Preface

Writing this thesis has been a journey, and I have learned a lot. First, I would like to thank my supervisor Robert Biegler. He has been in charge of implementing and computing the different tasks and variables in labview and excel. The thesis literally would not exist without him. He has also been an incredible source of feedback and advice, for which I am very grateful. Second I would like to thank Gerit Pfuhl for testing participants in Tromsø, as well as providing insightful comments on methods and analyses. I would also like to thank Kyrre Svarva for helping me translate the bullshit questionnaire into Norwegian. There would not be anything to analyse without my participants, so I would like to thank them all for showing up both days answering odd questions and making a substantial amount of confidence intervals. Lastly, I would like to thank Sindre and Elise for proofreading the thesis, as well as mum and dad for occasionally checking in to make sure I was still alive. It's been grand!

Abstract

Introduction. Miscalibration of prediction errors has been suggested as a parameter gone awry in both psychosis and autism spectrum disorders. The aim of this study was to investigate this claim by having participants participate in a task measuring precision of long-term and short-term memory over two days. On day one they had to go through discrimination training, where they learned to recognize one specific shape, as well as completing questionnaires measuring traits associated with psychosis (CAPE-42) and autism (short AQ and SQ) as well as the bullshit receptivity questionnaire. Day two they had to complete 1 long-term precision task, as well as two short-term memory precision tasks. Participants were recruited from Trondheim and Tromsø and were mainly students (N=53 after exclusion). I found no apparent relationship between miscalibration of precision in short-term memory and long-term memory on psychosis. Score on the short SQ showed a weak negative relationship with long-term and short-term precision miscalibration. Interesting correlations were found between ability to detect bullshit, and tendencies towards psychosis and autism (AQ). These relationships could prove interesting to investigate further in later studies with a larger sample, including people with diagnosed autism and psychosis.

Contents

Introduction

For years, psychiatrists and other health professionals have relied on psychiatric classification systems such as the DSM-V (the Diagnostic and Statistical Manual of Mental Disorders) and ICD-10 (the International Classification of Diseases) to identify and diagnose psychiatric disorders. However, this way of classifying mental disorders have been found wanting for several reasons, one being the apparent heterogeneity in patients receiving the same diagnosis (Wiecki, Poland, & Frank, 2015).

A good example of this is schizophrenia, where the five key symptoms are delusions, hallucinations, disorganized speech, disorganized or catatonic behaviour and negative symptoms (American Psychiatric Association, 2013). In DSM-V, a person needs to exhibit at least two of these five symptoms, whereby at least one of the symptoms must be either delusions, hallucinations or disorganized speech to be diagnosed with schizophrenia (American Psychiatric Association, 2013). Going by these criteria, two people with completely different symptoms will be diagnosed with the same disorder. This is problematic because we do not yet know whether the diagnoses correspond to single biological or psychological entities, nor if it can correctly predict the outcome of either illness or given treatment (some patients show great effect when treated with certain drugs, while other patients with the same diagnosis do not). In short, we still lack sufficient understanding of human cognition to provide a bridge between biological causes and behavioural outcomes (Montague, Dolan, Friston, & Dayan, 2012).

Recently, computational approaches have been proposed as a way to bridge this gap in knowledge (Wiecki et al., 2015) . Computational psychiatry assumes the human mind can be described by a set of algorithms that contain parameters, and these parameters are tuned slightly different in different people, which can be seen in expressions of personality. These parameters represent constructs that can be compared across groups, and correlated with symptom severity (Huys, Maia, & Frank, 2016). Some of this variation is expressions of personality, for instance impulsivity. Impulsivity can be divided into four different kinds; Temporal discounting (Chapman & Elstein, 1995), reward sensitivity (Mairin, Boden, Rucklidge[1], & Farmer, 2017), speed-accuracy trade-off (Mulder et al., 2010) and response inhibition (Kräplin et al., 2014). Variances in these different parameters are associated with for instance substance abuse and Attention-Deficit/Hyperactivity-Disorder (Mulder et al., 2010). Several tasks can be employed that test for instance response inhibition such as the Stroop task or the stop signal task (Kräplin et al., 2014). When compared to healthy controls, persons who suffer from pathological gambling or alcohol dependency showed slower stop signal reaction time (SSRT) scores, which is suggested as an indicator of impaired response inhibition. As such, while some variation in parameters is expressed in cognitive capacity such as working memory and attention, at some point variations in certain parameters become so disabling for the individual that it becomes a psychopathology. The question is which parameters are associated with psychopathology, and how can they be measured?

This thesis focuses on prediction errors (PEs) as a possible parameter gone awry in psychosis and/or autism, as suggested by Van de Cruys et al. (2014) and Frith (2005), as well as a possible Bayesian explanation for prediction errors and possible relationships to bias in detection of pseudo-profound bullshit (Pennycook, Cheyne, Barr, Koehler, & Fugelsang, 2015).

Prediction Errors

A prediction error is the mismatch between what one expects to experience when performing an action or observing an event, and what is experienced (Haker, Schneebeli, & Stephan, 2016). The individual receives sensory information (visual, tactile, auditory etc.,) which is then combined with the individual's existing knowledge and expectations regarding the sensory information, to make further predictions about what information is likely to be provided next (Griffiths, Langdon, Le Pelley, & Coltheart, 2014). An example of this can be the seen in the visual system. Imagine you are looking at a coffee mug. If you shake your head, the image of the mug will move across the retina (Frith, 2005). However, there is nothing in the signal detected by the retina (the mug moving), that can indicate whether this movement is due to you yourself shaking your head, or an independent external event (such as a weird sideways earthquake).

The problem of uncertainty can be solved through prediction. The brain can make predictions about what changes are likely to occur as a consequence of you for example shaking your head. This way, actions can be labelled as self-generated, and therefore distinguished from external events. This is called the forward model in the motor system, and is derived from commands sent to the musculo-skeletal system, that control the movements of limbs (Frith, 2005). In addition, the forward model can be divided into two separate types of predictions, namely the forward dynamic model and the forward output model. On one hand, you have the forward dynamic model that makes predictions about the action taken, for instance the trajectory of your arm when throwing a ball, or the speed of shaking your head. And on the other, you have the forward output model, which makes predictions about consequences of the action just performed. This could be how far the ball you just threw would go, or that the image of the cup would move due to you shaking your head. A good way to decide whether a sensory event was caused by you would therefore be to look at the size of the prediction error. If it is large, you probably did not cause the event, and if it is small, then you probably did. But our predictions of an event can never be 100% perfect, or rather, there will always be some noise unaccounted for; Maybe the ball you threw didn't go exactly where you thought it would, due to wind or overestimating your accuracy in throwing the ball. This deviation from what was expected and what actually happened could therefore be defined statistically: How large is the deviation compared to the expected variation in prediction (Pfuhl, Sandvik, Biegler, & Tjelmeland, 2015)? To be more precise, say you predicted to throw the ball 15 metres, +/- 3 metres. If you throw the ball 18 metres, your prediction lies within your expected range. However, if you continuously throw the ball 10 metres, this is shorter than your expected range. This discrepancy can be expressed as Cohen's d': namely how many standard deviations (SDs) away from the expected average is the current stimuli/measurements. However, this calculation is dependent on having realistic expectations, or rather of the standard deviations.

If, in the example with throwing the ball you continuously keep throwing the ball further or shorter than the 12-18 metre range, while you are insistent you are (or should be) within that range, your expected standard deviations are too small to accurately match reality. Your perceived precision is thereby higher than your actual precision, in this case. If you believe your predictions to be more precise than they are, then normal deviations will seem large compared to the expected variations, and would keep surprising you. This is illustrated in figure 1, where your expected throw range can be seen under the blue curve, as your perceived precision. However, because you are not as accurate in your estimated precision as you think, anything not under the blue curve will generate a prediction error.

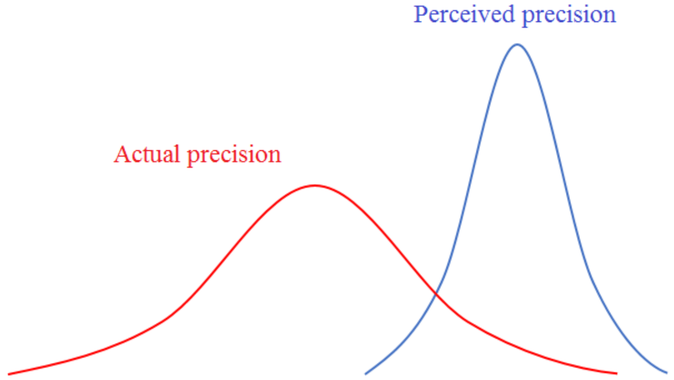

Figure 1:Illustration of actual and perceived precision.

Because we are able to predict the sensory consequences of our actions, our response to self-produced actions will be diminished/attenuated (Frith, 2005; Griffiths et al., 2014). An example of the attenuation of our own actions is tickling, for most people it is quite impossible to tickle oneself (Blakemore, Smith, Steel, Johnstone, & Frith, 2000). The process of integrating current sensory information with prior knowledge or assumptions is important to many perceptual processes. What then if for some reason, the prediction errors no longer concur with the reality of a situation, and a person continuously overestimate or underestimate their prediction errors? Inappropriate prediction errors have been proposed to play a role in both delusions and hallucinations, as experienced during psychosis (Fletcher & Frith, 2009), as well as autism (Van de Cruys, de-Wit, Evers, Boets, & Wagemans, 2013).

As stated above the size of a prediction error is determined by the deviation between the precision of the prediction and the variation of the sensory experience. It is therefore important to note that the size of the prediction error does not directly tell us anything about the relationship between our predictions and the perceived sensory experience, as seen in figure two: The prediction errors in e) and i) are the same, but the perceived precision of the respective predictions and sensory data are different.

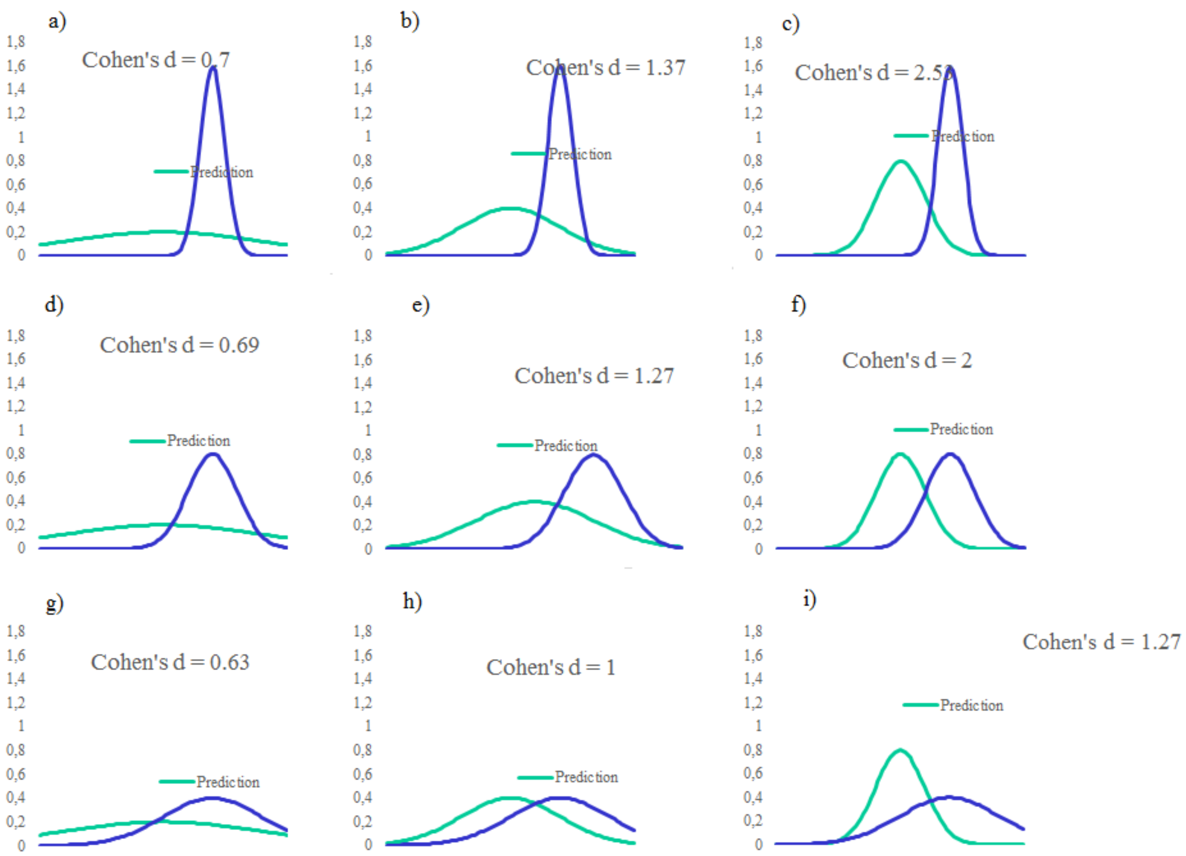

Figure 2: Differences in PEs as a result of variations in precision of predictions and sensory data. Figure provided by Robert Biegler.

One possible approach to estimating this relationship between predictions and the sensory experience, is Bayes' theorem presented in the next section.

Bayes' theorem

Through our senses, we perceive the world around us. What we see, hear, and smell shapes our perception and our worldview. However, our understanding of the world also shapes the way we perceive it. This mutual influence of our perceptions and our knowledge of the world could be explained by viewing our brain as working in a Bayesian fashion (Vilares & Kording, 2011). When we experience the rustling of leaves in a bush at night, we do not automatically know the cause of the rustling of the leaves. There could be several different explanations for the rustling of leaves; the wind, a squirrel or perhaps a hungry crocodile. Although the causes of the noise are different, the sensory data would be identical, as could also be demonstrated as the two possible 3D interpretations of the 2D drawings of the Necker cube, or whether you perceive a shape as convex or concave, depending on whether the light is located at the top or bottom (W. J. Adams, Graf, & Ernst, 2004). In other words, sensory data are ambiguous and inherently noisy. The ambiguity in our data leads to uncertainty, for instance the cause of the rustling of the leaves in the previous example.

