Cost evaluation during decision making in patients at early stages of psychosis

Anna O. Ermakova[1], Nimrod Gileadi[2], Franziska Knolle[2,3], Azucena Justicia Diaz[2,4], Rachel Anderson[2], Paul C. Fletcher[2,3,4,6], Michael Moutoussis[7], Graham K. Murray[2,3,4]

[1] Unit for Social & Community Psychiatry, WHO Collaborating Centre for Mental Health Services Development, East London NHS Foundation Trust

[2] Department of Psychiatry, University of Cambridge

[3] Behavioural and Clinical Neuroscience Institute, University of Cambridge

[4] Cambridgeshire and Peterborough NHS Foundation Trust

[5] Department of Psychology, University of Cambridge

[6] Institute of Metabolic Science, University of Cambridge

[7] Faculty of Brain Sciences, University College London

Correspondence to Dr Graham Murray gm285@cam.ac.uk

ABSTRACT

Jumping to conclusions during probabilistic reasoning is a cognitive bias reliably observed in psychosis, and linked to delusion formation. Although the reasons why people jump to conclusions are unknown, one suggestion is that they view sampling information as costly. However, previous computational modelling (Moutoussis, Bentall, El-Deredy, & Dayan, 2011) has provided evidence against it, suggesting that patients with chronic schizophrenia jump to conclusion because of noisy decision making. We therefore developed a novel version of the classical beads-task where the cost of information gathering is systematically manipulated throughout four blocks. For 31 individuals with early psychosis, and 31 healthy volunteers we examined the numbers of 'draws to decision' when information sampling had no, a fixed, or an escalating cost. Computational modelling was identical to previous work, and involved estimating a cost of information sampling parameter and a cognitive noise parameter. Overall patients sampled less information than controls. However, group differences in numbers of draws became less prominent at higher cost trials, as less information was sampled by both groups. The attenuation of group difference was not due to floor effects, as in the most costly block participants sampled more information than an ideal Bayesian agent. Computational modelling showed that patients attributed higher costs to information sampling than controls, but groups were similar in estimates of the noise parameter. Using a psychological manipulation and computational modelling, we provide evidence that early psychosis patients jump to conclusions because of attributing higher costs to sampling information, and not because of being primarily noisy decision makers.

INTRODUCTION

A consistent psychological finding in schizophrenia research is that patients, especially those with delusions, gather less information before reaching a decision. This tendency to draw a conclusion on the basis of little evidence has been called a jumping to conclusions (JTC) bias (Garety & Freeman, 2013). According to cognitive theories of psychosis, a JTC bias is a trait representing liability to delusions. People who jump to conclusions easily accept implausible ideas, discounting alternative explanations, thus ensuring the persistence of delusions (Garety & Freeman 1999; Garety et al. 2007; Garety et al. 2013). Reviews and meta-analyses confirm the specificity, strength and reliability of the association of JTC bias and psychotic symptoms (Dudley, Taylor, Wickham, & Hutton, 2016; Fine, Gardner, Craigie, & Gold, 2007; Garety & Freeman, 2013; Ross, McKay, Coltheart, & Langdon, 2015; S. H. So, Garety, Peters, & Kapur, 2010; S. H. wai So, Siu, Wong, Chan, & Garety, 2015).

The JTC bias is commonly measured in psychosis research using variants of the "beads in the jar" task (Huq, Garety, & Hemsley, 1988). A person is presented with beads drawn one at time from one of two jars containing beads of two colours mixed in opposite ratios (Garety, Hemsley, & Wessely, 1991; Huq et al., 1988). Jumping to conclusions has been operationally defined in the 'beads' tasks as making decisions after just one or two beads (Garety et al., 2005; Warman, Lysaker, Martin, Davis, & Haudenschield, 2007). The commonly used outcome in this task is the number of beads seen before choosing the jar, known as draws to decision (DTD). The task requires the participant to decide of how much information to sample before making a final decision. This behaviour can be compared to the behaviour of an ideal Bayesian reasoning agent (Huq et al., 1988). However, when people experience evidence seeking as costly, it is thought that gathering less information could be seen as optimal leading to monetary gains at the expense of accuracy (Furl & Averbeck, 2011).

Although the JTC bias has been well replicated, the neurocognitive mechanisms underlying it are unknown; many possible psychological explanations have been put forward, not all of which are mutually exclusive (Evans, Averbeck, & Furl, 2015). Motivational factors, such as intolerance of uncertainty (Bentall & Swarbrick, 2003; Broome et al., 2007), a "need for closure" (Colbert & Peters, 2002), a cost to self-esteem of seeming to need more information (Bentall & Swarbrick, 2003) or an abnormal "hypersalience of evidence" (Esslinger et al., 2013; Menon, Mizrahi, & Kapur, 2008; Speechley, Whitman, & Woodward, 2010) have been posited as potentially underlying the JTC bias. A common theme emerging from the intolerance of uncertainty, the need for closure, and the cost to self-esteem hypotheses is that patients experience an excessive cost of sampling information.

Computational models allow researchers to consider important latent factors influencing decisions. The "costed Bayesian model" (Moutoussis et al., 2011) incorporates a Bayesian consideration of future outcomes with the subjective benefits or penalty (cost) for gathering additional information on each trial and the noise during the decision making; Moutoussis and colleagues (2011) applied this computational model to the information sampling behaviour of a sample of chronic schizophrenia patients undertaking the beads task. They found, contrary to their expectations, that a higher perceived cost of the information gathering did not underpin the JTC bias. Therefore, they concluded that differences in the 'noise' of decision making were more useful in explaining the differences between patients and controls than the perceived cost of the information sampling. However, here we reason that a rejection of the "increased cost of information sampling" account of the JTC bias based on this finding is premature, as patients with chronic schizophrenia may not be representative of all psychosis patients, especially not for those at early stages of psychosis. A variety of different cognitive factors may contribute to the JTC bias; the balance of contributory factors may differ in different patient populations, with noisy decision making relating to executive cognitive impairments predominating in chronic, but perhaps not in early stages of psychosis. Furthermore, Moutoussis and colleagues (2011) applied their model to an existing dataset (Corcoran et al., 2008) which used the classic beads task. In this task, no explicit value was assigned to getting an answer correct or incorrect, and no explicit cost was assigned to gathering information. The authors themselves concluded that their work required replication, including incorporation of experimental manipulation of rewards and penalties.

