ANOVA shows exceedingly strong evidence (Figure 3b) for differences in the values for each of the conflict-uncertainty categories (beyond computer precision) with individual means listed in Table 1. A post-hoc analysis for individual differences shows strong evidence across each of the conditions except difficult-medium and easy-medium conditions (See Supp. Table S1).

The above results confirm our previous findings¹¹ on a larger cohort where participants show less evidence accumulation (lower threshold) and are slower to reach decision thresholds (lower drift rate) for *difficult uncertain* conditions (HCHU) relative to easy certain conditions (LCLU) with intermediate outcomes for the intermediate conditions.

Relationship between Conflict-Uncertainty HDDM estimates and Trans-diagnostic factors

We then conducted a correlation analysis in the sub-cohort ($n = 1387$) who completed all the questionnaires and trans-diagnostic factors estimated) between the HDDM parameters and the three trans-diagnostic factors while controlling for age and IQ

In keeping with our hypothesis, only on trials where the choices were similar and highly uncertain (*difficult-uncertain* HCHU) was a correlation observed between Compulsive Behaviour and Intrusive thought and threshold ($r = 0.05$, $p = 0.04$) (Figure 4), such that individuals high in compulsivity had higher thresholds. We found an unexpected and distinct pattern of association with social withdrawal, which was correlated negatively with thresholds in 4/5 conditions. The individual spearman correlation values are listed in See Supp. Table S2.

Insert Figure 4 here

For drift rate, there were no significant correlations between the 3 factors and each of the conditions except for LCLU ($r = 0.05, p < 0.05$) and HCMU ($r = 0.05, p < 0.05$), which correlated with Anxious-depression scale (factor 1).

Additionally, we also conducted a correlation analysis between the original 9 questionnaires and to the conflict-uncertainty parameters. Particularly noteworthy is the fact that, in contrast to the compulsivity dimension, scores on the OCD questionnaire did not reach significance in their association to thresholds in the difficult-uncertain condition ($r = 0.04, p = 0.16$). For contexts which correlated significantly with factor 3, a correlation with the Leibowitz Social Anxiety Scale score and AUDIT was also observed (See Supp. Table S3).

Analysis 2: HDDM estimates independent of context

Accuracy based estimates: The threshold (a) and drift rate (v) were estimated whose values were checked for convergence by visually inspecting the Monte Carlo chains. We then calculated the correlation between the 3 factors and these estimates. We found a statistically significant negative correlation only between the threshold and factor 3 ($r = -0.08, p = 0.002$) but not factor 1 ($r = -0.004, p = 0.88$) and factor 2 ($r = 0.03, p = 0.17$) while controlling for age and IQ levels. In terms of drift rate, factor2 ($r = -0.03, p = 0.33$) and factor 3 didn't correlate ($r = 0.04, p = 0.12$) but factor1 did ($r = 0.056, p = 0.04$).

Risk based estimates: The threshold (a), drift rate (v), and response bias (z) were estimated with choice (risky vs non-risky) and reaction time as the input variables. We then calculated the correlation between the 3 factors and these estimates. We found a statistically significant negative correlation only between the threshold and factor 3 ($r = -0.077, p = 0.004$) but not factor 1 ($r = -0.001, p = 0.98$) and factor 2 ($r = 0.03, p = 0.17$) while controlling for age and IQ levels. In terms of drift rate none of the factors correlated (factor1: $r = 0.03, p = 0.21$, factor2: $r = 0.03, p = 0.25$, factor3: $r = 0.02, p = 0.42$).

Together risk and accuracy-based estimates point to a generalised pattern of lower thresholds in social withdrawal. We then correlated the threshold parameter (a) with each of the questionnaires with accuracy and risk individually to understand their effect. As expected, the Leibowitz Social Anxiety Scale score which heavily contributes to factor 3, significantly correlated (risk: $r = -0.06, p = 0.02$; accuracy: $r = -0.06, p = 0.01$). Additionally, the AUDIT score also correlated (risk: $r = 0.09, p = 0.001$; accuracy: $r = 0.09, p = 0.001$) with threshold.

To verify that the correlation between the estimates and psychological factors were not driven by response time while selecting accurate choice, we checked the correlation between the response times of all the participants with the 3 factors. There was no significant correlation with factor3 ($r = 0.002$, $p = 0.93$) or factor2 ($r = 0.03$, $p = 0.29$) or factor1 ($r = 0.006$, $p = 0.83$).