How can we reduce this experienced uncertainty, and decide which hypothesis (wind, squirrel or crocodile) is more likely? After all, if the cause is just the wind or a squirrel, the appropriate actions would not matter all that much. However, if it indeed a hungry crocodile, running would be a preferable cause of action. To counter this uncertainty, we can integrate previously acquired knowledge and experience regarding this type of situation, which is called *a priori* information or just priors (Kording, 2014). In this case, the prior information could be information about the place we are located and fauna. Additionally, we observe other kinds of sensory information about the bush, for instance nearby tracks. This sensory information is called our likelihood (Kording, 2014; Vilares & Kording, 2011). In this way, Bayesian statistics is a rigorous way of calculating the probability of any given hypothesis in the presence of uncertainty and a way to make inferences considering the observed data (Kording, 2014; Perfors, Tenenbaum, Griffiths, & Xu, 2011). What follows is an example of how Bayes' theorem could work in a 'real' situation.

You are out walking, and you need to cross a river, or do a long detour that you estimate has a 5% chance of killing you. However, you see something that could either be a log, or possibly a crocodile in the water. If you cross the river and it is indeed a crocodile, you become dinner.

In 90% of cases where you see a crocodile, you are able to identify it as such. This is your detection rate. However, your false alarm rate is at 50% (because it's far better to mistake a log for a crocodile, than the other way around), which means you are able to discern a very lifelike log from a crocodile 50% of the time.

True positive: Actual crocodile detected

False positive: Log mistaken for crocodile

True negative: A log is detected as being just that, a log

False positive: A crocodile is mistaken for a log, and you are eaten.

Now imagine you do not know where you are. Your prior would therefore be uninformative, set at 50%. You then calculate that in 100 rivers, 50 of them should have crocodiles, and in 90% of the cases where you run across a crocodile, you are able to identify it, which would leave you at 45 (of 50) crocodiles detected. In the other 50 crossings without a crocodile, you would believe you saw a crocodile in 25 of the river crossings (these would be false alarms). Your posterior probability would then be 45/(45+25) = 45/70 = 0.64 (or 64%). This means you perceive the probability of dying when crossing the river to be larger than if you take the detour.

Now say you have informative priors, and you're in Norway. In a Norwegian river, the chance of something with an oblong shape floating something being a crocodile is one in 100 million. In a billion river crossings in Norway, in 10 cases the oblong shape would be a crocodile, but you would only be able to detect 9 of them. In half of the remaining 999999990 cases, you mistake half of them for a crocodile. The posterior probability in this case would then be as follows: 9/(499999995+1) = $1.8*10^{-8}$. This probability is smaller than the 5% of dying if taking a detour, so you cross the river.

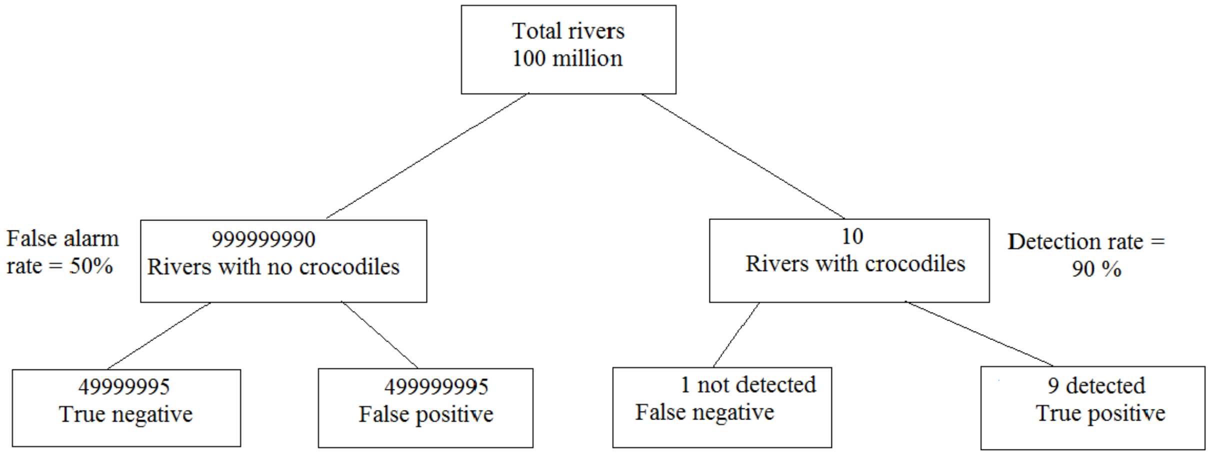

Figure 3: Visual representation of relationships between false alarm rate, detection rate, true negative, false positive, false negative and true positive.

In Bayesian models, degrees of belief about an event are represented as probability distributions (the probability of the rustling stemming from a squirrel, wind or crocodile). In accordance with how likely you find the hypotheses to be, you assign them weights (Petzschner, Glasauer, & Stephan, 2015). Therefore, the Bayesian framework is generative, because we assume that the observed data has been generated by some underlying process or mechanism, that we do not necessarily know anything about. As seen in this example, the rustling of the leaves is assumed to have been generated by whatever is hiding in the bushes (Perfors et al., 2011). In short, a generative model is an internal model which we use to describe and simulate the processes taking place in the world, that again give rise to the observed sensory input/observations.

When you combine the prior probability (belief about the world-state) and the likelihood (sensory data), you get what we call the *posterior probability*. The posterior probability is the belief assigned to the hypothesis, and becomes the prior for the next time you encounter similar events and the possible need to update your beliefs considering sensory information (Perfors et al., 2011).

As mentioned above, one assigns weights to the priors and likelihoods, and this is based on the perceived precision. Precision in a Bayesian framework is the confidence of certainty associated with the belief. For instance, you may believe your memory is very precise, or if we stick with the bush example, you may think your knowledge of the fauna is precise. And as such, you might assign more weight to your prior knowledge in this regard, than, say, your senses. Of course, this would also be the case if you believed your hearing to be very good, you would also assign more weight to the likelihood. In statistical terms, we speak of the precision as being the inverse of variance of a probability distribution (R. A. Adams, Stephan, Brown, Frith, & Friston, 2013; Petzschner et al., 2015).

Bayes' theorem in its simplest form can be written as seen in Equation 1 (Notredame, Pins, Deneve, & Jardri, 2015; Petzschner et al., 2015; Winkler, 1972):

$$p(\theta|x) = \frac{p(x|\theta)p(\theta)}{p(x)} \qquad \text{Equation 1}$$

$p(\theta|x)$ denotes the posterior probability, the probability of the percept resulting from combining the prior and the likelihood.
$p(\theta)$ represents the prior, the probability summarizing previous knowledge regarding the perceptual stimulus.
$p(x|\theta)$ summarise the likelihood, the evidence provided by relevant sensory organs
$p(x)$ is a normalising term, and is the sum of each of the possible hypotheses under consideration (Petzschner et al., 2015).

The equation represented here can be upon to test the probability different hypotheses in relation to each other as well, but this will not be expanded upon here.

Regarding the brain as working in a Bayesian fashion, can help us see the influence of top-down information vs. bottom-up information. Because the prior is previously existing knowledge of the event, before the new stimuli, it is essentially a measure of top-down influence on perception/whatever. And in accordance with this, the likelihood is a measure of the bottom-up influence of sensory information.

The respective weights, namely (w_x and w_θ), or the precision, are inversely proportional to uncertainty (aka variance) of the prior and likelihood (Petzschner et al., 2015)

$$w_x = 1 - w_\theta = \frac{\frac{1}{\sigma_x^2}}{\frac{1}{\sigma_x^2}+\frac{1}{\sigma_\theta^2}} \qquad \text{Equation 2}$$

When sensory input is noisy, the variance of the likelihood σ_x^2 is high, therefore the weight of the likelihood is small and the posterior estimates will be dominated by the prior. For instance, while walking in the darkness, you know your eyesight is not as reliable as it is during daylight, therefore you might not view it as precise as during daylight, and might rely more on your priors for interpretation of different stimuli. Conversely, the opposite could also be the case for small measurement noise, posterior estimates would be more driven by the likelihood and would be less prone to influences by the prior (Petzschner et al., 2015). The latter is demonstrated in Figure 4, where in addition to a perceived precise likelihood, you also have an uninformative prior.

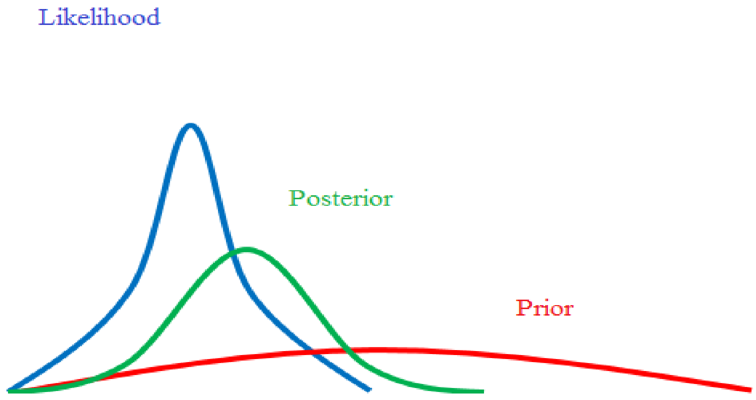

Figure 4: Demonstration of how the posterior shifts towards the likelihood for different degrees of uncertainty (peakedness of the curves). The less precise the prior, the more the posterior is shifted towards the likelihood. The positions of the prior and likelihood could also be switched around, so that the posterior would be biased in the direction of the prior if the prior was perceived to be more precise.

Seeing as the posterior in turn becomes the new prior, one's model of the world is generated, perhaps the prior then will be more precise, in which case things might look more like in figure 4:

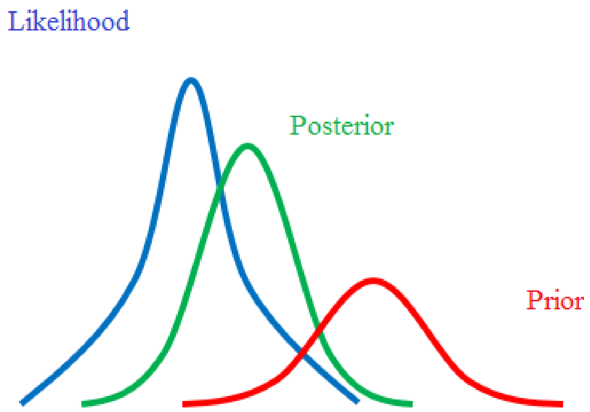

Figure 5: As the prior becomes more precise, so does the posterior probability, and it is not as much influenced by the likelihood, as in the previous example.

However, the measure of the precisions of likelihoods and priors are estimates, and is necessarily subjective. Because our estimates are not objective, we sometimes make mistakes at times, at which point you learn, and decrease your precision estimations to consider the source of the noise. But what happens if you systematically either overestimate or underestimate your perceived precision of likelihoods and/or priors? Miscalibrations of precision of prior or likelihood has been suggested to contribute to both psychosis and autism spectrum disorder (Fletcher & Frith, 2009; Frith, 2005; Pellicano & Burr, 2012).

Psychosis

Psychosis is a feature of several mental disorders, such as schizophrenia and bipolar disorder (American Psychiatric Association, 2013), but can also be found in the non-clinical population. The most prominent features of psychosis are hallucinations and delusions. Hallucinations are perceptions in the absence of causative stimuli, while delusions are unusual beliefs, often of prosecution and surveillance (Fletcher & Frith, 2009), and are prominent symptoms of psychosis. Common types of hallucinations are auditory hallucinations, where the person hears voices in their heads, running a commentary on the person's actions, or carrying a conversation or arguing. Delusions are fixed beliefs but unwarranted on basis of the available evidence, and come in many varieties and are often bizarre in nature: Believing that someone else is inserting their thoughts into one's mind, that one's thoughts are being broadcast, and that others can hear them are only some examples of common delusions. It is important to note that if a belief is socially "acceptable" or supported by culture and society, such as religion, it is not a delusion. The potential absurdity of delusions is neatly illustrated in this first-hand account of psychosis:

"When I woke up I felt violated, but it also dawned on me that I knew what I meant: the evil dictator had finally gained full access to my unconscious. He was going to make me into a serial killer, a part of his private army of psychopathic killers who were being used to terrorize and subdue the nation. I turned to the TV to make an emergency communication with my allies" - (Weiner, 2003)

In recent years, research has shown that psychotic symptoms such as hallucinations and delusions, or psychotic-like experiences, are not only found in clinical populations. In fact, healthy members of the general population also exhibit such experiences, to a lesser extent. These people are considered to represent a non-clinical psychosis phenotype, and are at higher risk of developing schizophrenia-spectrum disorder (Kelleher & Cannon, 2011). It is estimated that one can find benign subclinical paranoid beliefs in 15-20% of the population.

However, certain delusions are more specific to schizophrenia, such as the feeling of loss of agency, or a loss of control of ones' own body (Fletcher & Frith, 2009). It has been proposed that an error in the process of self-attenuation could be the reason behind this kind of delusion. Self-attenuation can be measured by force-matching tasks, where participants are asked to match a reference force, by either pressing directly on themselves, or by using a robot to indirectly reproduce the perceived pressure (Brown, Adams, Parees, Edwards, & Friston, 2013). An example of such a force-matching task was utilized by Shergill, Bays, Frith, and Wolpert (2003). Participants were paired together, resting either their left or right index fingers in a mould, connected to a force-transducer apparatus and a lever. The lever would then press down on the first participant's finger, and that participant then had to match that force when pressing down on the other participant's finger, who then had to press down on the first participants finger again and round and round it went. What Shergill et al. (2003) then found was that each participant overestimated the force the other had used to press down on their finger, thus escalating the force each trial. Blakemore et al. (2000) found that in response to tactile stimulation, healthy controls and psychiatric patients who did not display auditory hallucinations nor passivity, experienced self-produced stimuli as less intense than externally produced stimuli. However, psychiatric patients who did experience these symptoms, did not show this differentiation in perception between self-produced and externally produced stimuli, and rated the self-produced stimuli as intense as the externally generated stimuli (Blakemore et al., 2000).

Further exploring this phenomenon, Shergill et al. (2014) found that subjects with schizophrenia had reduced attenuation (a smaller loss of intensity) compared to the healthy controls. Put a different way, the subjects with schizophrenia did not experience the lessening of stimulus magnitude usually experienced when stimuli are self-generated. This suggests that these individuals would be unable to correctly predict the sensory consequences of their own actions.