The current study investigated the hypothesis that patients with early psychosis attribute higher costs to information sampling using a novel version of the traditional beads task and computational modelling. Focusing on patients at early stages of psychosis allowed us to investigate the JTC bias before the onset of a potential neuropsychological decline seen in some patients with chronic schizophrenia, and to study a largely unmedicated sample of psychosis patients. Specifically, we were interested in testing whether patients adapted their decision strategies when there is an explicit cost of information sampling. We, therefore, developed a variation of the beads task in which there were blocks with and without an explicit cost of information sampling, and we gave feedback for correct and incorrect answers. This manipulation allowed the comparison between groups on different cost schedules. However, it would also allow us to test the competing hypothesis which is that psychosis patients jump to conclusions because of primarily noisy decision making

behaviour. Under this account, patients should be insensitive to a cost manipulation in the novel setup of the paradigm and apply random decision making.

This study presents a novel investigation of the processes that lead to reduced information sampling in psychosis. We hypothesised that (1) psychosis patients would gather less information than controls when gathering information is cheap, and that (2) psychosis patients and control would adjust their information sampling according to experimental cost manipulations and that the adjustments would mitigate, but not abolish, the difference between the groups. Finally, we hypothesised that (3) the costed-Bayesian model applied to this paradigm and largely unmedicated early psychosis group would provide explanatory evidence for JTC bias in favour of less information sampling because of higher perceived costs rather than purely noisy decision making.

METHODS

Study participants

The study was approved by the Cambridgeshire 3 National Health Service research ethics committee. An early psychosis group (N=31) was recruited, consisting of individuals with first episode psychotic illness (N=14) or with At Risk Mental States (ARMS; N=17), from the Cambridge early intervention service in psychosis, CAMEO. Inclusion criteria were as follows: age 16–35 years, current psychotic symptoms meeting either ARMS or first episode of psychosis criteria according to the Comprehensive Assessment of At-Risk Mental States (CAARMS) (Morrison et al., 2012; Yung et al., 2005). Healthy volunteers (N=35) without a history of psychiatric illness or brain injury were recruited as control subjects. None of the participants had drug or alcohol dependence. Healthy volunteers have not reported any personal or family history of neurological or psychotic illnesses, and were matched with regard to age, gender, handedness, level of education, and maternal level of education. None of the patients with ARMS were taking antipsychotic medication, and four patients with FEP were on antipsychotic medication at the time of testing. All of the experiments were completed with the participant's written informed consent.

Jumping to Conclusions Task

This was a novel task (Figure 1), based on previously published tasks (Garety et al., 1991; Huq et al., 1988) of reasoning bias in psychosis, but amended in the light of decision-making theory, according to which the amount of evidence sought is inversely proportional to the costs of information sampling. These costs include the high subjective cost of uncertainty, and the cost to self-esteem or other factors (Moutoussis et al., 2011). Participants were told that there are two lakes, each containing black and gold fish in two different ratios (60:40). The ratios were explicitly stated and displayed on the introductory slide. A series of fish was drawn from one of the lakes; all the previously 'caught' fish were visible, in order to reduce the working memory load. The participants were informed that fish were being 'caught' randomly from either of the two lakes and then allowed to 'swim away'. We used a pseudorandomised order for each trial which was the same for all of the participants. The lake where the fish were drawn from was also pseudorandomised.

Participants could ask for a maximum of 20 fish to be shown. After each fish shown they either indicated whether the fish came from Lake G or B, or asked to see another fish. The trial terminated when the subject chose the lake. There were four blocks, each with the 10 trials of the predetermined sequences, in order to increase reliability. Block 1 was similar to the classical beads task, and was included to provide a reference point. The only difference was that feedback ('correct' or 'incorrect') was provided after each trial. In Block 2, a win was assigned to a correct decision (100 points) and a loss (–100 points) to an incorrect decision. In Block 3, the cost of each extra fish after the first one was introduced (–5 points) and was subtracted from the possible win or loss of 100 points for making a correct or incorrect decision respectively. Block 4 was similar to Block 3, but the information sampling cost was incrementally increased. The first fish would cost 0 points, the second –5 points, the third –15 points, etc.). Thus, the more fish would be sampled, the more points would be lost. Subjects performed the task at their own pace. Whether Lake G or B was correct was randomised. The task consisted of four blocks. Within each block there were 10 trials of predetermined sequences of fish, in order to increase reliability. All of the fish that were 'caught' during one trial were visible on the screen in order to minimise the working memory load. Block order was not randomised because the task increased in complexity.

The main outcome variable was the number of fish sampled (draws to decision, DTD). Secondary outcomes were the accuracy of the decision, calculated according to Bayes' theorem based on the probability of the chosen lake given the colour and number of fish seen (Everitt & Skrondal, 2010), and the dichotomous JTC variable, which is defined as making decision after 2 or less pieces of information.

Mathematical of ideal Bayesian behaviour in the Jumping to Conclusion Task

Rewards and costs in our formulation of the Jumping to Conclusion task were very explicit, allowing for a mathematically ideal behaviour to be defined. The agent is faced with a choice of three actions:

- Declare fish from black lake (DB)
- Declare fish from golden lake (DG)
- Ask for another fish – more information sampling (DS)

The ideal agent will pick the option which maximises its expected reward (or Action Value). For the first two choices, the action value is easy to quantify. For example:

$Q(D_G; n_d, n_g) = R_C P(G \mid n_d, n_g) - C_W P(B \mid n_d, n_g)$

Where:

$Q(D_G; n_d, n_g)$is the action value of declaring the lake gold, after drawing$n_d$fish and seeing $n_g$gold fish.

$P(G \mid n_d, n_g)$is the probability of the lake being gold, after drawing$n_d$fish and seeing$n_g$gold fish.

$R_C$is the reward for correctly declaring the colour of the lake.

$C_W$is the cost of incorrectly declaring the colour of the lake.

