Preserved metamemory and subjective costs of searching in Schizophrenia

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Abstract
Effort-based decision-making is linked to the motivational deficits seen in negative symptoms in schizophrenia, and several paradigms have been developed to measure motivation and effort. However, there is substantial research suggesting that cognitive deficits affect these processes, and current paradigms do not consider how cognitive functioning may affect effort-based decision-making. We here use a task inspired from ethology, the cache retrieval paradigm, to measure concomitantly cognitive ability and investment or motivation to find the cache. That is we measure precision of visual short-term memory, implicit metamemory, search effort and by using a mathematical model compute the subjective costs of searching. In a study on non-clinical participants we found that the more positive symptoms one has, the worse the precision of one’s memory, but metamemory and effort spent searching for the cache was not affected. In study 2 patients’ memory was worse but computing the subjective costs yielded no group differences. Our results show intact implicit representation of uncertainties and acting on them in schizophrenia.

Keywords: cognitive effort; decision making; computational psychiatry; neurocognition; motivation

Background
Motivation can be defined as the process of overcoming the costs of effortful actions to achieve desired outcomes (Chong, Bonnelle, & Husain, 2016). Studies on motivational deficits indicate that there is disruption in mechanisms underlying how rewards are processed to motivate behaviour (Barch, Pagliaccio, & Luking, 2016). Effort-cost computations require a representation of the value of the potential reward and how much that reward is worth relative to another reward (Shenhav, Botvinick, & Cohen, 2013). This valuation is affected by several factors in the individual such as the mood, the perceived / subjective cost, and the working memory capacity. In physical effort tasks one finds that schizophrenia patients with prominent negative symptoms prefer the easier task. That might be due to valuing the reward less or the costs of performing the action (button pressing) are higher in patients. In cognitive effort tasks there is often a similar confound between how much one values the reward and how cognitively demanding the task is. To tease those two factors apart we designed a novel task measuring cognitive ability, here the precision of visual short-term memory, how well the participant thinks she remembers the visual item, and invested effort in searching for the target. This allows us to compute the subjective costs incurred, i.e. cost is based on the perceived precision of memory and the invested search effort. We applied this task in study 1 on participants varying in their psychotic experiences, and in study 2 in patients with a diagnosis of schizophrenia and matched controls.

Methods
Study 1 had 52 non-clinical participants, varying in their symptom severity (targeted recruiting), and some were also relatives of patients with a psychotic disorder (N=16). Study 2 we recruited 16 patients with a diagnosis of schizophrenia and 15 matched controls in Stavanger, Norway. All participants performed the trail making task A and B, the digit symbol substitution task, and a novel shape precision task. Symptom severity was measured in study 2 with the PANSS in patients, and in study 1 with the CAPE-42 (Community assessment of psychotic experiences, (Stefanis et al., 2002)). The study was approved by the regional ethics committee (REK-2011/1198).

The shape precision task
The task, presented as a game, has four stages. 1) encoding of a squiggly shape (Fig 1A), 2) recognition of the shape among 30 similar shapes (Fig 1B). In this stage we measure accuracy of memory. The difference between the target shape and where the participant places the point of origin aka best guess, is the error. 3) making of a capture area as a proxy for metamemory or how confident one is to have included the target shape (Fig 1C). This is the believed or perceived accuracy. 4) search phase. There are high probability trials where there is a 5 in 6 chance to find the target again if searched sufficiently, and medium probability trials with a 2 in 3 chance to find the target if one searches long enough (Fig 1D). As for the capture area, search is simulated to be radial, i.e. it starts from the origin and proceeds outward in all directions, drawn on the circumference only. Trials in which the target does not exist let us measure the maximum investment a person is willing to spent searching. Note that it is rational to search approximately as far as one indicated in stage 3), that is a range...
corresponding to one’s belief. Searching less indicates amotion, searching more perseverance or sunk costs. There were a total of 45 trials, 30 trials with a 5/6 chance to find the target (and hence 5 trials for measuring maximal search investment), and 15 trials with a 2/3 chance to find the target (and 5 trials measuring maximal investment).