Several studies have shown that participants with paranoid schizophrenia, or high-paranoid participants in studies are more certain about incorrect judgments (Moritz et al., 2015). In turn, their confidence in correct responses is diminished compared to controls which shows a gap in their confidence. The overconfidence in errors in these paranoia-prone individuals was exaggerated if the participant judged the question to be easy, or felt competent. This mismatch in confidence could lead to what is known as knowledge corruption, where large parts of what a person believes to be factually true, is contaminated or corrupted. In fact, an over-confidence in errors is considered a risk factor and fodder for new formation of delusional beliefs, which may aggravate the behavioural and emotional consequences of false beliefs. These findings hint at differences in perceived subjective difficulty influencing this confidence mismatch in errors.

In addition, it has been established that cognitive biases are heightened in people with schizophrenia, and other psychotic disorders (Balzan, Woodward, Delfabbro, & Moritz, 2016). This has been linked to the formation and maintenance of delusions, and may even correlate with sub-clinical delusion-proneness, suggesting that cognitive biases may be an important precursor to the development of psychotic symptoms.

One such well-known cognitive bias (particularly in schizophrenia), is the ‘jumping to conclusions’ bias, or JTC for short. Here deluded patients are shown to reach conclusions based on significantly less evidence than healthy controls, and it is hypothesised that probabilistic inference may be abnormal in these deluded individuals. It was found that deluded subjects had a tendency to request less information regarding the event before reaching a decision, and to express higher levels of certainty than control groups (Huq, Garety, & Hemsley, 1988). The JTC bias is deftly demonstrated in varieties of the urn task, that “a sequence of red and blue beads will be drawn from one of two urns. One urn, R, has a majority of red beads, and the other, B, has the corresponding majority of blue beads. Participants are then presented with beads, one by one, and their task is to determine which of the urns the beads are pulled from (Moutoussis, Bentall, El-Deredy, & Dayan, 2011). The interesting finding is that deluded patients require fewer draws of the urn, to decide which urn the beads stem from.

However, overconfidence in errors may be one of the cognitive constructs responsible for raising the level of conviction necessary to form and maintain a delusional belief. People without schizophrenia are more likely to attach “not trustworthy”/not precise to such cognitive errors and memories, and the perceptions and judgements as trivial and/or implausible. The bias is also not likely to be an artefact of heightened memory deficits, as some metamemory studies failed to detect significant differences on objective memory performance, between schizophrenia patients and healthy control groups. There is also evidence of heightened overconfidence in errors among patients with first-episode psychosis (Balzan et al., 2016; Moritz, Woodward, & Chen, 2006).

Autism

Autism spectrum disorders are a continuum of disorders of development, encompassing varying degrees of severity, with heterogenous phenotypes and includes conditions such as: Asperger's syndrome, atypical autism and early childhood autism. While these conditions vary in their severity, all these conditions are characterized by persistent deficits in social communication and interaction with others, restricted and repetitive patterns of behaviours and interests as well as abnormal reactivity or interest in sensory stimuli and aspects of the environment (Barlow & Durand, 2011; Haker et al., 2016; Kern et al., 2007). However, because the diagnosis of autism requires impairments in each of these areas, it is difficult to establish whether these traits stem from the same cause, or different causes (Happé, Angelica, & Plomin, 2006). In a twin study that looked at autistic traits in the general population, they found heterogeneity among the three traits, which suggests that different genes might be responsible for these components of ASD (Ronald et al., 2006).

The spectrum ranges from severe forms; Where the individual may not have acquired speech even as an adult, and may be incredibly dependent on others for support - to light expressions of autistic traits that are barely noticeable to the outside eye, due to learned coping mechanisms. For instance; in contrast to the more severe early childhood autism, people diagnosed with Asperger syndrome lack the general retardation in language, and it is not associated with intellectual disabilities. This showcases the diversity of symptoms and degrees of severity found within the autism spectrum (Haker et al., 2016).

Most affected individuals also show motor skill deficits or clumsiness, where both fine and gross motor skills can be affected (Van Damme, Simons, Sabbe, & van West, 2015). The symptoms of the disorder may go unnoticed for a while, until increasing social demands and expected developmental milestones are not met. Examples of this can be a significant delay in the acquisition of speech, which would not be as noticeable until the age of 4-5 years. Interestingly, the characteristics of the disorder might become less noticeable as the person ages, due to learned coping mechanisms (Haker et al., 2016). It is estimated that around 1% of the child and adult population is affected by ASD (Allison, Auyeung, & Baron-Cohen, 2012), and affects more males than females (Bourgeron, 2015). Interestingly, Baron-Cohen et al. (2013) found that females with anorexia nervosa showed elevated autistic traits, as measured by the autism quotient (AQ), systemizing quotient (SQ) and the empathizing quotient (EQ). The process of diagnosing autism can be a lengthy one due to the heterogeneity of the disorder, in fact, it can take several years from the point of first signs of concern and eventual diagnosis, and the average age of diagnosis is 11 years old (Howlin & Asgharian, 1999).

It has also been noted, that some people with ASD show an impeccable attention to detail, in both perception and memory (Baron-Cohen, Ashwin, Ashwin, Tavassoli, &

Chakrabarti, 2009). A study by O'riordan, Plaisted, Driver, and Baron-Cohen (2001) found that in a difficult conjunctive visual search task, children with autism had both faster reaction times and search rates compared to healthy controls. Individuals with autism has also repeatedly been found to score higher on measures of sensory sensitivity (Crane, Goddard, & Pring, 2009; Tavassoli, Miller, Schoen, Nielsen, & Baron-Cohen, 2014; Ward et al., 2017). This is often described in the terms of hyper- and hypo- sensitivity. Hyper-sensitivity could be described as acute, heightened or excessive sensitivity to stimuli: Light can be perceived as almost unbearingly bright, and sounds to be extremely loud. This stimuli "assault" can cause great discomfort and even pain to the individuals affected (Robertson & Simmons, 2013). Hypo-sensitivity is the opposite, where the individual underreacts to sensory stimuli, or in some cases actively seeks them out. Both hyper- and hypo- sensitivity has been found to be much more common in individuals in the general population who score high on measures of autism (Robertson & Simmons, 2013).

Prediction errors, psychosis and autism

We discussed earlier how prediction errors are the result of violations of our predictions, both small and large, and how large enough prediction errors should cause us to update our model of the world. This process drives learning. But what happens if there is something wrong with the prediction errors? It is important to distinguish between the perceived precision of priors and likelihoods, and objective precision. Indeed, the size of a prediction error depends on two things, the perceived precision of the prior or prediction, and the perceived precision of the likelihood/sensory data, and how large the discrepancy is between these two, as was discussed in previous sections. Prediction errors elicit learning, or brings sensory information to one's attention due to its salience.

Fletcher and Frith (2009) postulate that there is something wrong in the way the prediction errors in patients with schizophrenia are used and quantified. Seeing as the size of the prediction error is meaningless without an estimate of how precise it is, it is important not only to consider the size or magnitude of the prediction error, but also how precise it is. If so, a relatively small prediction error might be given undue weight (if the precision is overestimated), leading to a false inference. In other words, you would pay more attention to the prediction error than if it was deemed to be less precise. In schizophrenia for instance, it is plausible that such aberrations in prediction errors could be seen as small changes in perceptual and motor function. This could help explain the sensations of passivity and lack of control over their actions, experienced by people suffering from schizophrenia with hallucinations and delusions. Higher up in the system, such misallocation of weight to "unimportant" prediction errors, could lead to stimuli feeling salient and important, in turn making it difficult to turn attention towards appropriate aspects of the environment (Fletcher & Frith, 2009).

Therefore, it is not unlikely that a small alteration in this prediction error mechanism could lead to a state where increasingly flexible and imaginative inferences no longer accommodate the unreliable and persistent prediction errors. This tiny alteration will not be large enough to produce gross impairments in sensory of motor function, but may be sufficient to make for the formation of delusions (Fletcher & Frith, 2009). In short, new evidence in form of sensations is not properly integrated which leads to aberrant prediction errors. However, Fletcher and Frith (2009) do not make any predictions regarding how the prediction errors become aberrant, as this could be the result of 1) prior perceived to be more precise than is realistic, or 2) the likelihood is perceived to be more precise than is realistic. Haker et al. (2016) states that there are two primary ways of reducing prediction errors, by either acting to make your prediction come true, or learning from it; shifting your average closer to the present experience.

Van de Cruys et al. (2014) propose that individuals with ASD assign too much precision to their prediction errors, regardless of how small or important they may seem, and therefore continuously overestimate the degrees of change in their environments. They situate that a core deficit in ASD, may very well be a fault in meta-learning; Learning when to, and when not to learn (Van de Cruys, Van der Hallen, & Wagemans, 2017). In other words: Being able to tell which prediction errors matter (and should be assigned high precision) and which prediction errors should be ignored (assigned low precision). As mentioned in earlier sections, atypical attention is an early sign of ASD, and could be explained by what Van de Cruys et al. (2014) coined as high, inflexible precision of prediction errors (HIPPEA).

If prediction errors with no real predictive value are assigned undue high precision, this could (in theory) trigger new learning from every new event, which in turn would make for a highly specialized form of learning, highly influenced by noise that should be ignored: In practice, what is learned would only be applicable in an extremely narrow range of situations. If everything is important, then nothing truly is, and each new piece of information would trigger new learning that would be deemed a new exception from previous experiences. In other words: There would be no generalizability of what is learned outside that one exact situation, which may serve the person well in certain situations and tasks. But this certainly is the exception that confirms the rule. Interactions with a certain degree of noise would prove difficult to interpret for these individuals, social interactions being an excellent example of this, as interactions seldom occur precisely in the same way (Van de Cruys et al., 2014).

Perceived precision of priors and likelihoods have also been proposed to play a role in autism spectrum disorders. Pellicano and Burr (2012) argue that abnormalities at the level of the prior could account for the unusual sensation and perception found in autism, both the hypersensitivity to new stimuli, as well as hyposensitivity and sensory seeking behaviours. To be more precise, they propose that either at the level of construction or when combining it with sensory information, the priors in autism are unusually weakened. The suggestion here is that people with autism have broader priors, which means they perceive their priors to be less reliable, due to large variance (assigned less precision). This possible phenomenon with broader priors/less precise priors, has been coined ‘hypo-priors’ (in essence: ‘less than normal priors’), illustrated in figure 2. But, hypo-prior is a misleading term, because the “opposite” of a hypo-prior would then logically be a prior regarded as being very precise, when in fact, hyper-prior is a term already used to describe a higher-order prior in a hierarchical system. A ‘hypo-prior’ should then following this logic, be a lower-order prior in this hierarchical system. Therefore the established term broad prior will be used. Figure 6 illustrates the differences between broad and normal priors, and the shift of the posterior accordingly.

If people with autism indeed have broader priors, it is to be expected that these individuals will have less of a limiting framework for interpreting stimuli, and this should have significant effect on perceptual experiences. As an extension of this, it could be predicted that such broad priors could result in more precise perception, as they would distort sensory signals less than normal priors. This is because in a Bayesian model, the priors sacrifice sensation accuracy in exchange for overall improved precision or reliability and reduction of error. Indeed, this prediction seem to have some merit, as there is evidence that people with elevated autistic traits are less susceptible to visual illusions (Chouinard, Noulty, Sperandio, & Landry, 2013; Walter, Dassonville, & Bochsler, 2009).

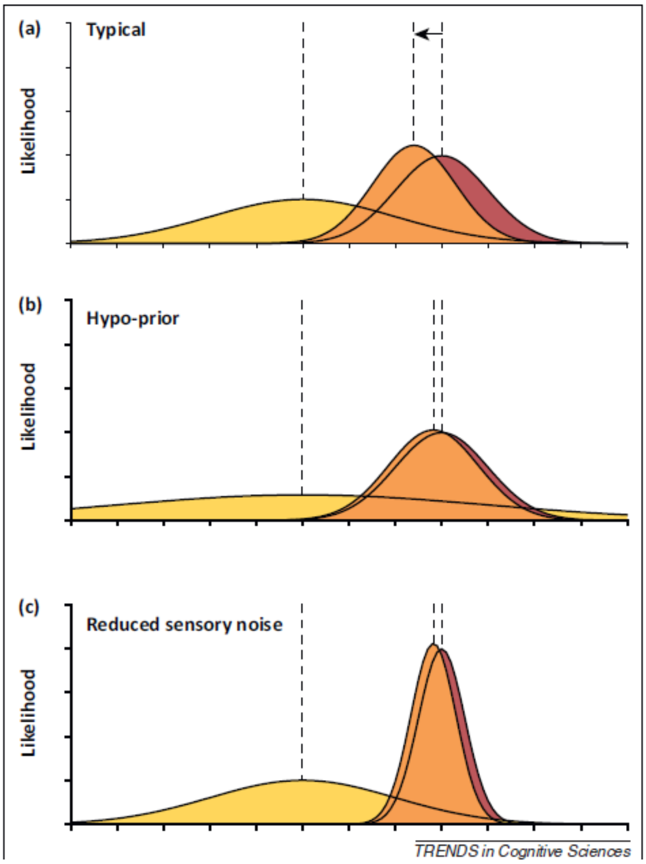

Figure 6, Individual differences in Bayesian perception, as adapted from (Brock, 2012). (a) Shows typical perception, where the prior (yellow) is given less weight than the likelihood (red), yet still influences the posterior. (b) Shows a hypo-prior/broad prior, where the prior has little to no influence at all, posterior highly influenced by likelihood. (c) Reduced sensory noise. Adapted from Brock (2012).

However, while being more influenced by their likelihoods can cause some perceptive advantages, there are reasons why we have memory, and rely on previous knowledge when interpreting new sensory experiences. Therefore, broad priors will impede, and stagger performance in situations where priors help resolve ambiguity (Pellicano & Burr, 2012). Also, seeing as priors work as a 'frame of reference', if they are too broad, they will not be able to make up for variations in the stimuli caused by noise, rather than actual variations in the stimuli. These hypo-priors could also lead to reduced capacity for generalisation during learning. Instead, the person with hypo-priors would end up 'overfitting' his or her model to noisy data, instead of the general trend.