(n_d, n_g)In our task, $R_C = C_W$, so:

$Q(D_G; n_d, n_g) = R_C[P(G \mid n_d, n_g) - P(B \mid n_d, n_g)] = R_C[2P(G \mid n_d, n_g) - 1]$

Similarly:

$Q(D_B; n_d, n_g) = R_C[P(B \mid n_d, n_g) - P(G \mid n_d, n_g)] = R_C[1 - 2P(G \mid n_d, n_g)]$

Using Bayes' theorem, and assuming that a gold lake and a black lake are equally probable:

$$P(G \mid n_d, n_g) = \frac{P(n_d, n_g \mid G)P(G)}{P(n_d, n_g \mid G)P(G) + P(n_d, n_g \mid B)P(B)} = \frac{P(n_d, n_g \mid G)}{P(n_d, n_g \mid G) + P(n_d, n_g \mid B)}$$

$$P(n_d, n_g \mid G) = \binom{n_g}{n_d} P(g \mid G)^{n_g}[1 - P(g \mid G)]^{n_d - n_g}$$

$$P(n_d, n_g \mid B) = \binom{n_g}{n_d} P(g \mid B)^{n_g}[1 - P(g \mid B)]^{n_d - n_g}$$

$$P(G \mid n_d, n_g) = \frac{P(g \mid G)^{n_g}[1 - P(g \mid G)]^{n_d - n_g}}{P(g \mid G)^{n_g}[1 - P(g \mid G)]^{n_d - n_g} + P(g \mid B)^{n_g}[1 - P(g \mid B)]^{n_d - n_g}}$$

When calculating the action value of sampling again, the choice will have resulted in a new state and

further choices will be based on the new state: if the agent is at state s, the cost of sampling again is $C_S(n_d)$[1], and the value of a state is given by $V(s)$, we can retrieve the action value for sampling again by summing over the new possible states, weighted by their probabilities.

$$Q(D_S; s) = -C_S + \sum_{L \in \{G,B\}} P(L \mid s) \sum_{s'} V(s')P(s' \mid L)$$

For our task, the possible outcomes for sampling again are getting a black fish (going from (n_d, n_g) to $(n_d + 1, n_g)$) and getting a gold fish (going from $(n_d, n_g)$to $(n_d + 1, n_g + 1)$)

$$\begin{aligned} Q(D_S; n_d, n_g) \quad = \quad & -C_S(n_d) \\ & +P(G \mid n_d, n_g) \times \{V(n_d + 1, n_g + 1)P(g \mid G) + V(n_d + 1, n_g)P(b \mid G)\} \\ & +P(B \mid n_d, n_g) \times \{V(n_d + 1, n_g + 1)P(g \mid B) + V(n_d + 1, n_g)P(b \mid B)\} \end{aligned}$$

The ideal agent will always chose the action with the maximum value, so:

$$V(n_d, n_g) = max\{Q(D_G; n_d, n_g), Q(D_B; n_d, n_g), Q(D_S; n_d, n_g)\}$$

In our experiment, the number of draws was limited to 20, so in the last draw, $D_S$is not an option, and the state value can be calculated directly from the fish counts. Once all possible state values for $n_d = 20$ have been calculated, it's possible to calculate action and state values for $n_d = 19$ and downwards to $n_d = 1$.

When given the same sequence of fish as human participants, on average the ideal Bayesian agent sampled 20, 20, 3.5 and 1 fish in each of the four blocks, respectively, achieving total winnings of 1070 points (Table 1). For no cost (Block 1 and 2), an ideal Bayesian agent samples all the fish and has p=0.835 of being correct (actually 100%, but we assume infinite fish). For constant cost (5 points, Block 3), it samples until the difference between black and gold fish (Nb-Ng) is 2, with p=0.692 probability. For increasing cost (Block 4), it guesses after the first fish, so there's 0.6 probability. It should be noted that the value of 1 in Block 4 for the Bayesian agent is a more hasty decision than either the control group or the patient group exhibited on the task, indicating that the floor effects did not operate on the task.

Computational Modelling

[1]For our experiment, C_S is a function of the number of fish seen so far.

In addition to the statistical analysis above, we conducted further analysis using a computational model used for a similar experiment (Moutoussis et al., 2011). This model is based on the behaviour of an ideal Bayesian agent operating on the "beads" problem. The ideal Bayesian agent has a known cost associated with sampling more data, and known reward values for guessing the colour correctly. The agent makes choices that maximise its expected reward. Behaviour under these assumptions is explored. To adapt this model to human behaviour, a noise parameter is introduced, which allows the ideal Bayesian decisions (which are deterministic) to be corrupted with probability governed by the noise parameter (Moutoussis et al., 2011).

Thus there are two parameters that could describe a participant's behaviour:

- CS: the cost of sampling, is a measure of how much cost the participant assigns to getting more information, compared to the final reward. High values of CS mean that decisions are made early.
- T: the noise parameter. As this value increases, the probability of the participant following the ideal behaviour (for their given value of CS) decreases, and their actions become more uniformly random.

Given sufficient data, one could estimate these two parameters for each participant, and make statistical claims about different participant groups given those values. Unfortunately, deriving these parameters from our experimental data is difficult: there are different combinations of the cost and noise parameters that could explain one participant's behaviour, and the available data are not sufficient to estimate a pair of parameters for each participant.

Instead, we used what is known as a random effects model: we assumed that a participant's model parameters are drawn from a group distribution of parameters. Instead of estimating each individual participant's parameters, we estimate the group's distribution, characterised by a mean and a variance. So instead of fitting CS and T for each participant, we try to estimate the mean and variance for CS and for T for the whole group. For a group of, for example, 30 participants with 10 data points each, we use 300 data points to estimate 4 values (i.e. mean and variance for each of the two parameter distributions), rather than 2 different parameters for each of the 30 participants (i.e. 60 parameters in total). This allows us to get meaningful and statistically correct results from a smaller data set.

To do this parameter estimation, we used a technique called EM (expectation maximization), using code adapted from Moutoussis et al. (2011). This is an optimization method that tries to find maximum-likelihood (ML) parameters for a model, given experimental data.

For our experiments, we ran between 25 iterations of the EM algorithm. Runs took about 30s per iteration per participant on a single core of an Intel Core2 Duo CPU and 4GB of RAM.