The (cache retrieval) model

We define the distance from the position of the target as \( r = \sqrt{x_1^2 + x_2^2} \) if it exists. \( \pi(z = 1) = p \) and \( \pi(z = 0) = 1 - p \) with \( z = 1 \) if the target is present, and \( z = 0 \) if the target is not present. Here, \( p \) is either 5/6 or 2/3, known to the participant. We assume a normal distribution, i.e., \( x|z = N_2(0, \sigma \sim 2 \times I_2) \) where \( I_2 \) is the identity matrix. The search cost from the origin to radius \( r \) is \( \alpha r^2 \), and the reward for finding the target is \( \beta \). Here, \( \beta \) is 10 points, known to the participant. Search started at the origin (participant’s best guess) and continues outwards until the target is found or until \( r = r_0 \).

The density for \( r \) is \( \pi(r|z = 1) = r/\sigma^2 \exp \left\{ -r^2/2\sigma^2 \right\} \), for \( r > 0 \). The net gain of search as a function of \( z \) and \( r \) is:

\[
g(r, z) = \begin{cases} 
- \alpha r_0^2 & \text{if } z = 0, \\
- \alpha r_0^2 & \text{if } z = 1, r > r_0, \\
\beta - \alpha r_0^2 & \text{if } z = 1, r \leq r_0.
\end{cases}
\]

and the expected net gain becomes after integrating out the two integrals

\[
E[g(r, z)] = \left[ p\beta - 2p\alpha\sigma^2 \right] - \frac{r_0^2}{2\sigma^2} + \frac{2}{\sigma^2} \left\{ 2p\alpha\sigma^2 - p\beta \right\} + \exp \left\{ \frac{-r_0^2}{2\sigma^2} \right\} \left[ 2p\alpha\sigma^2 - p\beta \right].
\]

When taking the derivative with respect to \( r_0 \) we get \( r_0^{opt} = \frac{\alpha \sigma}{\sqrt{2 \ln(2 p^{-1})}} \) and solving for \( \alpha \) (costs), gives

\[
\alpha = \frac{p\beta}{\left[ 2\sigma^2 p^{-1}\right]^{\frac{1}{2}} \left( 1 - p \right) \left( \exp \left\{ \frac{r_0^2}{2\sigma^2} \right\} - \frac{p}{1-p} \right)}.
\]

Thus, there is an analytical solution if one models cost as \( \alpha r^2 \). For different cost functions and the 1D case numerical solutions are required (Pfuhl, Tjelmeland, Molden, & Biegler, 2009), and are not presented here.

Here, we measure the invested effort as search angle, and the variance is calculated from the capture area as this is the subjective estimate of how far one should search, or believed precision in one’s memory. Using equation 2 we can calculate these subjective costs of searching. We can also calculate the required cost by using the error between the origin and the target as the search radius. Finally, we can also calculated the cost by accuracy of searching, i.e., the variance is based on the true error (Origin-Target). Note, subjective costs will be high if the believed accuracy is low and hence a large capture area made but this is not followed up by a similar sized search. Subjective costs have to be low if the actual search exceeds the believed accuracy.

Results

In Study 1 we found that error in memory (accuracy in remembering the correct squiggy shape) is larger the more positive symptoms one has: \( \beta = 0.63, t_{52} = 3.91, p < .001 \) but not the more negative symptoms one had: \( \beta = -0.20, t = -1.23, p = .22 \). However, if one’s memory is less precise one also makes larger capture areas irrespective of the severity of symptoms, indicating intact implicit metamemory. Subjective costs were higher in the high probability condition, \( t_{52} = 7.68, p < .0001, d = 1.055 \) and the more positive symptoms someone had the lower the subjective costs were, high probability condition: \( \rho = -0.398, p = .003 \), and low probability condition: \( \rho = -0.281, p = .043 \). The more negative symptoms a person had was also associated with lower subjective
Figure 2: The more positive symptoms the lower the subjective costs of searching (search was longer due to a real and perceived larger error in one’s memory)

costs, but that did not reach statistical significance (high probability condition: $\rho = -0.272$, $p = .051$; low probability condition: $\rho = -0.253$, $p = .070$). Still, the more symptoms a person had, the more likely the person would search more than indicated by her belief, suggesting some perseverance instead of amotivation.