Discussion

We first validated our previous observations¹¹ in a larger cohort demonstrating that within difficult-uncertain contexts, evidence accumulation is lower and at a slow rate (Figure 3). In keeping with our hypothesis, individuals with tendencies towards compulsive behaviours and intrusive thoughts show greater amount of evidence accumulated (threshold). This observation was absent with the individual compulsivity measure itself, thus highlighting the superiority of the trans-diagnostic approach. This result is in agreement with previous findings where compulsive subjects accumulated more evidence^{9,11,22,23} especially in ambiguous contexts, where choices are similar in value but show high return uncertainty.

The characteristic features of OCD such as indecisiveness, excessive information gathering⁴², and repetitive checking are driven by the uncertainty corresponding to the choice^{1,6,17,18,22,43}. Here we show that general population who score highly on a dimension of compulsive behaviours and intrusive thoughts demonstrate a similar cognitive profile to patients diagnosed with OCD¹¹ thus demonstrating similarities across a dimensional and categorical approach. Individuals with underlying compulsive personality traits may become increasingly cautious and perfectionistic in the context of greater difficulty and uncertainty. This might result in dysfunctional behaviour in failing to make decisions and fulfil roles and responsibilities in a timely manner. The population sampled varied across the spectrum and although individuals were recruited in a general online manner (i.e. not through clinics), many had clinically significant levels of compulsive symptomatology (e.g. OCD symptoms, alcohol dependence), suggesting they may be living with one or more disorders of compulsion.

This study adopted a trans-diagnostic approach, based on the idea that these dimensions of symptomatology may show a better fit to underlying cognitive or brain changes than disorder-based measures. This proved true in this dataset; the simple association between OCD symptom severity and exit thresholds was not significant for the *difficult-uncertain* condition, while the compulsivity dimension was. This follows a pattern seen in other

datasets studying these same factors, where for example associations between metacognitive changes (excessive confidence and poorer metacognitive accuracy) are more strongly linked to individual differences in this compulsive factor than OCD symptom severity itself^{29,33}. The same is true for confidence biases in the opposing direction, where the anxious-depression factor appears to have a stronger association to reductions in confidence than depression or anxiety alone^{29,33}.

An exploratory analysis revealed a generalized inverse relationship between the amount of evidence accumulated and social withdrawal. This finding appears to be independent of context. Social anxiety disorder or generalized social phobia is a debilitating condition in which an individual experiences an overwhelming fear of social interactions or performance demanding situations as they feel they are being judged and tends to avoid social situations^{44,45}. Here, social anxiety appears to be associated with lower evidence accumulation suggesting more rapid impulsive decision making irrespective of the decision-making scenario. Classically, patients with SAD display behaviours linked to being shy, submissive, behaviourally inhibited, and risk-averse^{46,47}. Our findings suggest social anxiety may be related to inadequate evaluation of evidence. This is consistent with the concept of ‘jumping to conclusions’^{48,49} in which a subject might rapidly interpret someone glancing at them or yawning in specific personal negative judgmental terms without adequately considering the objective evidence. However, these findings are somewhat at odds with recent work indicating an excess of deliberation, at least in social contexts, is associated with scores on this same dimension⁵⁰. Perhaps it is the nature/outcome of the deliberation that is at issue, consistent with cognitive behavioural therapy approaches for social anxiety to better evaluate and consider the objective evidence prior to making a decision that they are being judged socially. Future studies designed to probe this directly will be needed to follow-up on this interesting result.

The study is not without limitations. We have used a discretized approach to study conflict and uncertainty rather than a continuous regressor based approach. As the rationale of the 2-step task design³⁰ 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.

Thus, we replicate and extend our original findings dimensionally in a larger normative data set demonstrating specific impairments in evidence accumulation in *difficult uncertain*

contexts in those with traits characterized by compulsivity and intrusive thoughts. We further highlight rapid decision making, or a ‘jumping to conclusions’ style of decision making in those with social anxiety. Our findings suggest potential targets for cognitive behavioural therapy approaches.

Author Contributions: AM designed the method, analysed the data and, drafted the manuscript. CMG collected the data, analysed behavioural data and drafted the manuscript. VV designed the method, analysed the data and, drafted the manuscript.