Once the ML parameters for a given group are estimated, they can be interpreted using the integrated Bayesian Information Criterion (iBIC (Huys et al., 2012, 2015)), which uses the likelihood values of best-fit parameters for two different models to decide which model best represents the data. It contains a penalty term for models which have more parameters and can be used as a form of hypothesis testing: if one model has all participant parameters coming from one distribution (4 parameters), and a second model separates the control and unhealthy groups (8 parameters), a comparison of iBIC values can be used to decide if splitting the groups is justified.

Rating scales and questionnaires

The participants underwent a general psychiatric interview and assessment (Table 2) using the Comprehensive Assessment of At Risk Mental States (CAARMS) (Morrison et al., 2012; Yung et al., 2005), the Positive and Negative Symptom Scale (PANSS) (Kay, Fiszbein, & Opler, 1987), the Scale for the Assessment of Negative Symptoms (SANS) (Andreasen, 1989) and the Global Assessment of Functioning (GAF) (Hall, 1995). The Beck Depression Inventory (BDI) (Beck, Steer, & Brown, 1996) was used to assess depressive symptoms during the last 2 weeks. IQ was estimated using the Culture Fair Intelligence Test (Cattell & Cattell, 1973). Schizotypy was measured with the 21-item Peters et al. Delusions Inventory (PDI-21) (Peters, Joseph, Day, & Garety, 2004).

Statistical analysis of the behavioural data

The effect of manipulations of wins, losses and costs on the DTD and accuracy was assessed by repeated-measures analysis of variance (ANOVA) using SPSS 21 (IBM Corp.). We looked at the trend of reducing DTD with increasing costs of decision making of the last three blocks only in order to better interpret the group × block interactions (the last three blocks are matched in terms of an explicit value of a correct response, whereas the first block has no explicit value of a correct response). Although DTD was not normally distributed, repeated-measures ANOVA is robust to violations of normality, and was therefore an appropriate test to run. IQ and depressive symptoms scores were initially included as covariates and dropped from the subsequent analysis where non-significant. We report two-tailed p-values, which were significant at $p<0.05$. When the assumption of

sphericity was violated we applied Greenhouse–Geisser corrections. We also examined whether DTD was correlated with the severity of psychotic symptoms in the patient group (CAARMS positive symptoms) and with schizotypy scores on the PDI in controls using Spearman's correlation coefficients. The intra-class correlation coefficients (ICCs) were used to estimate the consistency of decision making. We calculated the ICCs of the mean number of choices in each block separately for patients and controls.

For completeness and to help relate our study to prior literature, we report data on the dichotomous variable JTC, defined as making a decision after receiving one or two pieces of information.

RESULTS

Demographical characteristics of the participants

In Table 2 the socio-demographic and cognitive parameters as well as clinical measures of the participants are presented. Although healthy volunteers had higher IQ, compared to the psychosis group, the difference was not significant, and the groups were matched with regard to level of maternal education and number of years of education. The control and patient group did not differ with regard to gender or age. There were significantly more smokers in the patient groups compared with the control group, and some of the patient group used more recreational drugs. For all of the other measures (e.g. alcohol or cannabis) there were no significant group differences. As expected there are significant differences between the healthy volunteers and the patients in all subscales of CAARMS (Table 3), on the self-reported depression questionnaire (BDI) and self-reported schizotypy scores (PDI). In patient group only we have performed additional clinical assessments. The mean (±SD) score for PANSS positive symptoms was 13.68 (±3.99); for PANSS negative symptoms 9.87 (±4.88); SANS 0.35 (±0.75) and GAF 55.00 (±18.54).

Group differences in the number of DTD and points

Inspection of Figure 2A reveals that in all of the blocks, the controls took more draws to decision than the patients. Mauchly's test indicated that the assumption of sphericity was not violated ($W(5)=0.211$, $p<0.001$). On mixed-model ANOVA, there were significant main effects of block

($F(1)=94.49$, $p<0.001$ and of group ($F(1)=5.99$, $p=0.017$) on the number of DTD. The interaction between the group and the block was also significant ($F(3)=39.37$, $p=0.006$). This indicates that, depending on the group, block change had different effects on DTD. Post-hoc Bonferroni-corrected tests demonstrated that group differences were significant in the first two blocks (Block 1: $p=0.007$; Block 2: $p=0.028$), whereas in Block 3 and 4 there were no group differences (Block 3: $p=0.059$; Block 4: $p=0.419$). The group differences became increasingly reduced as the cost of decision-making became increasingly high. Controls behaviour was more similar to the ideal Bayesian agent than patients on the first three blocks but not Block 4 (Table 1). Group differences in the probability of being correct were very similar to the results in the number of DTD (Figure 2B).

Analysing the point won/lost in Block 2-4 (Figure 3), we identified four outliers in each group that significantly exceeded ±2SD threshold. After excluding these subjects, the mixed-model ANOVA revealed a significant effect for block ($F(2)=93.73$, $p<0.001$), a marginally significant interaction between block x group ($F(2)=2.52$, $p=0.086$) and a significant groups effect ($F(1)=4.14$, $p=0.047$). Bonferroni corrected post-hoc analysis showed that patients won significantly fewer points in Block 2 ($F(2)=4.65$, $p=0.035$), but did not differ from controls in Block 3 and 4 (both $p>0.3$).

Percentage and count of people displaying a JTC reasoning style are presented in Table 4.

Intra-class correlations of DTD and SD of the mean DTD

Intra-class correlation coefficients (ICCs) of the mean number of DTD within each block were calculated separately for patients and controls. Within all blocks in both groups the correlations were very high, indicating that behaviour was consistent within each block (ICC values: Block 1: patients 0.965, controls 0.943; Block 2: patients 0.982, controls 0.973; Block 3: patients 0.972, controls 0.976; and Block 4: patients 0.973, controls 0.978).

Correlation of symptoms and IQ with DTD

We calculated two-tailed Spearman's correlations with positive psychotic symptoms in patients and with PDI scores in controls. In the patient group, we used a summary score of the three CAARMS subscales that quantify positive psychotic symptoms, namely Unusual Thought Content, Non-Bizzare Ideas (mainly persecutory ideas) and Perceptual Aberrations. An additional advantage of the summary measure is that it provides one measure to reduce the number of correlations that need to

be performed. We also ran correlations BDI scores because the groups differed on this measure. In the group with psychotic symptoms the correlations with the overall CAARMS score were significant in the first three blocks (Block 1: rho=–0.515, p=0.003; Block 2: rho= –0.489, p=0.005; Block 3: rho= –0.491, p=0.005). There were no correlations in the psychotic symptoms group between DTD and BDI score (for all p>0.1).