Also, having exceedingly broad priors would in theory create smaller prediction errors, as demonstrated in figure 6. If your hypothesis is "anything can happen", and then a spaceship comes crashing down, you will not be as surprised, because you were open to "anything could happen". This would in theory lead to small prediction errors.

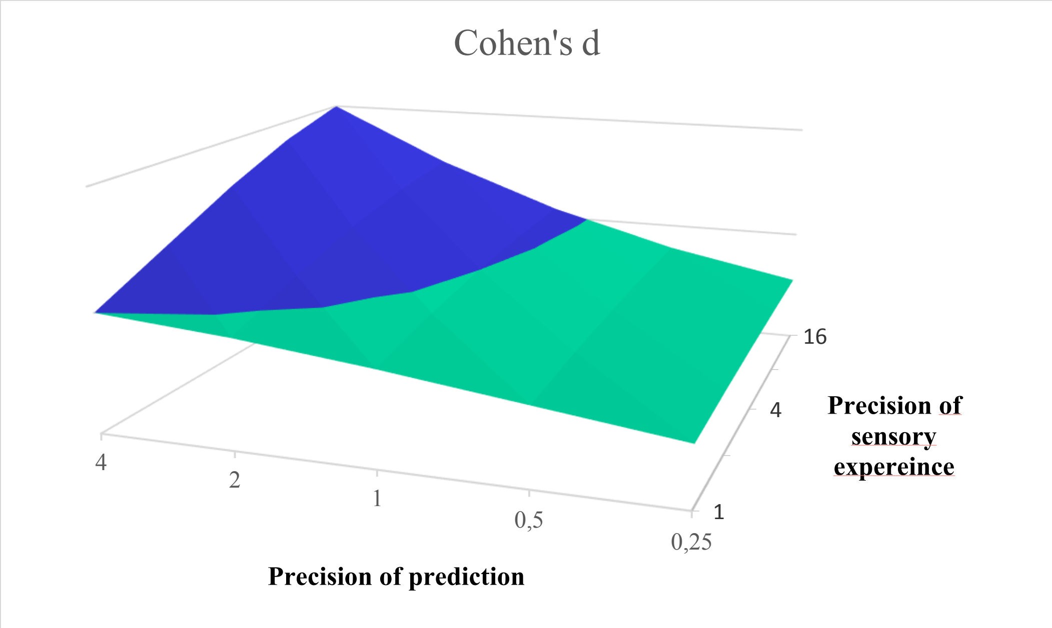

Figure 7: Cohen's d (size of prediction error or PEs) is seen on the vertical axis. The dark-blue part of the figure represents those who overestimate PEs, where the highest prediction errors are caused by high perceived precision of both predictions and the sensory evidence. The border between the blue and green parts represent those with appropriate PEs in a given situation, while the light green parts of the figure represent those who for some reason underestimate the size of their prediction errors. Figure provided by Robert Biegler.

On bullshit

The perceived precision of our hypotheses could possibly tie into people's abilities to detect discrepancies in statements as well. For instance, if you were given four words, and your task is to guess which category these words fall into, your hypotheses regarding the categories would have varying degrees of specificity. If the words are Chihuahua, Labrador, Corgi and Dalmatian, a broad category could be "living thing", a less broad category could be "animal", and a more precise category would be "dog" (Perfors et al., 2011). The more general and vague your hypothesis is, the more evidence will be compatible with it which also means the probability of getting the same data even though your hypothesis is not true, is also greater. Therefore, if you think a statement presented to you is more precise than it really is, you will overestimate how much the statement should change your mind, and by extension how much you should believe in your hypothesis if you find compatible evidence. In a post-alternative facts world, identifying such biases could prove important. An example of statements that are perceived to be precise, but in reality, are vague and could be true for many other people as well, are Barnum-statements, which are typically found in horoscopes. These are statements such as "You sometimes get angry, and then regret your actions afterwards", or "You have great need for other people to like and admire you" (Forer, 1949; Pennycook et al., 2015).

An interesting study undertaken by Pennycook et al. (2015) aimed to find out just how receptive different groups of people are to what they coined as ‘pseudo-profound bullshit’ (or BS). Here, they defined ‘pseudo-profound bullshit’ as a statement that in contrast to mere nonsense, implies meaning but does not contain any real meaning or truth (Pennycook et al., 2015). An example of such a statement, taken from their BS questionnaire, could be:

“Good health imparts reality to subtle creativity”.

While the syntactic structure is correct, this sentence is vague and does not convey any real meaning or knowledge, which is the hallmark of a BS-statement. The goal of such a statement, according to Pennycook et al. (2015), is to impress and be engaging, rather than to inform. They proposed two potential reasons why people were susceptible to BS-statements: Firstly, some individuals may be predisposed to accept BS-statements as profound, due to an exceedingly open mind which could make them more susceptible to accept statements as profound. Secondly, people might be unable to detect the bullshit, mistaking vagueness for profundity. Mistaking the vagueness of statements for profundity could be the result of failing to detect when there is conflicting information within a statement, so called conflict monitoring. In addition, it is plausible to believe that engaging in reflective thinking should be correlated with the rate of finding meaning in BS-statements, as engaging in reflective thinking should cause one to scrutinize whether something makes sense at face value or not.

Pennycook et al. (2015) found that those more receptive to bullshit were less reflective and lower in cognitive ability, and more prone to ontological confusions and conspiratorial ideation, and were more likely to hold religious and paranormal beliefs, and were more likely to endorse complementary and alternative medicine. They also found that increased BS was associated with better performance on measures of analytic thinking.

Hypotheses

In this thesis, I aim to answer whether tendencies towards autism and positive symptoms of psychosis are related to an overestimation of prediction errors. And if there is in fact an overestimation, to what extent is that attributable to overestimating the precisions of priors versus the precisions of likelihoods? Does such miscalibration in memory for perceptual detail relate to biases in the acceptance of abstract claims (bullshit)? Are there people who underestimate prediction errors, and if so, how do they compare?

H1. Van de Cruys et al. (2014) argue that persistent surprise caused by overestimating prediction errors leads to detail-focused processing in autism. Therefore, the more prediction error is overestimated (as measured by the relevant indices), the more short-term memory should be perceived to be more precise than long-term memory.

H2. The more precise short-term memory is, compared to long-term memory, the more short-term memory will be perceived to be more precise than long-term memory.

H3. The more prediction error is overestimated, the greater is the short autism quotient score (AQ) (Allison et al., 2012).

H4. The more prediction error is overestimated, the greater is the short systemizing score (Wakabayashi et al., 2006)

H5. The more prediction error is overestimated, the greater is the score on the positive subscale of the CAPE-42 (Commnity Assessment of Psychic Experiences, Stefanis et al., 2002; Mark & Touloupoulou, 2016).

H6. The more prediction error is overestimated, the greater is the tendency to accept bullshit (Pennycook et al., 2015), as measured by Bullshit bias c (Macmillan & Creelman, 1991).

Methods

Open Science Framework Preregistration

There are several practices that contributes to bad science, whether intended or not. Francis (2012) points out that in psychological research, there is a certain publication bias, because there are too many positive results when seen in light of sample sizes and effect sizes. In comparison, null-results are seldom reported. Simmons, Nelson, and Simonsohn (2011) and Ioannidis (2005) argue that one can easily influence significance levels, by either adding subjects until a significant result is achieved, or stopping when you have reached your desired effect size and significance levels. This is also true for redefining your hypotheses after you have already looked at data.

Some of these biases can be avoided by signing eventual research projects up for preregistration. When preregistering your research project, you fill in how many participants you intend to recruit, and when you plan to stop recruiting. You also specify how you are conducting your study, specifying parameters and variables, and what methods you intend to use to analyse your data. Indeed, you also preregister your hypotheses. This way, you avoid being tempted to redefine hypotheses and add subjects till you get a desired result etc. This thesis project was uploaded to “The Open Science Framework”, prior to data collection, a link to the preregistration can be found in Appendix G.

Participants

In this study, participants consisted of students from UiT (The Arctic University of Norway) and NTNU (Norwegian University of Technology and Sciences). The participants from UiT had to take the tests as a course requirement. Participants from NTNU were mainly acquaintances of the researcher and their background ranged from psychology to engineering. Participants recruited at NTNU had the opportunity to win a gift card (valued at 500NOK), provided they showed up on both day 1 and day 2 of the experiment.

Table 1

Demographics

	Before Exclusion	After exclusion
Number	82	53
Males	24	16
Females	58	37
Mean age (SD)	24.04 (4.40)	23.64 (2.47)

Procedure

Day1 of the study, participants were asked to make up a 6-digit ID number they would be able to remember the following day, and it was suggested they make a combination of birthdate and birth-month of someone they knew. If they were not able to do this, they were given a ID number by the experimenter. This ID would ensure anonymity as well as enable us to match responses across the two experiment days. For the participants tested at NTNU, a computer lab was utilized. To ensure anonymity, the data was immediately saved to a memory stick by the experimenter, and thereby deleted from the servers. Data was deleted from the PCs at the computer lab after each task was completed. For the discrimination task and questionnaires, participants were given verbal information, as well as explanations in the programme of what to do. As for the precision tasks of day 2, they were given verbal instructions, as well as written instructions on paper (APPENDIX ???), and the instructions provided in the programme. Participants also had to go through a short demo of the precision tasks to ensure they had understood the task. The experimenter was available for questions during testing.

Tasks and materials

The experiment took place over two days, where participants were required to attend both days. All tests were run on PCs, that used the operating system Windows.

Discrimination practice and questionnaires, day 1.

Each participant was shown 1 of 6 predetermined shapes, that are all different phase shifts of the same shape. This shape would then be their target shape (S+) for the rest of the discrimination training, and was the shape they should remember. Each of the possible target shapes had a number of associated shapes, the (S-). First, the participants were shown the target shape, and told to remember it. Then they would be shown (at random) either the target shape (S+), or one of the alternative phased shapes, the (S-). At each trial, the participants were told to indicate whether the shape was the target shape, or not – a yes / no decision. The shape might look like this:

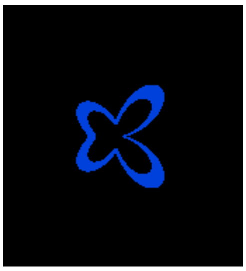

Figure 8: Possible shape for the discrimination training.

The six possible shapes were one of 6 predetermined shapes that differed by phase shifts of 60 degrees. The sequence of the S+ and S- is random, and the first S- was 60 degrees from the target shape, either clockwise or anticlockwise. Whenever the participants made a correct choice, regardless of whether an S+ or S- had been identified, the distance between the S+ and the two S- (clockwise and anticlockwise) was reduced by one step, thereby increasing the difficulty slightly for each correct choice made. However, if the participant failed to correctly identify an S+ or an S-, the distance would be increased (thereby making it easier) by n = 4 steps in this experiment. This titration procedure should make the task gradually more difficult, until the participants reach a level where they get, on average n/(n+1) choices right.

Each block of discrimination practice was made up of eight trials. In-between each block, the participants were asked to answer questions from the receptivity to bullshit questionnaire, autism quotient, systemizing quotient and the CAPE-42, as well as two additional questions added to the CAPE-42.

There were 21 blocks of discrimination training with eight trials per block. In between the discrimination training blocks there were 20 blocks of questions from the questionnaires, with five questions per block, with a total of 100 questions. Receptivity to bullshit questionnaire: 1-20, AQ: 21-30, SQ: 31-55, CAPE-42 (+ 2 additional control questions): 56-100. Example can find in Appendix A.

Precision tasks, day 2

On day 2, the participants went through three precision-tasks developed by Pfuhl et al. (2015). The instructions for the participants can be found in Appendix F

Long-term memory with long-term shapes

In the first precision of shape task, the aim is to measure how well they remember the target shape (S+) from the previous day, as seen in Figure 9. The participants were first presented with a circle with 18 shapes from the same set as the shape they used during the discrimination practice (A). Participants were supposed to identify their target shape (S+) in this circle To do this, they had to click the circle in the corresponding area of the shape they identify as their target shape (B). Then the participants were told to draw a confidence wedge, within which they were confident their target shape was located (C).

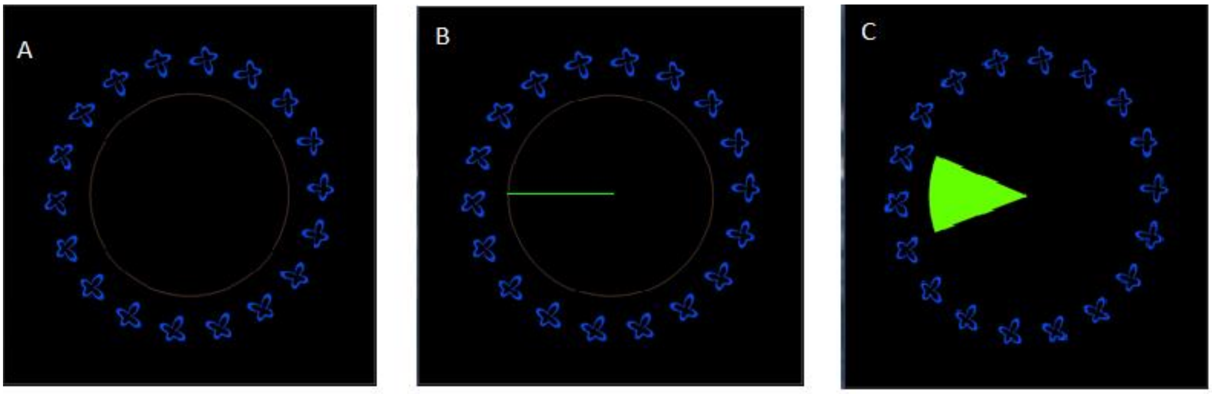

Figure 9: Long term memory precision task. A) Wheel of shapes. B) Pinpoint shape phase C) Confidence interval phase.

To draw the wedge, participants had to move their mouse to cover what they deemed a sufficient area to include the target shape, with the pin-point as the centre of the wedge, and hit 'Ctrl'. The wedge should be just wide enough to encompass their shape, if possible. In this precision task, participants were not given feedback on performance, as it would not be desirable for any learning to occur at this stage in the experiment.

The actual precision of the participant's memory in this task is the inverse of the variance that is calculated as the average squared deviation between the actual target angle (S+) and the initial search angle in each trial. Perceived precision of memory is calculated analogously, as the inverse of a variance calculated as the squared angle from the centre of a confidence interval to its edge.