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Conflict of Interest: The authors declare no conflict of interest

Figure Legends

Figure 1 shows the sequential learning task (a) Time-evolution of various stages in the sequential learning task including type of transition at stage1 (b) the slow Gaussian walk of the reward probabilities of the each of the four stimuli (blue and orange) at stage2 for 200 trials ³¹

Figure 2 Hierarchical drift-diffusion model (HDDM) with conflict and uncertainty. (a) Risk/uncertainty as a function of second stage reward probability (equation 2) which follows an inverted U- curve with categories explained in Table (1d), (b) Pictorial representation of the structure of the HDDM with input variables and estimates for conflict-uncertainty based estimation, (c) Pictorial representation of the conflict and uncertainty calculated from the reward probabilities at stage2, (d) shows the table with probability range of the two choices and their combinations to form each of the uncertainty conditions, (e) An example of risky and non-risky choice in the risk/uncertainty function and (f) Pictorial representation of HDDM with input variables (choice: accuracy or risk, response time (RT)) for context-independent parameter estimation.

Figure 3 shows the Hierarchical drift diffusion model estimates (a) shows the threshold parameter and (b) shows the drift rate (v) parameter for each of the conflict-uncertainty conditions. Abbreviations: difficult-certain (HCLU); difficult-medium (HCMU); difficult-uncertain (HCHU); easy-certain (LCLU); easy-medium (LCMU)

Figure 4 shows the scatter plot between threshold (a) in difficult-uncertain(HCHU) condition and compulsive behaviour and intrusive thought' (Factor 2) ($p = 0.04$).