In study 2 (preliminary data) we found that patients with a diagnosis of schizophrenia had less accurate memory, $t_{29} = -2.249$, $p = .032$, $d = -0.808$, but had similar implicit metamemory as the age- and gender matched control group, i.e. the capture area was made large enough to include the target in around 60% in both groups: $t_{29} = 1.45$, $p = .157$, $d = .522$ (Fig 2). Within the patient group we found no relationship between symptom severity and accuracy of memory or implicit metamemory, but our sample is too small yet. Regarding search effort, both groups searched further than indicated by the capture area they made, approximately twice as far. Notably, there was a non-significant tendency for controls to search less in the 2/3 probability condition whereas patients searched similarly in both probability conditions, i.e. the interaction between the conditions and the groups was $F(1, 28) = 1.999$, $p = .168$, $\eta^2 = .066$.

The results follow model prediction, i.e. subjective costs were higher in the high probability condition, $F(1, 28) = 46.461$, $p < .001$, $\eta^2 = .616$ but there was no difference between patients and the healthy control group, $F(1, 28) = 3.095$, $p = .089$, $\eta^2 = .1$ (Fig 3). Note, that one patient did not engage in searching, having no incurred costs. Furthermore, the similar subjective costs are not so surprising, because patients had to search more given their lower accuracy, accordingly costs by accuracy was similar too, $F(1, 29) = .026$, $p = .872$, $\eta^2 = 0$.

**Discussion**

In both studies we found that psychotic experiences are related to less precise visual short-term memory, but implicit metamemory was not related to symptom severity or diag-

Figure 3: Patients have less accurate memory but do adjust for it, i.e. make appropriate capture areas

Figure 4: Search in the two probability conditions (left boxplot: 2/3 chance, right boxplot: 5/6 chance to find target, both groups incur similar subjective costs of searching
nosis. Bliksted, Videbech, Fagerlund, and Frith (2017) found that positive, not negative symptoms were related to premorbid IQ, but functional IQ was related to negative symptoms in first episode patients. To our surprise, we did not find overconfidence in one’s memory among patients or participants with more psychotic symptoms. This contradicts a range of studies using explicit confidence ratings and finding a confidence gap in patients, particularly stronger confidence in false memories (Eifler et al., 2015; Moritz, Woodward, Jelinek, & Klinge, 2008). However, patients are to some extent aware of their cognitive abilities (Lysaker et al., 2008) and our task assesses metamemory more implicitly by asking for a capture area. Indeed, Nicholson, Williams, Grainger, Lind, and Carruthers (2019) also found intact implicit but not explicit metacognition in participants with an autism spectrum disorder. This suggests less dependence on prefrontal areas for such nonverbal monitoring of one’s memory.

Patients seemed to discriminate less between the two probability of reward conditions as they searched similarly long in the no chance trials. Surprisingly also was that search was approximately twice as large as indicated by the capture area among all participants. By using the perceived precision, or how well a participant thinks she remembers the shape, and the invested clicks (search radius), we computed subjective costs based on our model, and found some overcompensation in participants with many positive symptoms (study 1), but no difference between controls and patients on the subjective costs of searching (study 2). The search behaviour showed no motivational deficit by diagnosis or symptom severity in our task, and also no increased subjective costs. It also shows that implicit uncertainty (or precision) of one’s memory guides search behaviour (Pfuhl, Barrera, Living, & Biegler, 2013) and is in contrast to a recent study finding that motivational deficits account for some cognitive deficits and cognitive performance was spared in a subgroup of patients (Moritz et al., 2017). Note, that objective costs, i.e., number of clicks made, were actually higher the further one searched.

Behaviour depends on the representation of uncertainty in the brain, and we might or might not be able to consciously access those uncertainties and report them explicitly (verbally). Still, our actions are based on those internal representations irrespective of whether we can verbally express these uncertainties. Here, we asked for a more implicit estimate of one’s memory, instead of Likert-scale confidence ratings and found that psychotic experiences seem not to affect this kind of uncertainty representation.

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References