Short-term memory with short-term shapes

In this short-term memory task using a short-term set of shapes, we aimed to measure how well participants were able to remember shapes after a short amount of time had passed, as well as measure how much confidence they put in their judgment. This task uses a different set of shapes from the previous tasks presented (discrimination training and the LTM task). Participants were first presented with a fixation cross (A), and asked to click it to start the trial. Then they were presented with the shape they were supposed to remember that trial for 1 second, before it disappears (B). A circle of 18 shapes from the corresponding set of shapes then appears (C), and participants were again told to pinpoint which shape they had seen (D), and to draw a wedge just wide enough they would be certain their target shape was included (E). In this task the participants were given feedback during the task as seen in Fig 3 (F), as well as points awarded/deducted at the end of the trial (G).

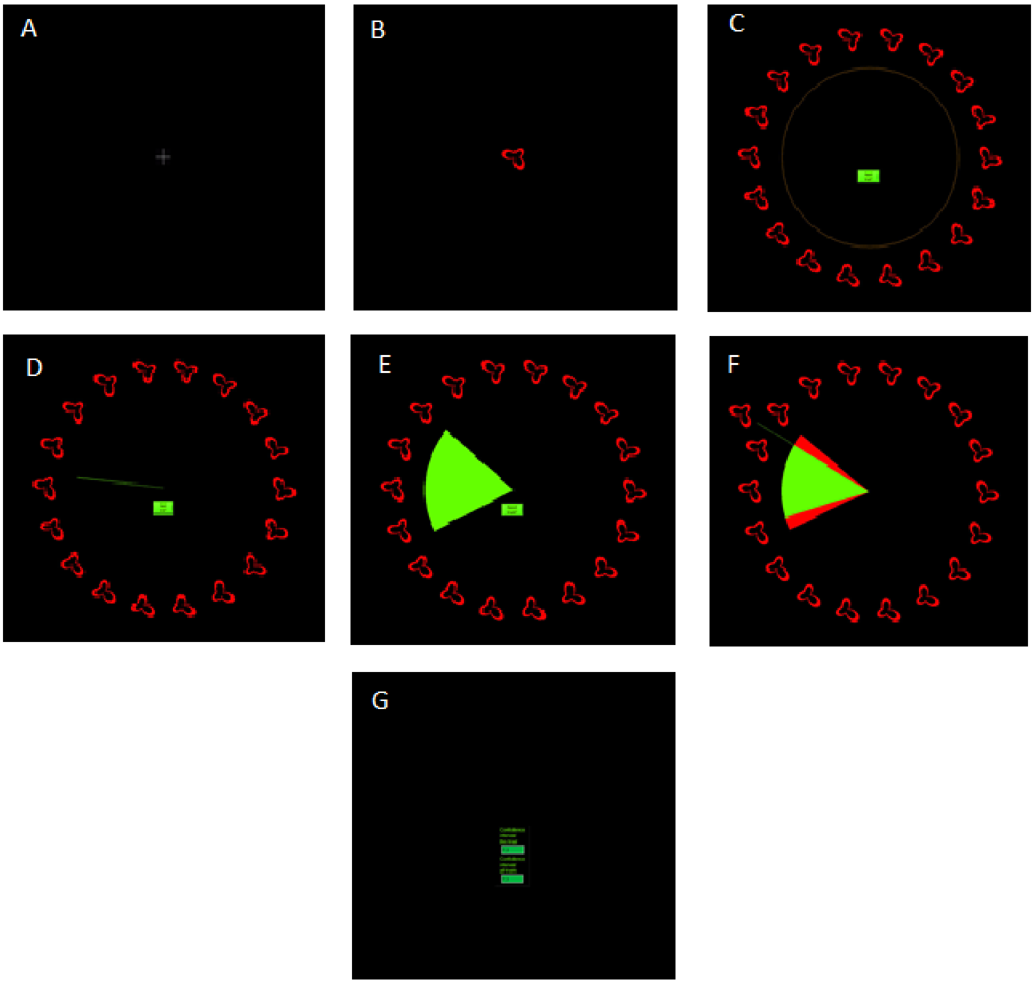

Figure 10: STM w/ STM shapes. A) Fixation cross. B) The target shape to be remembered and located during this task,. C) Wheel of shapes. D) Pinpoint phase. E) Confidence phase. F) Feedback phase 1. G) Points phase.

Participants were explained they would be given 8 points if the wedge was just wide enough to include their target shape, but if it was too wide they would get a deduction in points. If the wedge did not contain their target shape/they failed to locate the shape, they received 0 points.

This task measured their short-term memory by calculating how well they were able to locate the target shape (actual precision) comparing the difference between the actual target angle (S+) and their initial search angle, but also their confidence in their memory and judgment, as seen by drawing a confidence wedge.

Short-term memory with long-term shapes

This task aims to measure the relative influence of top-down information and bottom-up information in participants.

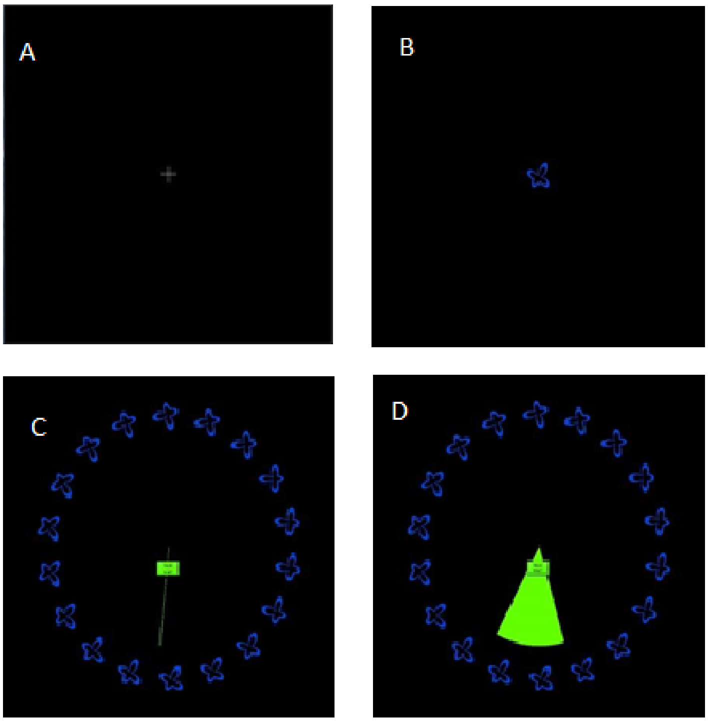

Figure 11: STM with LTM shapes. A) Fixation cross. B) Target shape. C) Pinpoint phase, D) Confidence interval phase

The procedure of this task is identical in procedure to the previous STM-task, however the set of shapes used in this task is the set of shapes used for both the discrimination training, as well as the LTM-task. Participants are told to remember the shape they see flashed for 1 second on the screen, not the one they trained to remember the previous day. In addition, this task does not provide feedback to the participants in any form.

In this task, we wished to measure the relative top-down influence vs. bottom-up influence on memory. As this uses the same set of shapes used in discrimination training, the participants should be primed to that shape. This can be utilized by asking participants to ignore that shape, and instead focus on the one they are presented, and asking them to pinpoint that shape. We can measure this by calculating how skewed towards the trained-for target shape the participants' answers are, and subtracting from that the location of the actual target shape.

Questionnaires and indices

In addition to the tasks mentioned above, the participants were required to fill out questions from the bullshit receptivity scale, autism spectrum quotient (AQ), the systemizing quotient (SQ) and the Community Assessment of Psychic Experiences (CAPE-42). All questionnaires were available in both English and Norwegian.

Bullshit receptivity scale (BSR)

This questionnaire was developed by Pennycook et al. (2015) to measure people's receptivity to bullshit. The scale is based on both actual tweets and particularly vague tweets from the 'Twitter' account of Deepak Chopra, that were considered to, when scrutinized, not to make any sense at all. In this study, the 20 questions from experiment 4 of Pennycook et al. (2015) were used. Here 10 of the questions consisted of BSR statements such as: "*We are in the midst of a self-aware blossoming of being that will align us with the nexus itself",* and the other 10 were motivational statements such as "*Only those who will risk going too far can possibly find out how far one can go".* These questions were mixed together. Participants were asked to rate how profound they found the statements, on a scale from 1-5: 1= Not at all profound, 2 = Somewhat profound, 3 = Fairly profound, 4 = Definitely profound, and 5 = Very profound. Statements that participants judged to be "not at all profound" or "somewhat profound" were classified as a "miss", whereas "Fairly profound", "Definitely profound" and "Very profound" were regarded as a "hit".

Pennycook et al. (2015) suggested two mechanisms that could explain why people might rate bullshit as profound, namely sensitivity to bullshit (how good you are at detecting it), and a response bias, where some people simply are more biased to rate bullshit as profound. Thus, there are two separate measures: Bullshit sensitivity (Bullshit d'), and Bullshit bias (c). The questionnaire and instructions can be found in Appendix B.

Bullshit receptivity d' is calculated as described by Anderson (2015) and MacMillan and Creelman (1991), in this case subtracting profundity ratings for pseudo-profound bullshit from ratings for the motivational quotations (Pennycook et al., 2015). To avoid infinite values of d', if a rate = 0, it was replaced by 1/2n, where n was the number of either bullshit or else motivational items to which a participant responded. For the same reason, if a rate = 1, we replaced it by 1-1/2n. Then d' = z(false alarm rate) – z(hit rate).

Bullshit receptivity bias c, or how prone people were to judge pseudo-profound bullshit as profound was calculated as described by MacMillan and Creelman (1991). The same hit and false alarm rates were used as for the calculation of d'. Then c = -0.5*(z(hit rate) + z(false alarm rate)).

Short Autism Spectrum Quotient (AQ)

The AQ developed by Baron-Cohen, Wheelwright, Skinner, Martin, and Clubley (2001), is a "brief" questionnaire developed to measure where any adult of normal intelligence is located on the autism spectrum. The final version of the AQ consists of 50 questions, with 10 questions assessing 5 different areas: *social skill, attention switching, attention to detail, communication and imagination* (Baron-Cohen, Wheelwright, Skinner, Martin, & Clubley, 2001). During the testing of the AQ, they found that participants who had previously been diagnosed with AS/HFA scored significantly higher than controls. A group of controls were asked to take the test 2 weeks after first being administered the questionnaire, and they did not differ statistically. In addition, within the AS/HFA sample, a group of parents were asked to fill out the AQ for their children, who had filled out the questionnaire as well. They found that if anything, the parents rated their children more highly, which indicates that the scores were not inflated, and if anything more conservative (Baron-Cohen et al., 2001)). As for the internal consistency of the questionnaire, all 5 areas/themes (*social skill, attention switching, attention to detail, communication and imagination)* reported a moderate to high Cronbach's alpha. Participants or parents had to indicate the degree to which they agreed or disagreed on a four-point scale: *strongly agree, slightly agree, slightly disagree and strongly disagree*. Where half the questions are phrased to elicit a "disagree" response, and the other half an "agree" response.

However, the full-length version of the AQ, while well replicated, is too long to be used in busy primary care practice (Allison et al., 2012). Therefore, a 10-question version of the questionnaire vas developed by Allison et al. (2012), to be used at clinics. Participants or parents had to indicate the degree to which they agreed or disagreed on a four-point scale: *strongly agree, slightly agree, slightly disagree and strongly disagree*. Hits, indicating an autistic trait does not differentiate between the *strongly or slightly* options, and are given the binary value of 1. Still centred around the five subdomains, the short AQ selected two items from each subdomain. To determine which 10 items should be included in the questionnaire, a discrimination index for each item was calculated by subtracting the proportion of participants who scored 1 (a hit for autistic trait) on each item in the control group from the proportion of participants who scored 1 in the control group. Good items scored between 0.3-0.7 on the discrimination index, and the two highest grossing items from each subdomain were selected as part of the short-AQ. The questionnaire and instructions can be found in Appendix C

Short Systemizing quotient (SQ)

The SQ, developed by Baron-Cohen, Richler, Bisarya, Gurunathan, and Wheelwright (2003) is an instrument for measuring someone's interest in systems. Based on the extreme male brain hypothesis (EMB) in autism. This questionnaire measures systemizing, on the grounds that people with autism often show impaired empathizing, but intact or even superior systemizing, relative to mental age. During the development of the questionnaire, people with HFA and AS as well as a control group were sent the SQ (as well as the empathizing quotient, EQ) by post. Where one group did the SQ first, and then the EQ, while the other group did the questionnaires in reverse order. They found that in the general population, males scored significantly higher than females on systemizing. However, participants with AS/HFA also scored significantly higher on systemizing than matched controls. No apparent group differences were found in relation to the control/filler questions (Baron-Cohen et al., 2003).

The original SQ consists of 60 questions in total, whereas 40 of those measure systemizing, and 20 are filler questions meant to "distract". Answers are forced choice, with the four possible responses being *Definitely agree, slightly agree, slightly disagree* and *definitely disagree.* Half of the questions elicit points if the participants answers either *definitely agree (2 points) or slightly agree (1 point)*, while the other half elicits points if either *slightly disagree (1 point)* or *strongly disagree (2 points)* are chosen, while the filler questions score no points (Baron-Cohen et al., 2003). The questions are comprised of situations from every-day life.

However, the researchers were unsure whether all 60 items were needed to reliably measure systemizing, and therefore set out to construct a short version of the SQ (Wakabayashi et al., 2006). When running a principal component analysis, it suggested the SQ consisted of one-component, where 25 of the 40 items had loadings above 0.40, and the internal consistency/ Cronbach's alpha of these high-loaded items were 0.90 (Wakabayashi et al., 2006). This suggested that 25/40 items were sufficient to measure systemizing. It utilizes the same scoring as the original SQ, where the hits are codes as 1, regardless of it being a "*slightly" or "definitely"* response, and the misses were coded as 0. The questionnaire and instructions can be found in Appendix D

CAPE-42

The Community Assessment of Psychic Experiences (CAPE) is a 40-item self-report instrument used to detect experiences of psychosis in the general population. It consists of 20 positive symptom items, 14 negative symptom items, and eight depressive symptom items, and was developed by Stefanis et al. (2002). The CAPE was developed using, amongst other instruments, the PDI-21 and PDI-40 (E. Peters, Joseph, Day, & Garety, 2004; E. R. Peters, Joseph, & Garety, 1999). The CAPE-42 is a forced choice questionnaire, with four possible answers*: Never, Sometimes, Often and Nearly always*. In the CAPE-42, they also had items asking for levels of distress after certain questions, which has been cut from the questionnaire used in this thesis. Results from a meta-analysis conducted by Mark and Toulopoulou (2016), suggested that that the CAPE scores were psychometrically reliable.