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Figures

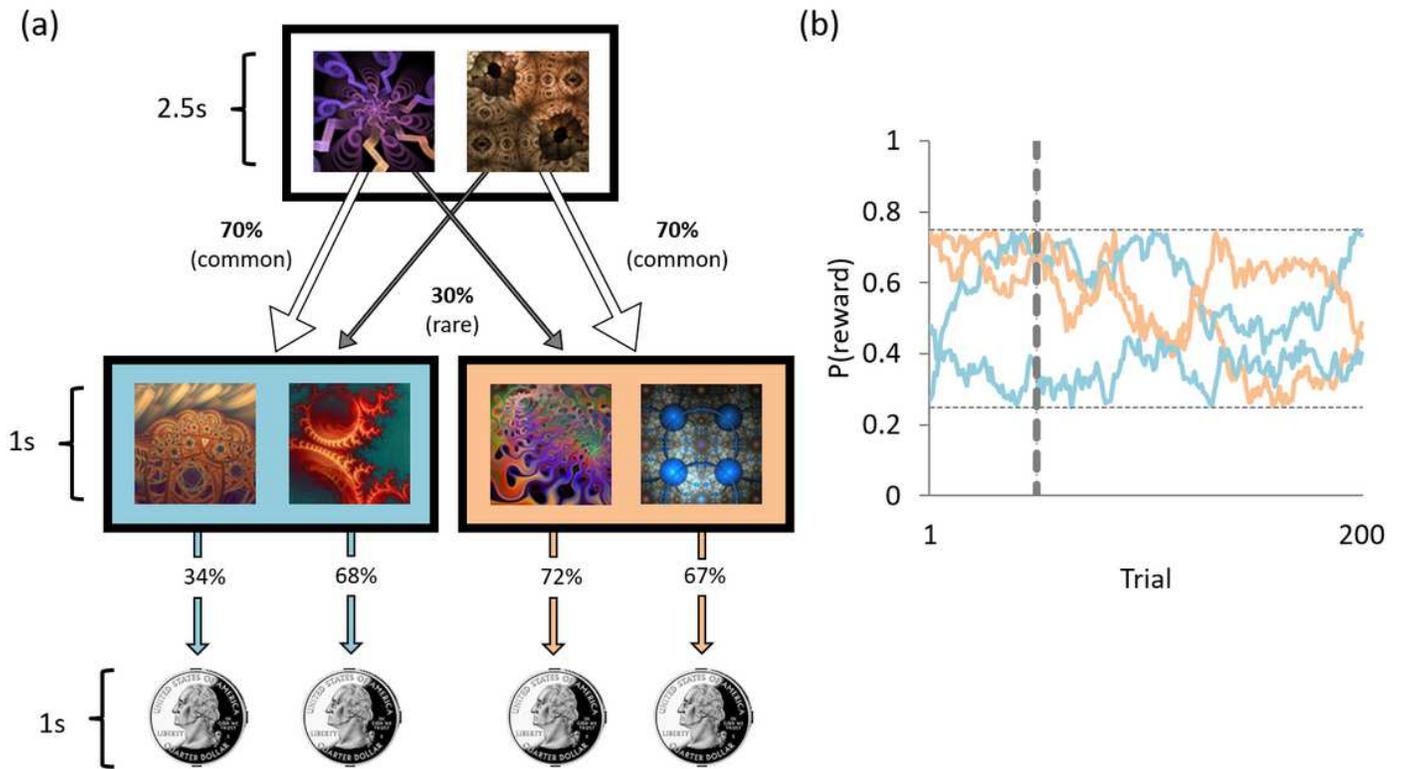


Figure 1

shows the sequential learning task (a) Time-evolution of various stages in the sequential learning task including type of transition at stage1 (b) the slow Gaussian walk of the reward probabilities of the each of the four stimuli (blue and orange) at stage2 for 200 trials 31