In controls, we found that there were significant correlations of DTD in Block 1 with the Distress (rho=-394, p=0.035) and Preoccupation (rho=–0.462, p=0.012) subscales of the PDI. DTD in Block 2 correlated with the Preoccupation subscale of PDI (rho=–0.387, p=0.038). There were no significant correlations with BDI scores (e.g. for Block 1 rho=-0.023, p=0.905).

In the patients we furthermore found a positive correlation between IQ and the first three blocks (Block 1: rho=–0.481, p=0.006; Block 2: rho=–0.362, p=0.045; Block 3: rho=–0.364, p=0.044). There was no such correlation in the controls.

Group differences in the probability of being correct (accuracy).

Mauchly's test indicated that the assumption of sphericity has not been violated (W(5)=0.667, p<0.001). There was a significant main effect of block on the probability of being correct (F(3)=53.502, p<0.001) and a significant effect of group (F(1)=5.514, p=0.022). There was a significant interaction between the group and the block (F(1)=2.791, p=0.042), indicating that as the cost of decision making increased, the group differences became attenuated.

Computational Modelling Results

Our computational analysis found that in Block 1-3, patients with early psychosis assigned a higher cost to sampling more data than healthy controls (Table 5). For example, in Block 1, where there was no explicit cost, the modelled mean cost of sampling in the controls was very low 1.9✕10-3, and in patients 1.7. The modelled variance was also higher for the patient group (13) compared to the controls (2.0X10-6). The estimated noise parameters were similar in each group. For example, in Block 1, the mean noise parameter for controls were 3.0 and 3.6, and 4.2 and 2.9 in patients.

In Block 3, where an explicit cost of 5 points per fish sampled was assigned, the model finds that patients very slightly overestimated the cost of sampling compared to the assigned cost (estimated mean cost of sample for patients 5.2), whereas the controls underestimated it (estimated mean cost of sample 1.6).

In Block 4, we explicitly told participants that the cost for additional information is not fixed, but increases with amount of information requested. We did not fit the computational model to Block 4 because the model does not take into account the increasing cost structure set up.

To test the null hypothesis that both groups are drawn from the same distribution of behaviour parameters, we used iBIC. Table 6 shows the results of that calculation, where the null hypothesis can be rejected with strong evidence. For example, in Block 1, despite the fact the iBIC penalises the use of extra parameters substantially, when fitting CSm, CSv, Tm and Tv, separately for each group iBIC was 3450.2, compared to a iBIC of 3489.7 for fitting them as one combined group. Taken together, the iBIC can be used to compare the hypothesis about the two models of interest. In our case those are the following two: 1) unhealthy and healthy groups have independent CS and T parameter distributions, characterised by 8 numbers (mean and variance for CS and for T, for each group); and 2) all participants come from the same pool of noise and cost parameters, characterised by 4 numbers. The iBIC suggests that hypothesis 1 is better explained by the separate model in Blocks 1 and 2, and by the combined model in Block 3.

DISCUSSION

Our study shows that early psychosis patients generally gather less information before coming to a conclusion compared to healthy controls. Both groups slightly increased their DTD when rewarded for a correct answer (Block 2), and significantly decreased their DTD when there was an explicit cost for the sampling of information (Block 3 and 4). The decrease was strongest in Block 4 including the incremental cost increase for each 'extra fish.' These effects were especially strong in controls, as they gathered significantly more information during Block 1 and 2 compared to patients. Thus, patients had a smalle0 "baseline" against which to exhibit a change in DTD with increasing cost. However, we emphasise that an ideal Bayesian decision agent would still sample fewer information in than controls or patients in Block 3 and 4. This indicates that potential floor effects may not be responsible for the decreased reduction of DTD in patients compared to controls. Together with our

modelling results, this finding rather supports the hypothesis that independent of the objective cost-value of information, patients with early psychosis experience information sampling as more costly than controls.

In this novel version of the beads task using blocks with explicit costs, jumping to conclusions can be an advantageous strategy, because sampling a large amount of very costly information would cancel out the potential gain due to correctly identifying the lake. Consistent with this, group differences were especially strong in the first two blocks, where information sampling was free. In Block 3, when there was only a small cost of information, both groups responded to that change by lowering the number fish sampled. The difference between the groups was marginally significant on Block 3, where patients still applied fewer DTD ($p=0.06$). However, further increasing the information sampling cost completely abolished the group differences. Our data furthermore show that patients were significantly worse in overall accuracy (i.e. probability of being correct at the time of making the decision) and total points won indicating the application of an unsuccessful strategy. In general, these results show that healthy controls were more flexible in adapting their information sampling to the changed task BLOCKS. They increased the number of fish sampled when there was a reward for the correct decision, and decreased it when information sampling had a cost. Patients also decreased the number of DTD when information sampling became more costly, but not as much as the controls, suggesting that the patients view information sampling generally as costly, somewhat independent of the actual value and the feedback. The results on Block 1 and 2, furthermore, indicate that psychosis patients have difficulties integrating feedback appropriately to update their future decisions. This is similar to results we reported in a recent study on the win-stay/lose-shift behaviour in a partially overlapping early psychosis group (Ermakova et al., 2017).