In addition to the 42 statements in the original questionnaire, two control questions were added, to screen for people who did not answer the questionnaire seriously. These statements were: *"Do you ever feel that you have a famous historic personality?"* and "*Have you ever experienced a mental collapse where you become another person?"*.

CAPE-42 positive (CAPE-pos): The CAPE-42 positive subscale was the only subscale explicitly used in this study, and is the average ratng of the positive subscale items. The questionnaire can be found in Appendix E.

Precision indices

Actual LTM variance is calculated as the sum of squared deviations of the best guess regarding the correct shape from the actually correct shape, divided by n-1 in the 10 trials of the long-term memory test. It thus is the sample variance of best guesses in the long-term memory task.

Perceived LTM variance is calculated as the sum of squared angles between the centre and edge of the confidence interval set by the participant in the long-term memory task, divided by n-1 in the 10 trials of the long-term memory test.

Actual STM variance is calculated as the sum of squared deviations of the best guess regarding the correct shape from the actually correct shape, divided by n-1 in the 27 trials of the short-term memory test with new shapes. It thus is the sample variance of best guesses in the short-term memory task.

Perceived STM variance is calculated as the sum of squared angles between the centre and edge of the confidence interval set by the participant in the short-term memory task, divided by n-1 in the 27 trials of the short-term memory test with new shapes.

LTM precision miscalibration (LTM) is measured by the logarithm of ratio of perceived LTM variance/actual LTM variance. Numbers > 0 reflect overestimation of LTM precision numbers < 0 underestimation.

STM precision miscalibration (STM in tables) is measured by the logarithm of the ratio of perceived STM variance/actual STM variance. Numbers > 0 reflect overestimation of STM precision numbers < 0 underestimation.

Overall prediction error miscalibration (Total PE), which may be over- or underestimation of total prediction error, is measured by the logarithm of the ratio of sum of perceived LTM and STM variances/sum of actual LTM and STM variances. Therefore, if there is high correlations between Total PE and STM precision miscalibration and LTM precision miscalibration, it is because this measure is made up of the same numbers as those measures.

Relative perceived precision (Perceived precision): with precision being inverse variance, if short-term memory is perceived to be more precise than long-term memory, that is reflected in a greater value of the ratio of perceived LTM variance/perceived STM variance. This is the predicted actual weighting of sensory data (the likelihood) over priors, based on the actual precisions of STM and LTM.

Relative actual precision (Actual precision): with precision being inverse variance, if actual short-term memory is more precise than actual long-term memory, that is reflected in a greater value of the ratio of actual LTM variance/actual STM variance.

LTM acquisition on Day 1 is calculated by averaging the difference between the Day 1 target shape and the alternative shapes over the last 20 trials of Day 1 training.

Data analysis/Analysis plan

When the collection of data was finished, the day 1 and day 2 results were assembled into an excel file, to calculate the variables in the indices mentioned in the previous section.

Data exclusion: Participants who only managed to identify the correct shape in 80% of the trials during discrimination training limited to phase shifts between target shape and alternatives of over 30degrees were omitted. If participants omitted more than one third of responses that contributed to any index calculated, they were excluded. For responses to the questionnaires, participants who gave the same response to more than two thirds of all questions, those who gave the same response to all questions within a block in half or more of blocks, not counting consistent choices of the lower score in CAPE-42 and its additional control questions. Participants whose responses to the control questions averaged more than 1.5, or the top 10% (whichever is less) were also excluded from the data analysis. If participants used different IDs from day 1 to day 2 of the testing, they were also excluded from the analysis.

Statistical analyses were run in both JASP version 0.8.2.0and IBM SPSS, version 24, on a 15.6” Lenovo Ideapad, running Windows 8.1. Due to some of the intended predictor variables violating the assumption of collinearity, I was not able to analyse the data as first intended in the OSF preregistration; A MANCOVA with the LTM PE, STM PE, total PE, perceived precision and actual precision as predictors, and AQ, SQ, CAPE-positive, BS c as outcome variables. Therefore, I ran five Bayesian regressions with LTM precision miscalibration and STM precision miscalibration as predictor variables, and perceived precision of likelihood, autism quotient score, systemizing score, CAPE-positive score, and bullshit bias were the outcome variables. Corresponding regular multiple regressions were run as well. In addition, an exploratory Bayesian correlation was run with all the variables (LTM PE, STM PE, Total PE, Perceived precision, actual precision, BS d', BS c, AQ, SQ and Cape-positive), Kendall's tau was used instead of Pearson, as the non-questionnaire variables were not normally distributed, and the sample was limited. After analysing the data from the correlation, I found some interesting relationships between AQ and BS d', and CAPE-positive and d', and decided to examine this relationship closer by running both a regular and Bayesian regression with d' as the outcome variable and AQ and CAPE-positive as predictors.

Results

Table 1

Descriptive statistics

	Valid	Missing	Mean	Std. Dev	Variance	Minimum	Maximum
LTM miscalibration	53	0	-0.61	1.52	2.3	-4.59	1.75
STM miscalibration	53	0	-0.58	0.95	0.90	-3.25	1.06
Total PE	53	0	-0.77	1.05	1.10	-3.16	1.13
Rel. Perceived precision	53	0	-0.47	0.71	0.50	-2.26	1.01
Rel. Actual precision	53	0	-0.43	1.58	2.49	-4.01	4.05
Bullshit d'	53	0	0.95	0.84	0.71	-1.10	2.93
Bullshit c	53	0	0.31	0.62	0.38	-1.24	1.65
AQ	53	0	0.35	0.18	0.03	0.00	0.80
SQ	53	0	0.71	0.31	0.10	0.00	1.48
Cape Positive	53	0	1.37	0.21	0.05	1.05	2.15

Bayesian Regression analyses

A quick summary

Models: The regression models considered; Contains the null model (intercept only, if not some covariates are declared as nuisance.

P(M): The prior probability of the model; by default, all models have equal prior probability

P(M|data): Probability of the model given the data; i.e., Posterior probability of the model

BFM: Bayes factor in favour of the model relative to the remaining models

BF10: Bayes factor in favour of the model compared to the null model (i.e, intercept only)

% error: Proportional error of the computation of the Bayes factor.

Table 3

Bayesian regression: Effects of LTM precision miscalibration and STM precision miscalibration on the relative perceived precision of likelihood.

Models	P(M)	P(M|data)	BF M	BF 10	error %
Null model	0.25	0.56	3.76	1	
LTM misc.	0.25	0.19	0.70	0.34	0.002
STM misc.	0.25	0.17	0.60	0.30	0.003
STM + LTM miscal.	0.25	0.09	0.294	0.16	0.01

This regression looked at the potential effect of LTM precision miscalibration and STM precision miscalibration, on perceived precision. The alternative hypothesis is that either of these measures will show an effect on perceived precision. The null-hypothesis postualtes that there is no relationship. Bayes’factor (BF10) favours the null-hypothesis, as the Bayes factor favouring LTM precision miscalibration in the model is 0.34, with an error of 0.002, and BF10 = 0.30 with an error of 0.003 favouring the model with STM precision miscalibration. The joint model for the two has a Bayes factor of 0.16 and error of 0.01. These Bayes' factors are smaller than 1, and the null model is therefore favoured. As such, the results do not support the hypothesis that the more prediction error is overestimated, the more STM should be perceived to be more precise than LTM.

Table 4

Bayesian regression: Effects of LTM precision miscalibration and STM precision miscalibration on the short AQ

Models	P(M)	P(M|data)	BF M	BF 10	error %
Null model	0.25	0.60	4.51	1	
LTM misc.	0.25	0.17	0.60	0.28	0.003
STM misc.	0.25	0.17	0.60	0.28	0.003
STM + LTM misc.	0.25	0.07	0.21	0.11	0.006

This regression looked at the possible effects of LTM precision miscalibration and STM precision miscalibration on the short AQ. The Bayes factor favouring LTM precision miscalibration is 0.28, with an error of 0.003, and the BF10 favouring the STM precision miscalibration model is 0.28 with an error of 0.003%. The joint model of LTM and STM precision miscalibration has a Bayes factor of 0.11. These results are all < 1, which means the null hypothesis is favoured. This means the hypothesis that as PE is overestimated, the AQ score becomes greater, is not supported.

Table 5

Bayesian regression: LTM precision miscalibration and STM precision miscalibration on short SQ

Models	P(M)	P(M|data)	BF M	BF 10	error %
Null model	0.25	0.22	0.86	1	
LTM misc.	0.25	0.50	3.05	2.26	4.683e -4
STM misc.	0.25	0.06	0.20	0.28	0.003
STM + LTM misc.	0.25	0.21	0.81	0.96	0.002

This regression looked at the possible effects of LTM PE miscalibration and STM PE miscalibration on the short SQ. The Bayes factor in favour of including LTM PE as a predictor in the regression model, as opposed to not including LTM PE as a predictor is 2.26 with an error of 4.68e-4%. This indicates weak (anecdotal) evidence for the alternative hypothesis (Jarosz & Wiley, 2014; Wetzels et al., 2011). But at the same time, the error % is so small, that this Bayes factor cannot be completely dismissed either. The Bayes factor favouring STM PEs inclusion in the model is 0.28, with an error of 0.003. For the joint LTM PE and STM PE model, the BF10 is 0.96. LTM PE alone best predicts the SQ score.

Table 6

Bayesian regression: Effect of LTM precision miscalibration and STM precision miscalibration on CAPE-positive.

Models	P(M)	P(M|data)	BF M	BF 10	error %
Null model	0.25	0.51	3.16	1	
LTM misc.	0.25	0.17	0.61	0.33	0.002
STM misc.	0.25	0.20	0.76	0.39	0.002
STM + LTM misc.	0.25	0.12	0.40	0.23	0.007

This regression looked at the possible effects of LTM precision miscalibration and STM precision miscalibration on the CAPE-positive score. The Bayes factor in favour of including LTM precision miscalibration as a predictor in the regression model, as opposed to not including this variable as a predictor is 0.33 with error of 0.002. For STM precision miscalibration, the Bayes factor for inclusion in the model is 0.39 with error 0.002. The joint model of the two has a Bayes factor of 0.23. These results favour the null model.

Table 7

Bayesian regression: Effect LTM precision miscalibration and STM precision miscalibration on Bullshit bias c.

Models	P(M)	P(M|data)	BF M	BF 10	error %
Null model	0.25	0.46	2.56	1	
LTM misc.	0.25	0.22	0.82	0.47	0.002
STM misc.	0.25	0.22	0.84	0.47	0.002
STM + LTM misc.	0.25	0.11	0.36	0.23	0.007

The regression showed in Table 5 looked at the possible effects of LTM precision miscalibration and STM precision miscalibration on Bullshit bias c. The Bayes factor in favour of including LTM misc. alone in the model is 0.47 with error 0.002. BF10 in favour of including STM misc. alone in the model is 0.47, with an error % of 0.002, and the Bayes factor supporting the joint model is 0.23 with error 0.007. Therefore, the null model supports our data best.

Table 9

Summary-table of multiple regressions performed, with LTM precision miscalibration and STM precision miscalibration as predictors and perceived precision, AQ, SQ, CAPE-positive and Bullshit-C as outcome variables.

Variable	**Adjusted R^2**	**B**	**SEB**	**β**	**t**	**Sig.**	**F-test (sig)**
	Perceived precision						
	-0.02						0.49 (.62)
Constant		-0.47	0.12		-4.02	< .001	
LTM misc.		0.06	0.07	0.13	0.89	0.38	
STM misc.		-0.08	0.11	-0.10	-0.70	0.49	
	AQ						
	-0.04						.016 (.98)
Constant		0.35	0.03		12.05	< .001	
LTM misc.		0.00	0.02	-0.02	-0.11	0.91	
STM misc.		0.01	0.03	0.03	0.17	0.87	
	SQ						
	0.06						2.85 (.07)
Constant		0.68	0.05		13.74	< .001	
LTM misc.		-0.07	0.03	-0.34	-2.39	0.02	
STM misc.		0.03	0.05	0.10	0.72	0.47	
	CAPE-pos						
	0.00						0.94 (.40)
Constant		1.36	0.04		39.04	< .001	
LTM misc.		0.02	0.02	0.15	1.01	0.32	
STM misc.		-0.04	0.03	-0.18	-1.20	0.24	
	BS C						
	0.00						0.97 (.39)
Constant		0.23	0.10		2.28	0.03	
LTM misc.		-0.05	0.06	-0.12	-0.80	0.43	
STM misc.		-0.08	0.10	-0.12	-0.83	0.41	

A multiple linear regression was calculated to predict the relative perceived precision based on with LTM precision miscalibration and STM precision miscalibration. The regression equation was not significant ($F(2, 50) = 0.49$, $p = 0.62$), with an R^2 of 0.02. Neither LTM misc. ($\beta = 0.13$, p = 0.38), nor STM misc. ($\beta = -0.10$, $p = 0.49$), could significantly predict perceived precision.

A multiple linear regression was calculated to predict the short AQ score based on LTM precision miscalibration and STM precision miscalibration. The regression equation was not significant ($F(2, 50) = 0.02$, $p = 0.98$), with an R^2 of 0.001. Neither LTM misc. ($\beta = -0.02$, $p = 0.91$) nor STM misc. ($\beta = 0.03$, $p = 0.87$) significantly predicted short AQ score.

A multiple linear regression was calculated to predict the short SQ score based on LTM precision miscalibration and STM precision miscalibration. The regression equation was not significant ($F(2, 50) = 2.85$, $p = 0.07$), with an R^2 of 0.10. LTM precision miscalibration was found to significantly predict the SQ score ($\beta = -0.34$, $p = 0.02$). This indicates that as LTM precision miscalibration increase, the SQ score will decrease, which is the opposite of what was predicted. STM PE was not able to significantly predict SQ score ($\beta = 0.10$, $p = 0.47$).