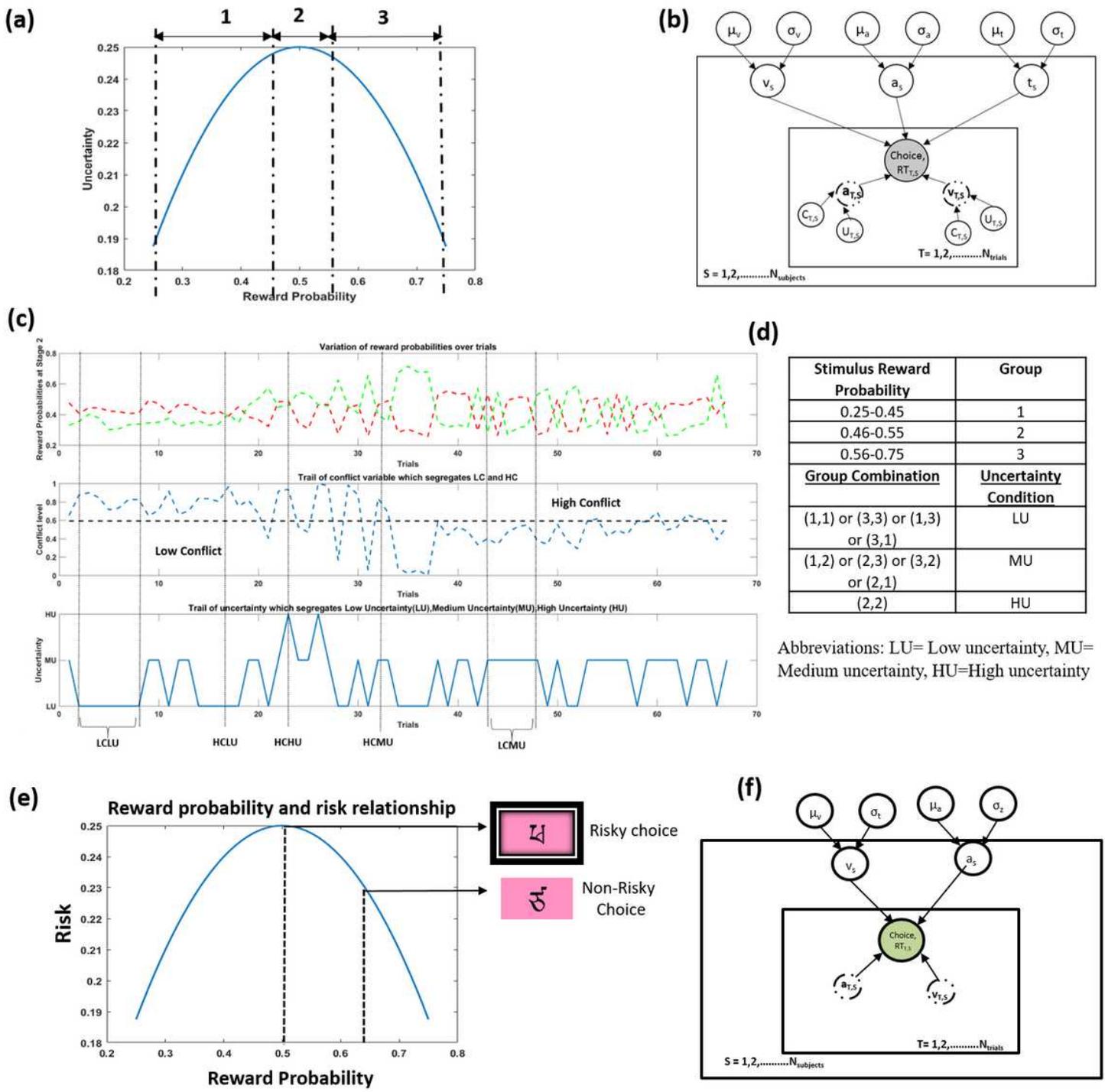


Figure 2

Hierarchical drift-diffusion model (HDDM) with conflict and uncertainty. (a) Risk/uncertainty as a function of second stage reward probability (equation 2) which follows an inverted U-curve with categories explained in Table (1d), (b) Pictorial representation of the structure of the HDDM with input variables and estimates for conflict-uncertainty based estimation, (c) Pictorial representation of the conflict and uncertainty calculated from the reward probabilities at stage2, (d) shows the table with probability range of the two choices and their combinations to form each of the uncertainty conditions,

(e) An example of risky and non-risky choice in the risk/uncertainty function and (f) Pictorial representation of HDDM with input variables (choice: accuracy or risk, response time (RT)) for context-independent parameter estimation.

** evidence for difference between categories (Table 3)

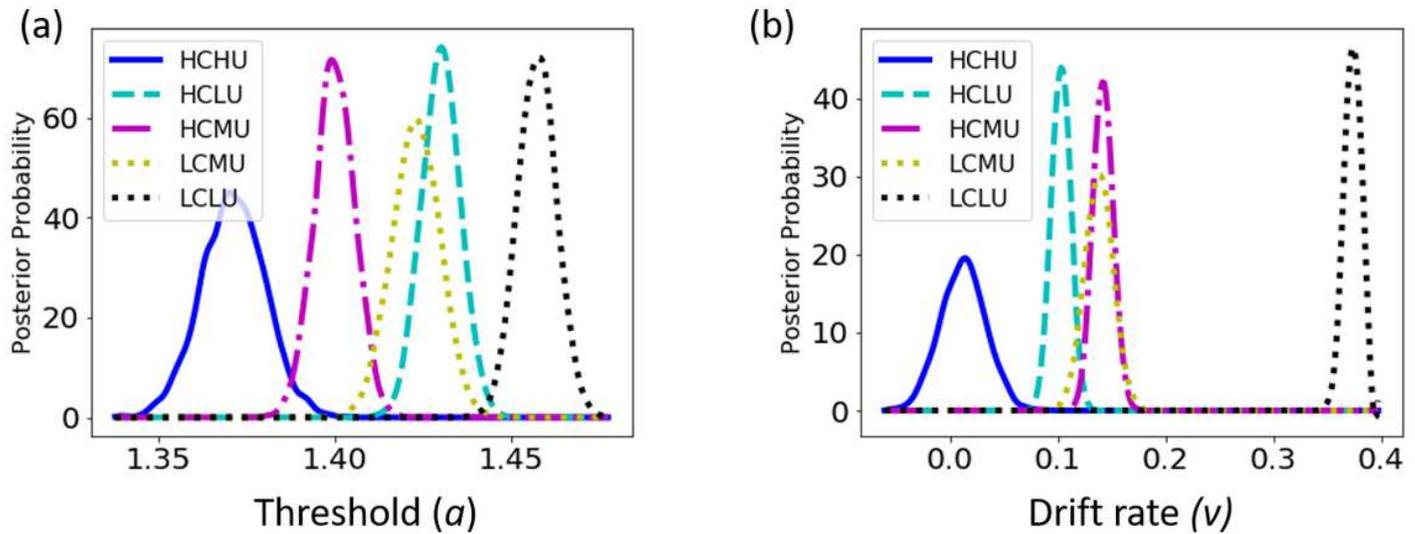


Figure 3

shows the Hierarchical drift diffusion model estimates (a) shows the threshold parameter and (b) shows the drift rate (v) parameter for each of the conflict-uncertainty conditions. Abbreviations: difficult-certain (HCLU); difficult-medium (HCMU); difficult-uncertain (HCHU); easy-certain (LCLU); easy-medium (LCMU)