The variance in DTD across the two groups was similar and the ICCs were all greater than 0.94, indicating consistent decision making behaviour across the 10 trials in each block and within each group. If patients were acting more randomly, they would apply noisier and more variable decision making behaviour, but we did not observe this, which is in contrast to Moutoussis et al. (2011). Concluding from their Bayesian modelling data, they proposed that patients had more noise in their responses, leading to the reduced number of DTD. When modelling our data in a similar way, we found a difference between the groups in the perceived cost of information sampling, but not in the noise of the decision behaviour. Indeed, the computational model derived noise parameters were similar between the groups in all blocks with very slightly higher noise in patients in Blocks 1 and 3, and very slightly higher noise in controls in Block 2. We suggest that the contrast between our

findings and Moutoussis et al. (2011) may be mainly due to the differences in the patient groups used in the two studies. Whereas Moutoussis et al. (2011) used chronic schizophrenia patients with a potential neuropsychological decline and a slightly lower IQ, our study used patients at early stages with preserved cognitive functioning. Although we altered also our task to specifically investigate information sampling in relation to cost evaluation, Block 1 was very similar to the previous study. It differed in providing feedback (i.e. 'correct' or 'incorrect') after each decision, which potentially led the patients to stick to the same strategy throughout, which might be why we also did not see differences in the noise parameter in Block 1. However, as argued above it rather seems that patients are unable to integrate the feedback appropriately. When analysing the objective cost of information sampling in Block 3, we found that patients slightly overestimated the cost, while the controls underestimated it. We, furthermore, noticed that key contributors to the best fit parameters are those who jump to conclusions most: participants who consistently made a decision after viewing only one fish. The proportion of those individuals was significantly higher among the patients.

The percentage of people with psychosis who demonstrated JTC reasoning style in our study was relatively low, at 26%, compared to previous studies that report 40% of individuals (Dudley et al., 2011) or, half to two-thirds of the individuals with delusions (S. H. So et al., 2010). Likewise, our objective DTD values were slightly higher than that in most other studies. This might be due to the use of early stage psychosis patients and presence of feedback in our task compared to previous studies. Feedback has been shown to increase information sampling and accuracy both in patients with delusions and in controls (Lincoln, Ziegler, Mehl, & Rief, 2010).

Additionally, we found a correlation between IQ and DTD in the first three blocks in the patient group, so we cannot completely exclude the contribution of intelligence to the information-gathering bias. Some argue that impaired executive functions or working memory deficits contribute to the JTC bias (Falcone et al., 2015; Garety et al., 2013). A low IQ could lead to a low tolerance for uncertainty and an equivalent high cost of the information sampling, as well as the inability to integrate feedback in order to update future decisions. If more information is unpleasant, because it exceeds one's capacity to utilise it, it could be viewed as costly. However, the fact that the correlation does not appear in controls argues against this. Therefore, low IQ is likely to contribute to the JTC bias, but cannot solely explain its existence in psychosis.

Rather than focusing on ICD-10 or DSM-V schizophrenia patients, we studied a group of patients early in their course of psychosis. All patients in our study suffered from current psychotic symptoms. Psychosis is often viewed as an upper part of the continuum, ranging from rare occurrences of delusions or hallucinations at one end, through individuals with many 'schizotypal' traits (van Os, Linscott, Myin-Germeys, Delespaul, & Krabbendam, 2009). Consistent with this approach, we found that the more severe patients' positive symptoms were, the less information they sampled. To investigate the idea of the psychosis continuum further, we looked at the correlations between information sampling and schizotypy characteristics in healthy volunteers. In this group, we found a negative correlation between the number of DTD and the scores on the distress and preoccupation subscales of the PDI, indicating that less information sampling is associated with higher scores. This is consistent with studies by Colbert and Peters (2002) and Lee et al. (2011), as well as the recent meta-analysis by Ross et al. (2015), in keeping with a continuum model of psychosis.

Summary

In summary, we found that early psychosis patients demonstrate a hasty decision-making style compared with healthy volunteers, sampling significantly less information. Our data are not consistent with the account that patients sample less information because they are in general more noisy decision makers. Rather, our data suggest that patients with psychosis sample less information before making a decision because they attribute a higher cost to information sampling. Whilst, psychosis patients were less able to adapt to the changing demands of the task, we note that they did alter their decision making style in response to the changing explicit costs of information. This indicates that this impulsive decision making style is not fixed in psychosis, consistent with the possibility that it may be a treatment target, e.g. for psychotherapy (Moritz et al., 2014). Patients performed worse with increased total score for positive symptoms.

Figure Captions

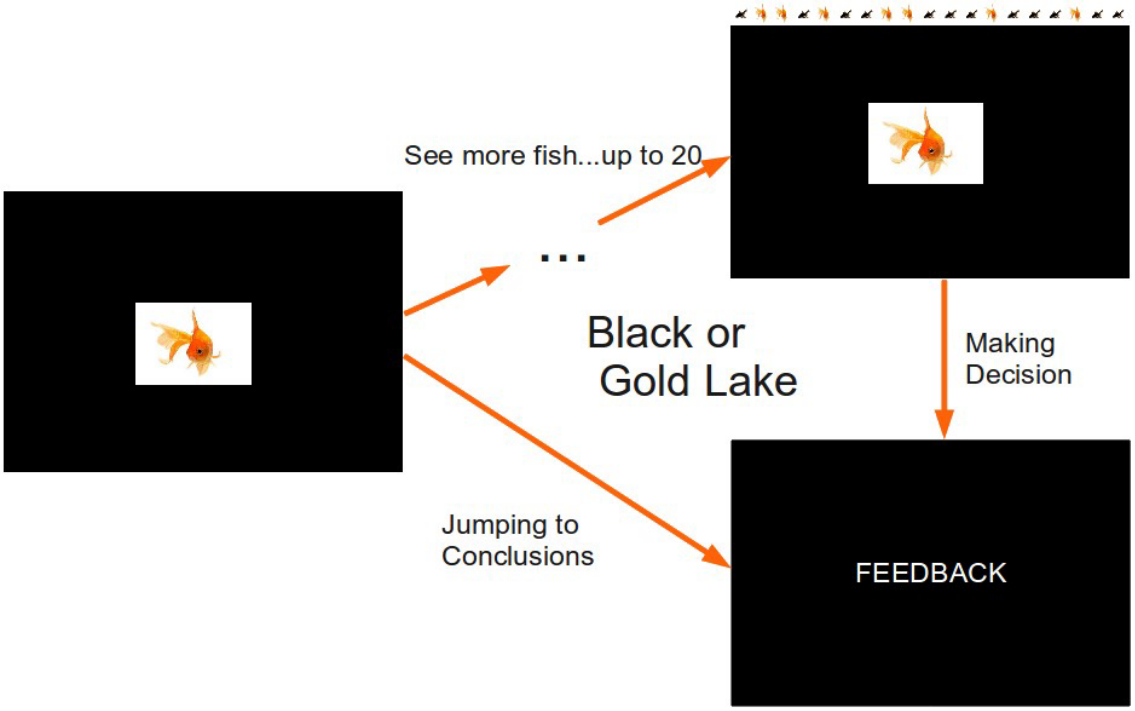

Figure 1: Experimental design of a single trial. In 50% of the trials fish were coming from the black lake, and in 50% they were coming from the gold lake. The order was pseudorandomised, so that the same sequences were used for all participants. Feedback, depending on the block, was either the words 'Correct' or 'Incorrect' in Block 1 or the number of points won or lost)during the trial in all subsequent blocks.