A multiple linear regression was calculated to predict the CAPE-positive score based on LTM precision miscalibration and STM precision miscalibration. The regression equation was not significant ($F(2, 50) = 0.94$, $p = 0.40$, with an R^2 of 0.04. Neither LTM precision miscalibration ($\beta = 0.15$, $p = 0.31$) nor STM precision miscalibration ($\beta = -0.176$, $p = 0.237$) was able to significantly predict CAPE-positive. As such this does not support the hypothesis that PE increase, so will the CAPE-positive score.

The last linear multiple regression tested whether LTM precision miscalibration and STM precision miscalibration had any predictive effect on the tendency to accept bullshit (BS C). The model was not significant ($F(2, 50) =0.97$, $p = 0.39$), with an R^2 of 0.04. Neither LTM PE ($\beta = -0.12$, $p = 0.43$) nor STM PE ($\beta = -0.12$, $p = 0.41$) were able to significantly predict change in BS C. The hypothesis that as PE miscalibration increase, so does the tendency to accept bullshit was not supported.

Exploratory analyses

Table 10

Table X: Summary of Bayesian correlation, with LTM precision miscalibration, STM precision miscalibration, Total PE, Perceived precision, Actual precision, Bullshit d', Bullshit C, AQ, SQ and CAPE- positive.

		1	2	3	4	5	6	7	8	9	10
LTM miscal.	Kendall's tau	-									
	BF_{10}	-									
STM miscal.	Kendall's tau	0.22	-								
	BF_{10}	2.38	-								
Total PE	Kendall's tau	0.64***	0.55***	-							
	BF_{10}	7.15e +8	3.406e +6	-							
Relative perceived precision	Kendall's tau	0.05	-0.01	0.08	-						
	BF_{10}	0.2	0.18	0.25	-						
Relative actual precision	Kendall's tau	-0.51***	0.18	-0.21	0.23	-					
	BF_{10}	198477.1	0.96	2.08	3.53	-					
Bullshit d'	Kendall's tau	0.04	0.17	0.12	-0.02	0.14	-				
	BF_{10}	0.19	0.79	0.39	0.18	0.48	-				
Bullshit C	Kendall's tau	-0.06	-0.1	-0.11	0	-0.03	-0.33**	-			
	BF_{10}	0.21	0.31	0.35	0.18	0.19	60.81	-			
AQ	Kendall's tau	-0.05	0	0.03	0.13	0.14	0.29*	-0.29*	-		
	BF_{10}	0.2	0.18	0.18	0.46	0.49	17.63	17.76	-		
SQ	Kendall's tau	-0.17	0.05	-0.12	-0.1	0.18	-0.13	-0.12	0.05	-	
	BF_{10}	0.83	0.2	0.37	0.3	0.96	0.45	0.39	0.2	-	
CAPE-positive	Kendall's tau	0.05	-0.1	0.01	0.22	-0.06	-0.26	0.05	-0.2	-0.01	-
	BF_{10}	0.21	0.31	0.18	2.61	0.21	7.14	0.21	1.42	0.18	-

$^{*}BF_{10} > 10$, $^{**}BF_{10} > 30$, $^{***}BF_{10} > 100$

Bayesian correlations

The Kendalls' tau correlation coefficient is interpreted as normal correlation.

BF_{10}: Indicates how likely the data is under the current hypothesis. For instance, if the $^{*}BF_{10} >$ 10, that means the data are at least 10 times more likely under the chosen hypothesis, which in this case is a two-sided hypothesis that the population correlation is not equal to 0 (JASP team, 2017).

Correlations

Table X shows the Bayesian correlations. Using Bayesian correlation with Kendall's tau, several correlations between variables were found. Total PE miscalibration correlated highly with both LTM precision miscalibration $r_\tau(53) = 0.64$, $BF_{10} = 7.15e+8$, and STM precision miscalibration $r_\tau(53) = 0.55$, $BF_{10} = 3.406e+6$. LTM precision miscalibration also showed a high negative correlation with relative actual precision $r_\tau(53) = -0.51$, $BF_{10} =$ 198477.1. As mentioned in the methods section, these correlations are a result of the same artefacts going into the variables, and will not be considered further.

Bullshit c shows a moderate negative correlation with Bullshit d' $r_\tau(53) = -0.33$, BF10 = 60.81, which indicates that bullshit sensitivity is associated with a bias to reject bullshit. Bullshit c also shows a small negative correlation with AQ: $r_\tau(53) = -\ 0.29$, $BF_{10} = 17.76$. This negative relationship indicates that tendencies towards autism is associated with a bias to reject bullshit.

Bullshit d' shows a small positive correlation with AQ: $r_\tau(53) = 0.29$, $BF_{10} = 17.63$, this indicates that tendencies towards autism is associated with a greater ability to distinguish between motivational quotes and bullshit.

In addition, CAPE-positive showed a small negative correlation with Bullshit d' CAPE-positive $r_\tau(53) = -\ 0.26$, $BF_{10} = 7.14$, which indicates that a tendency to psychosis is associated with a poorer ability to distinguish bullshit from motivational quotes. While this correlation was not flagged in the output provided by JASP, according to Jarosz and Wiley (2014), a Bayes factor of 7.14 is considered substantial, and therefore warrants closer inspection.

Lastly, Relative actual precision has a weak but positive correlation with relative perceived precision $r_\tau(53) = 0.23$, $BF_{10} = 3.53$. This supports the hypothesis that the more precise short-term memory is compared to long-term memory, the more short-term memory is perceived to be more precise than long-term memory.

Table 11

Bayesian regression: Effects of AQ and CAPE-positive on Bullshit d'

Models	P(M)	P(M|data)	BF M	BF 10	error %
Null model	0.25	0.03	0.10	1.00	
AQ	0.25	0.24	0.93	7.42	8.56e -5
CAPE-positive	0.25	0.19	0.69	5.84	1.30e -4
AQ + CAPE-positive	0.25	0.55	3.60	17.10	0.004

This regression explored the effect of AQ and CAPE-positive on Bullshit d'. The alternative hypothesis is that either of these two measures will show an effect on Bullshit d'. The Bayes factor in favour of including AQ in the model as opposed to not including AQ was 7.42, with an error of 8.56e-5. As for CAPE-positive, Bayes factor was 5.84, with an error 1.30e-4. The strength of both these Bayes factors are considered substantial by Jarosz and Wiley (2014). In addition, the joint model of AQ and CAPE-positive shows has a Bayes factor of 17.10, with an error of 0.004, which is considered strong evidence for this hypothesis. A model that includes both AQ and CAPE-positive best predicts Bullshit d' and is therefore favoured.

Table 12

Exploratory multiple regression: Effects of AQ and CAPE-positive on Bullshit d'

Variable	Adjusted R^2	B	SEB	*β*	*t*	*Sig.*	F-test (sig)
	0.19						6.91 (0.002)
Constant		1.99	0.79		2.51	0.02	
AQ		1.45	0.62	0.30	2.34	0.02	
CAPE-positive		-1.13	0.51	-0.29	-2.21	0.03	

To be able to look at the directional relationship between AQ and CAPE-positive on Bullshit d', I also performed a regular multiple regression. The regression equation was significant ($F(2, 50) = 6.91$, $p = 0.002$, with an R^2 of 0.217. The model was able to significantly predict 21.7% of the variation of Bullshit d'. Both AQ ($\beta = 0.30$, $p = 0.02$) and CAPE-positive ($\beta = -0.29$, $p = 0.03$) contributed significantly to the model. These results indicate that as AQ score increases, the ability to distinguish bullshit from motivational quotes increases, while an increase in CAPE-positive decreases the ability to distinguish bullshit from motivational quotes.

Discussion

The present study looked at the actual and perceived precision in visual memory along the autism-psychosis continuum, as well as possible relationships with the ability to detect pseudo-profound bullshit. Precision miscalibration in short-term memory and long-term memory were central variables in this study. Miscalibration in long-term memory was calculated by dividing the perceived LTM variance (size of squared confidence interval) by the actual variance (squared distance between the best guess and actual shape). The miscalibration in short-term memory was calculated in a corresponding way, only with perceived and actual STM variance. As expected, I found large correlations between long-term memory precision miscalibration and total prediction error miscalibration and short-term memory precision miscalibration and total prediction error. These findings are not meaningful however: The total prediction error miscalibration is the sum of perceived LTM and STM variances divided by the sum of actual LTM and STM variances. These three measures of prediction error miscalibration are based on the same numbers, and therefore correlate highly, which also proved to be somewhat problematic for the data analysis which is why only LTM and STM precision miscalibration was included in the regressions.

Van de Cruys et al. (2014) argued that a result of overestimating prediction errors would be persistent surprise, that in turn would lead to detail-focused processing. Therefore, I hypothesised that the more prediction error is overestimated, the more short-term memory should be perceived to be more precise than long-term memory. The results from my analyses did not support this hypothesis however, as there was no apparent relationship between the total prediction error and the relative perceived precision variable, nor did either of the LTM or STM precision miscalibration variables successfully predict any change in relative perceived precision. This could tie in with one of the other hypotheses: That the more PE was overestimated, the greater the short autism quotient would be. If there was support for this hypothesis, I would have found positive values of STM precision miscalibration and LTM precision miscalibration, and a predictive relationship with the short AQ, which I did not. Again these findings were not in line with the theory put forth by Van de Cruys et al. (2014). It is important to note however, that while Van de Cruys et al. (2014) expect that only people who overestimate their prediction errors would score as autistic, negative numbers could also contribute to the correlation and regression if people with negative scores on either LTM or STM precision miscalibration also have low AQ scores. While it is possible there simply is not any relationship between the prediction error miscalibrations and autism, there are several limits to this study, and especially sample limitations that could impact the findings; The sample size was small and it would have given the analysis more power if it contained a larger range of scores and participants, particularly extreme scores on either AQ or the LTM and STM precision miscalibration variables. Having some people with an autism diagnosis would therefore have been helpful in accurately figuring out if there is any relationship between overestimation of prediction errors and autism.

There are a few other possible reasons why my data apparently does not support this particular theory of Van de Cruys et al. (2014). First; van de Cruys makes his prediction about people with ASD, and how they continuously overestimate their prediction errors (Haker et al., 2016; Van de Cruys et al., 2014), while my data indicates that my sample overall tended to underestimate their prediction-errors rather than overestimate them, as indicated by more negative values of STM PE and LTM PE miscalibration. This is interesting, because the literature thus far has been more concerned about those who overestimate prediction errors, but as can be seen in TABLE X, there are people who do the opposite and underestimate their prediction errors as well. What could the implications of continuously underestimating your prediction errors be? It is possible that it could impact learning to some extent. If you underestimate your prediction errors, then you also underestimate how much you should learn from an event. An example of this is continuously misjudging how much time you need to complete a task, and yet fail to learn that you should estimate more time the next time around.

I also predicted that the more prediction error is overestimated, the greater the short systemizing quotient (SQ) score would be. As both the systemizing and the autism quotient are used as indications of autistic traits, it is logical to think that you might find similar results when looking at the STM and LTM precision miscalibrations and possible effects on AQ and SQ. The interesting finding here is that, while weak, LTM precision miscalibration showed a negative relationship with SQ. This means, that as LTM precision miscalibration was increased (as indicated by positive values), the SQ was indicated to decrease, and is the exact opposite of what was predicted. In this project, that would mean that participants made too large confidence intervals relative to their ability to pinpoint the shape in the long-term memory task.

I predicted that the more precise STM was compared to LTM, the more STM would also be perceived to be more precise than LTM, as seen in the relationship between actual and relative perceived precision. Larger values of both relative actual precision and relative perceived precision indicates more precise short-term memory than long-term memory (both perceived and actual). Overall, people tended to perceive their STM to be more precise compared to LTM, and this was also reflected in the relative actual precision, with people performing better on the STM-task, compared to the LTM-task. I found weak evidence to confirm this hypothesis, as evident by the small positive correlation between the two variables, and the small Bayes factor. However weak, this association indicates that the size of confidence intervals used in STM trials, and their ability to pinpoint the actual shape in the STM trials is related. This implicates a tendency in our data, that people are at least partly aware of the actual precision of their visual STM memory. And while there are some miscalibration, it seems people's beliefs about their precision has at least some basis in reality, at least where STM is concerned.

Based on the theories put forth by Frith (2005) and Fletcher and Frith (2009), I also predicted that overestimation of prediction error miscalibration would be associated with psychosis, as measured by the positive sub-scale of CAPE-42. This hypothesis was not supported either. While it is possible the results could have looked different if I had a wider range of scores, it is difficult to predict. I found no support for the hypothesis stating that as prediction error miscalibration increased, so would the bias towards accepting bullshit.

In addition to the hypotheses, the explorative correlations turned up some interesting relationships between variables that we did not predict in our hypotheses. The short autism quotient score turned out to be associated with both bullshit bias and sensitivity to bullshit. Tendencies towards autism (AQ) showed a negative relationship with the tendency to accept bullshit as profound. While correlations do not imply causality, it could imply that people who score higher on autism are better at spotting these kinds of bullshit statements. This could be explained by a trait sometimes associated with autism, extreme attention to details (Baron-Cohen et al., 2009). To be more specific, someone who shows exaggerated attention to details, might be better at spotting possible discrepancies in the bullshit statements, such as that while the syntactic structure makes sense, the words put together do not.

Tendencies towards autism was also associated with the ability to differentiate between actual motivational statements and bullshit statements. This is seen in the positive correlation between the two. A larger value of d' (the sensitivity measure of bullshit vs. motivational statements), indicate a greater ability to distinguish signals from noise (Stanislaw & Todorov, 1999). Tendencies towards psychosis was, as opposed to AQ, associated with a poorer ability to distinguish motivational statements from bullshit. One possible reason for accepting bullshit could be that you are unable to properly notice how vague the statements are. Take Barnum statements as an example, in a horoscope you will find statements that will fit a very broad range of people "Leo should watch their temper, because they might end up hurting someone they care about", or "You are a person who people generally like and often open up to, however you also find that you have thoughts you do not want other to know". While these statements might seem very specific and written just for the person reading, they are actually very general and would fit a lot of people. This could tie in with overestimating the precision of the current data, which in our study would be the short-term memory precision. However, this would in practice mean that I should have found a negative correlation between Bullshit d' and STM precision miscalibration, which I did not and makes the explanation less likely. As a result of these unexpected relationships between Bullshit sensitivity and tendencies towards psychosis, and bullshit sensitivity and tendencies towards autism, I conducted an exploratory regression to have a closer look at the relationships.