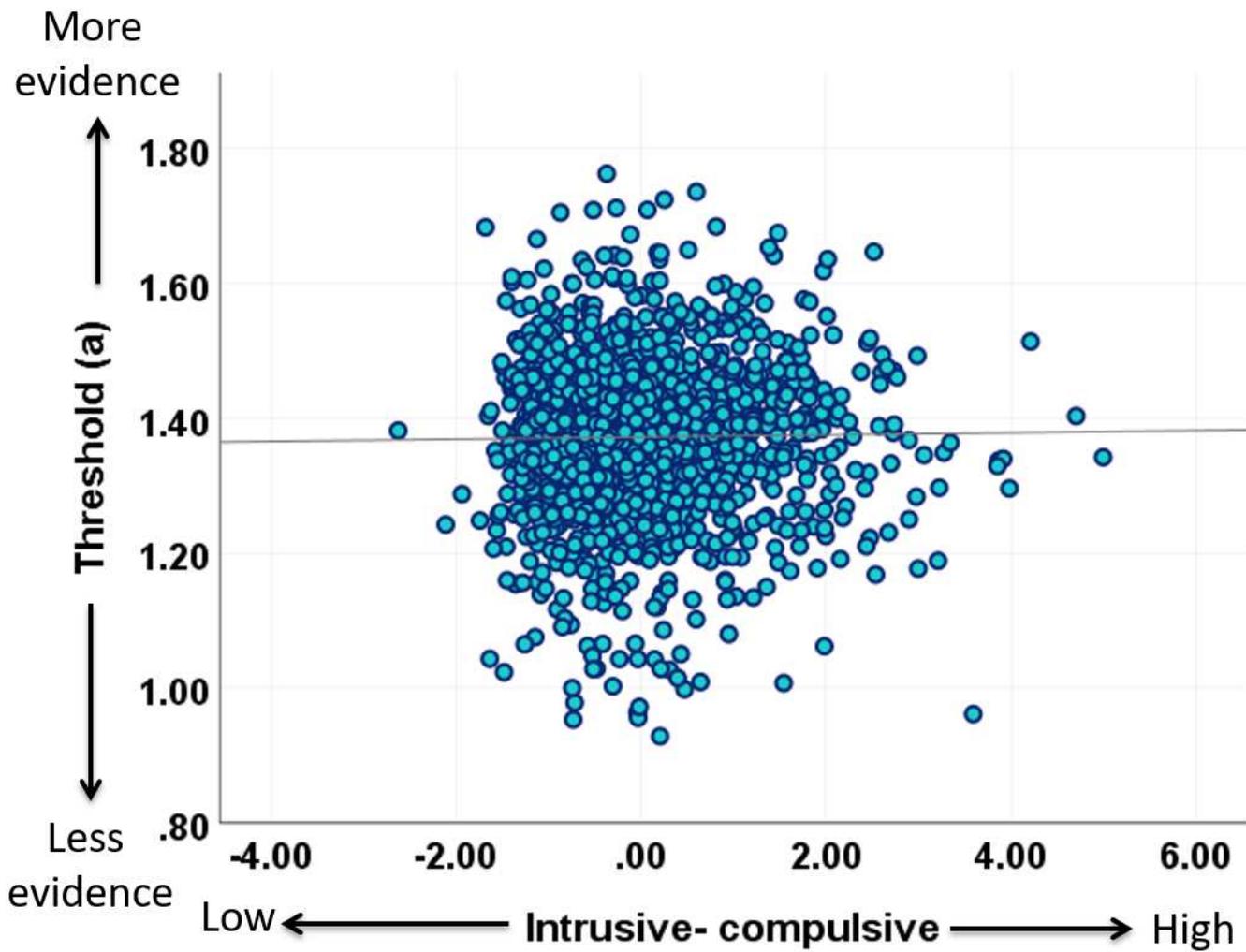


Figure 4

shows the scatter plot between threshold (a) in difficult-uncertain(HCHU) condition and compulsive behaviour and intrusive thought' (Factor 2) ($p = 0.04$).

Supplementary Files

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