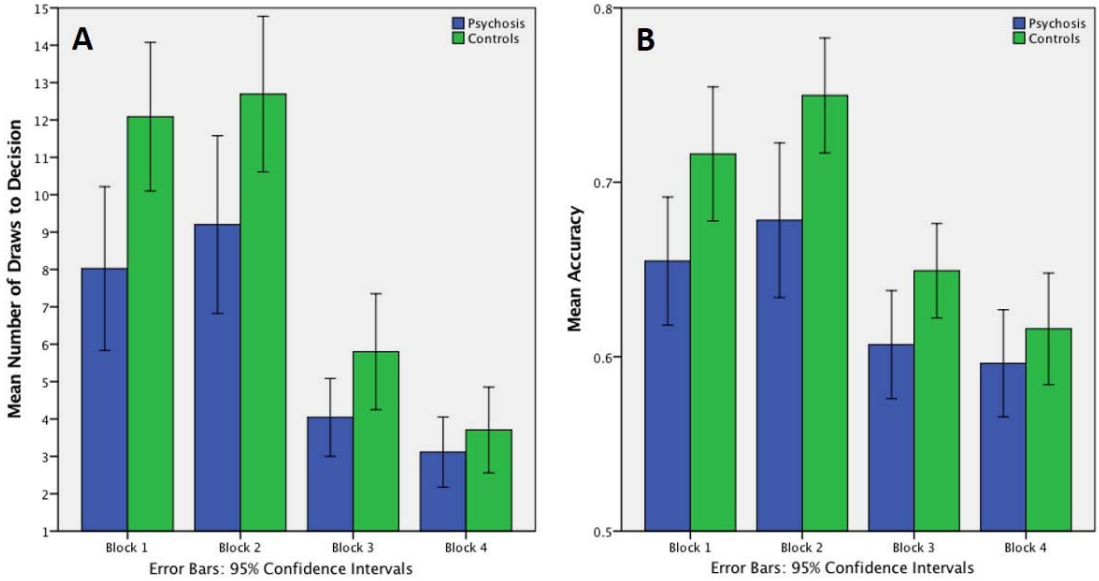

Figure 2: A) Mean number of draws to decision in the four blocks of the task. B) Probability of being correct (Accuracy) at the time of making the decision in four task blocks.

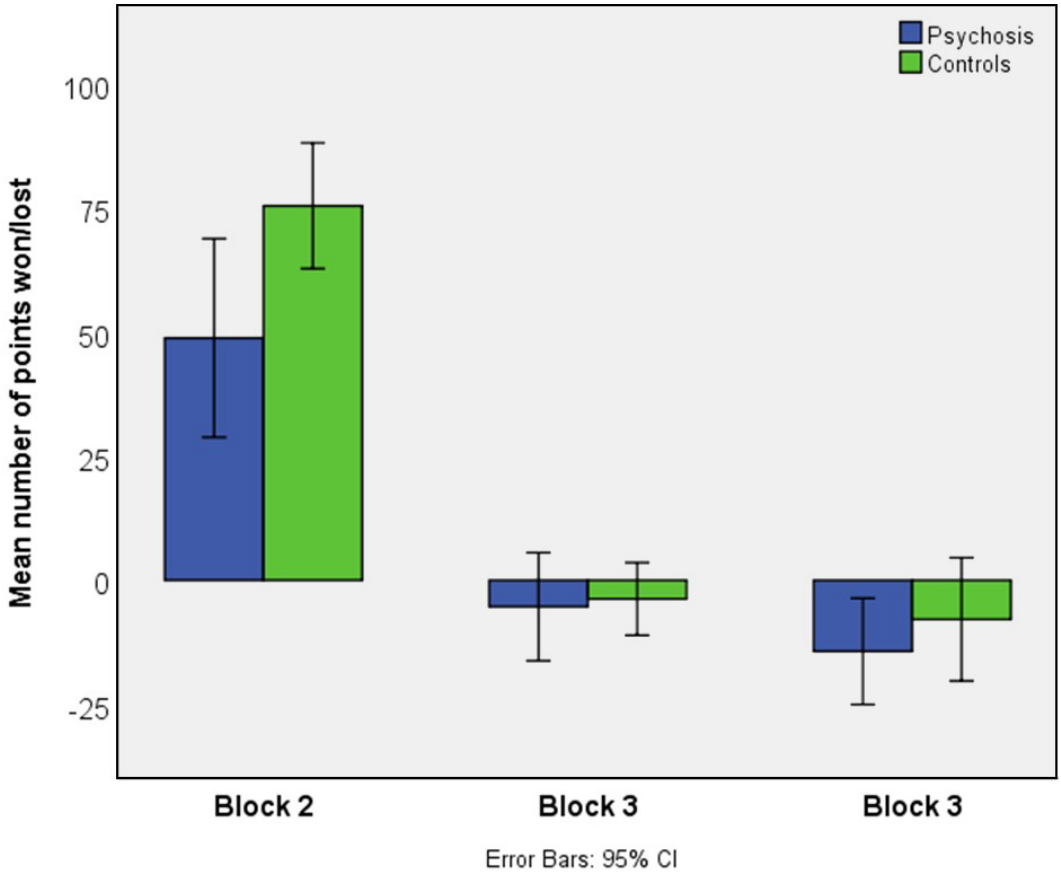

Figure 3: Mean number of point won or lost in Block 2-3 across all 10 trials.

Tables

Table 1. Information sampling in controls, patients and an ideal Bayesian agent.

Group	Control n=31	Psychosis n=31	Ideal Bayesian Agent
	Mean (SD)	Mean (SD)	
DTD 1	12.01 (5.42)	8.14 (6.16)	20
DTD 2	12.69 (5.67)	9.15 (6.31)	20
DTD 3	5.80 (4.23)	4.14 (2.64)	Nb-Ng=+-2
DTD 4	3.71 (3.12)	3.03 (2.09)	1
P corr 1	0.72 (0.10)	0.66 (0.10)	0.835
P corr 2	0.75 (0.09)	0.69 (0.11)	0.835
P corr 3	0.65 (0.07)	0.62 (0.08)	0.692
P corr 4	0.62 (0.09)	0.59 (0.08)	0.6

DTD, draws to decision (i.e. number of fish seen by the participant before reaching a decision); P corr, probability of being correct in Blocks 1 to 4; SD, standard deviation.

Table 2: Sample characteristics for healthy controls and people with psychotic symptoms.

Variable	Controls (n=31)		Early psychosis (n=31)		Statistics
	Mean	SD	Mean	SD	Value (df), Significance p<0.05
Age (years)	21.58	2.41	22.52	4.66	t(60)=0.993, p=0.325
Gender (male/female)	18/13		18/13		χ(1)=0.0, p=1
IQ	110.52	15.79	102.26	17.91	t(60)=–1.926, p=0.059
Level of education	2.35	0.79	2.00	1.17	U(2)=373.5, p=0.117
Mother's level of education	2.19	0.91	2.11	1.37	U(2)=440.0, p=0.884
Smoking (yes/no)*	6/25		18/13		χ(1)=9.79, p=0.004
Alcohol	2.42	0.85	1.78	1.37	U(2)=419.5, p=0.368
Cannabis	0.90	0.79	1.26	1.23	U(2)=430.0, p=0.459
Other drugs*	0.49	1.02	1.11	1.36	U(2)=355.5 , p=0.039
PDI-21*	4.45	2.34	7.83	4.58	t(45)=3.359, p=0.002
Distress*	9.52	6.94	24.00	15.32	t(45)=4.430, p<0.001
Preoccupation*	10.28	6.48	24.78	16.11	t(45)=4.341, p<0.001
Conviction*	13.31	8.13	26.56	17.11	t(45)=3.58, p=0.001
BDI*	3.40	3.90	25.34	14.12	t(57)=8.197, p<0.001
CAARMS Summary Score*	0.52	1.15	18.00	7.53	t(60)=12.776 , p<0.001

Education was measured on a 5-point scale (from no education to higher university degree). Intelligence was measured with a Culture Fair Intelligence Test. Smoking: 0=non-smoker, 1=smoker. Substance use was measured on a 5-point scale (from 0=never used to 5=daily user). Other drugs: hallucinogens, stimulants or sedatives. PDI, Peters Delusion Inventory. BDI, Beck Depression Inventory, CAARMS, Comprehensive Assessment of At Risk Mental States summary score is a summary score of Unusual Thought Content, Non-Bizzare Ideas and Perseptual Abnormalities intensity and frequency subscales (for individual subscales of CAARMS, and other clinical assessment measures see Table 2). χ, Pearson's chi-square; t, t-test, SD, standard deviation. U, Mann–Whitney test. *Significant differences.

Table 3. Clinical assessment measures for 31 patients with psychosis

	Mean	SD
UTC	2.44	2.19
UTC frequency	2.33	2.01
NBI	3.41	1.67
NBI frequency	3.52	1.48
PA	3.33	2.06
PA frequency	2.52	1.89
DS	0.59	1.28
DS frequency	0.96	1.99
ADB	1.81	1.82
ADB frequency	2.15	1.92
SS	1.59	1.48
SS frequency	1.30	1.44
GAF score	55.00	18.54
SANS score	0.35	0.75
PANSS positive	13.68	3.99
PANSS negative	9.87	4.88

BDI, Beck Depression Inventory; GAF, Global Assessment of Functioning. Comprehensive Assessment of At Risk Mental States (CAARMS) subscales: Unusual Thought Content (UTC), Non-Bizarre Ideas (NBI), Perceptual Abnormalities (PA), Disorganised Speech (DA), Aggression/Dangerous Behaviour (ADB), Suicidality and Self-Harm (SS). SANS, Scale for Assessment of Negative Symptoms

Table 4. Percentage and count of people who displayed JTC reasoning style.

Group	**Control n=31**		**Psychosis n=31**	
JTC	Count	%	Count	%
No JTC	18	58.1%	15	48.4%
JTC Blocks 1/2	0	0.0%	1	3.2%
JTC Blocks 3/4	11	35.5%	7	22.6%
JTC all Blocks	2	6.5%	8	25.8%

JTC (jumping to conclusions) is defined as reaching a decision after being given just one or two pieces of information.

Table 5: Best-fit distribution parameters for all groups in all experiments.

Group	CSM	CSV	TM	TV	LL
Block 1: No cost					
Control	1.9×10-3	2.0×10-6	3.4	13	-943.747
Psychosis	1.7	13	4.2	13	-762.993
Combined	0.7	2.2	3.6	13	-1735.65
Block 2: No cost, but win or loss (±100)					
Control	5.0 ×10-3	1.3×10-5	3.6	21	-841.202
Psychosis	3.0	44	2.9	7.5	-690.567
Combined	1.5	13	2.5	7.0	-1549.28
Block 3: Fixed cost, plus win or loss (±100)					
Control	1.6	9.9	4.1	2.2	-707.604
Psychosis	5.2	100	4.4	2.2	-545.704
Combined	3.1	38	4.2	1.0	-1260.45

Best fit parameters were calculated for each participant group separately, and for the group formed by combining both participant groups. CS_M is the mean cost per sample for a particular group. CS_V is the variance of cost per sample within a particular group. T_M is the mean noise parameter for a particular group. Tv is the variance of the noise parameter within a particular group. LL is the log likelihood of the data given the parameters

Table 6: iBIC values for the model where all participants are drawn from the same distribution, vs the model where the healthy and unhealthy groups differ in their distributions.

Block	iBIC for combined	iBIC for separate	Difference
1 no cost	3489.7	3450.2	39.5 (Very strong)
2 no cost, but win or loss (±100)	3116.9	3100.3	16.7 (Very strong)
3 fixed cost, plus win or loss (±100)	2539.3	2543.4	-4.1 (Preference for combined model)

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