It turns out, that both AQ and CAPE-positive significantly predicted variations in sensitivity to bullshit, albeit in different directions when running the tests. An increase in the AQ score predicted an increased ability to distinguish bullshit from motivational statements. An increased score on CAPE-positive was negatively associated with the ability to distinguish bullshit from motivational statements. It is difficult to say anything conclusive from these results, other than that there is a difference in their ability to detect bullshit. To examine these relationships closer, adding measures of analytical and critical thinking might prove beneficial, to see exactly where the people with tendencies towards autism and psychosis differentiate.

Limitations:

The limitations of this study were mainly due to sample size. The sample size was smaller than we would have liked. Although the initial number of participants tested was within the sample size we proposed initially in the Open Science Framework preregistration, a sizeable portion of the participants still had to be excluded. I had to exclude many people. The sampling of participants could also have been more diverse. As the day 2 tasks could not be done on the researcher's computer, the computer labs at the institute had to be used. While this allowed me to test several participants at once, it also made it difficult to recruit participants from different campuses, and a wider range of age. Therefore, the sample contain an unfortunate homogenous student population. In addition, I did not have the time to run pilot tests before running the actual experimental tasks. Because of this, some limitations to how we computed some of the variables was not detected, which again limited how we could model the data.

The road ahead

For future projects, similar to this one, using the original and longer version of the AQ, instead of including SQ could prove advantageous, to get a better measure of the autistic traits. It would also be important to improve the measures of how LTM and STM combine with each other. Recruiting with a wider variety of tendencies towards autism and psychosis should also be of high priority. In addition, it would prove invaluable to be able to recruit a substantial number of participants, and properly motivate them to partake in the study and have them fill in even more extensive questionnaires. For instance, adding measures of analytical thinking and empathising would allow us to make finer distinctions between the tendencies than just potentially splitting participants into two groups. After all, psychosis and autism does show some comorbidity (Haker et al., 2016). This would be a similar approach to a study by Lindeman and Lipsanen (2016), where they were found evidence of religious individuals and sceptics not being homogenous groups, but consisting of various subgroups. It is possible that by just splitting people into people who show autistic traits and people who show more traits associated with psychosis, we might be missing out on meaningful relationships because we are ignoring possible group differences.

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Appendix

Appendix A: Discrimination training


MainWindow
Er dette målfiguren?
Ja
Nei

Appendix B: Bullshit Receptivity and instructions

Vi er interesserte i hvordan mennesker opplever dyp mening. Under finner du flere utsagn tatt fra relevante nettsider. Vennligst les hvert utsagn og bruk et øyeblikk på å tenke over hva utsagnet kan bety. Deretter vennligst angi hvor "dyp" du tror meningen er. Angitt på en fempunktsskala der (1) er "Ikke dyp mening i det hele tatt", (2) er "Noe dyp mening", (3) er "Nokså dyp mening", (4) er "Definitivt dyp mening", og (5) er "Veldig dyp mening"

Vi er interesserte i hvordan mennesker opplever dyp mening. Under finner du flere utsagn tatt fra relevante nettsider. Vennligst les hvert utsagn og bruk et øyeblikk på å tenke over hva utsagnet kan bety. Deretter vennligst angi hvor "dyp" du tror meningen er.

	1	2	3	4	5
Fremtiden forklarer irrasjonelle handlinger.					
Tilgivelse betyr å gi slipp på forhåpningene om en bedre fortid.					
Helhet stilner uendelige fenomener.					
Jeg lurer på hvor mange personer jeg har sett på i hele mitt liv uten å ha virkelig sett dem.					
Fantasien eksisterer innenfor eksponentielle hendelser i tid og rom.					
Kunst og kjærlighet er to sider av samme sak: Det er prosessen av å se seg selv i noe som ikke er deg.					
Innerst inne i ditt vesen ligger svaret; du vet hvem du er og du vet hva du vil.					
Skjult mening forvandler unik abstrakt skjønnhet.					
Læreren din kan åpne døren, men du må gå gjennom den selv.					
Vi er midt i en høyfrekvent oppblomstring av kommunikasjonstetthet som vil gi oss tilgang til selve kvantematerien.					
Vi er midt i en selvbevisst eksistensoppblomstring som vil innrette oss mot selve kjernen.					
Den kreative voksne er barnet som overlevde.					
En våt person frykter ikke regnet.					
Vitenskapen forteller oss i dag at naturens essens er glede.					
Bare de som er villige til å risikere å gå for langt kan finne ut hvor langt en kan gå.					
Bevissthet er framvekst av sammenheng, og av oss selv.					
Hver slutt er også en begynnelse. Vi vet det bare ikke på det aktuelle tidspunktet.					
Bevissthet består av kvanteenergifrekvenser (med «kvante» menes en avsløring av det ubegrensede).					
God helse gir realitet til subtil kreativitet.					
En elv skjærer seg gjennom en stein, ikke på grunn av dens styrke men på grunn av dens utholdenhet.					

Appendix C Short Autsim Quotien (AQ) and instructions

Vennligst fortell oss hvor du er enig i hvert av de følgende utsagnene. Angitt på en firepunktsskala, der (1) er “Helt uenig”, (2) er “Litt uenig”, (3) er “Litt enig” og, (4) er “Helt enig".

Vennligst fortell oss hvor mye du er enig med hver av følgende utsagn:

	1	2	3	4
Jeg legger ofte merke til små lyder som andre ikke legger merke til.				
Jeg er som regel mer opptatt av helheten enn av de små detaljene.				
Jeg synes det er lett å gjøre flere ting på en gang.				
Hvis jeg blir avbrutt, kan jeg lett komme i gang igjen med det jeg holdt på med.				
Jeg synes det er lett å ”lese mellom linjene” når noen snakker til meg.				
Jeg kan se det på folk hvis de kjeder seg når jeg snakker.				
Når jeg leser en fortelling, synes jeg det er vanskelig å forstå intensjonene (hensiktene) til rollefigurene i fortellingen.				
Jeg liker å samle informasjon om grupper eller kategorier av ting (f.eks. Bilmerker, fuglearter, togtyper, plantearter eller lignende).				
Jeg synes det er lett å skjønne hva folk tenker eller føler bare ved å se på ansiktsuttrykket deres.				
Jeg synes det er vanskligg å finne ut av folks intensjoner (hensikter).				

Appendix D Short Systemizing Quotient (SQ) and instructions

Vennligst fortell oss hvor du er enig i hvert av de følgende utsagnene. Angitt på en firepunktsskala, der (1) er “Helt uenig”, (2) er “Litt uenig”, (3) er “Litt enig” og, (4) er “Helt enig".

Vennligst fortell oss hvor mye du er enig med hvert av følgende utsagn:

	1	2	3	4
Hvis jeg skulle kjøpe bil, ville jeg skaffe meg nøyaktig informasjon om motorens ytelse.				
Hvis det hadde vært noe galt med det elektriske anlegget i hjemmet mitt, ville jeg vært i stand til å reparere det selv.				
Jeg leser sjelden artikler og nettsider som handler om ny teknologi.				
Jeg har ingen interesse av å forstå hvordan trådløs kommunikasjon (for eksempel mobiltelefoner) fungerer.				
Jeg liker ikke spill som krever høy grad av strategisk tenkning (for eksempel sjakk, Risk, Othello, bridge).				
Jeg er fascinert av hvordan maskiner virker.				
Når det gjelder matematikk, er jeg fascinert av reglene og systemene.				
Jeg synes det er vanskelig å forstå bruksanvisninger som skal vise hvordan man setter sammen ting.				
Hvis jeg skulle kjøpe meg ny PC, ville jeg skaffe meg nøyaktig informasjon om prosessorhastighet og harddiskkapasitet.				
Jeg synes det er vanskelig å lese og forstå kart.				
Når jeg ser på et møbel, tenker jeg ikke på detaljer som handler om hvordan det ble konstruert.				
Jeg synes det er vanskelig å finne fram i en ny by.				
Jeg pleier ikke se på TV-programmer om forskning eller lese artikler som handler om forskning og naturvitenskap.				
Hvis jeg skulle kjøpe nytt musikkanlegg, ville jeg vite alt om de tekniske finessene.				
Jeg synes det er lett å forstå hvordan oddsen fungerer i tipping.				
Jeg er ikke særlig pirkete når jeg pusser opp hjemme.				
Når jeg betrakter en bygning, bli jeg nysgjerrig på hvordan den er konstruert.				
Jeg synes det er vanskelig å forstå informasjon fra bankene om ulike investerings- og spareformer.				
Når jeg reiser med tog, tenker jeg ofte på hvordan nettverket av avganger og ankomster koordineres.				
Hvis jeg skulle kjøpe nytt kamera, ville jeg ikke sette meg grundig inn i kvaliteten på objektivet.				
Når jeg lytter til værmeldingen, er jeg lite interessert i de ulike værmønstrene.				

Når jeg betrakter et fjell, tenker jeg på hvordan det ble formet i sin tid.				
Det er lett for meg å se for meg hvordan de største veiene i mitt fylke er knyttet sammen.				
Når jeg sitter på et fly, tenker jeg ikke på aerodynamikken.				
Jeg er interessert i å kjenne veien en elv tar fra dens utspring til den renner ut i havet.				

Appendix E: CAPE-42 and instructions

Dette er et spørreskjema skapt for å måle særskilte følelser, forestillinger, og mentale opplevelser. Vi tror at disse er mye vanligere enn det som var tidligere antatt, og at de fleste mennesker har hatt slike opplevelser i løpet av sitt liv.Det er ingen «rette» eller «gale» svar på spørsmålene i dette spørreskjemaet. Det er dine oppriktige synspunkter og meninger vi er interesserte i. Det er viktig at alle spørsmålene blir besvart. Tenk ikke for lenge på hvert spørsmål - er du i tvil, er ofte den første innskytelsen det beste svaret. Svaralternativene er: Aldri (1), Iblant (2), Ofte (3), Nesten alltid (4). Hvis svaret er "Aldri", gå til neste spørsmål.

Dette er et spørreskjema skapt for å måle særskilte følelser, forestillinger, og mentale opplevelser. Vi tror at disse er mye vanligere enn det som var tidligere antatt, og at de fleste mennesker har hatt slike opplevelser i løpet av sitt liv.Det er ingen «rette» eller «gale» svar på spørsmålene i dette spørreskjemaet. Det er dine oppriktige synspunkter og meninger vi er interesserte i. Det er viktig at alle spørsmålene blir besvart. Tenk ikke for lenge på hvert spørsmål - er du i tvil, er ofte den første innskytelsen det beste svaret.

	1	2	3	4
Føler du deg noen gang trist?				
Har du noen gang følelsen av at folk kommer med hint om deg, eller sier ting med dobbel betydning?				
Har du noen gang følelsen av at du ikke er en spesielt livlig person?				
Har du noen gang følelsen av at du ikke er særlig god til å snakke for deg når du er i en samtale?				
Har du noen gang følelsen av at noe i et blad eller på TV er beregnet spesielt på deg?				
Har du noen gang følelsen av at enkelte personer er noe annet enn de gir seg ut for?				
Føler du deg noen gang forfulgt på en eller annen måte?				
Tror du på at folk har blitt bortført av romvesener, eller at dette kan ha hendt deg?				
Har du noen gang hatt følelsen av at du har svake eller ingen følelsesmessige reaksjoner når noe viktig/alvorlig har hendt?				
Føler du deg noen gang pessimistisk når det gjelder absolutt alt?				
Har du noen gang følelsen av at en konspirasjon er rettet mot deg?				
Har du noen gang følelsen av at du er forutbestemt til å være en veldig viktig person?				
Har du noen gang følelsen av at du ikke har noen framtid?				
Har du noen gang følelsen av at du er en veldig spesiell eller uvanlig person?				
Hender det at du føler det som om du ikke har lyst til å lever lenger?				

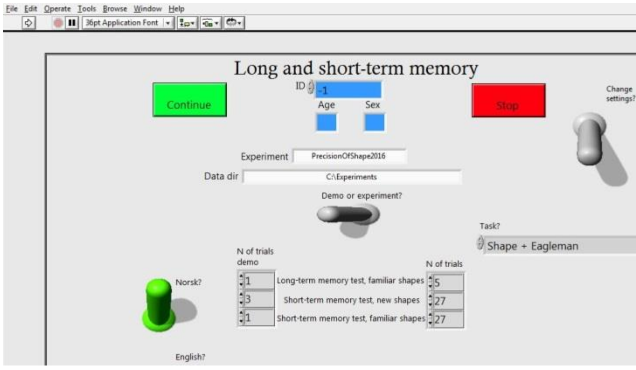
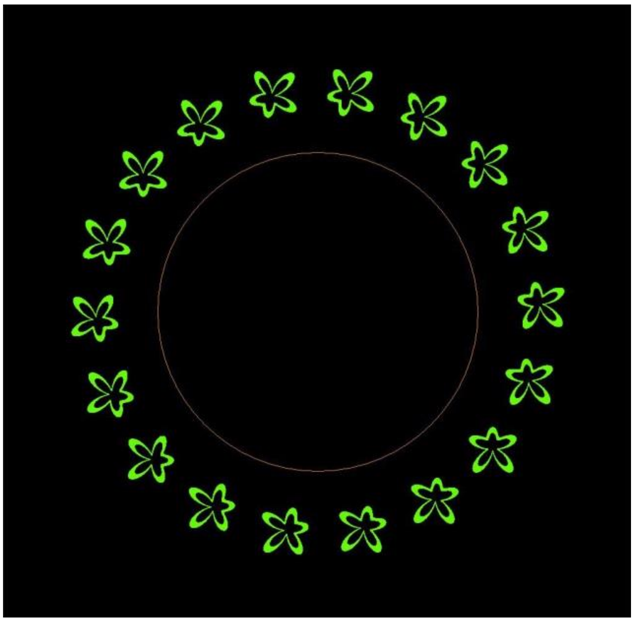
Hender det at du tror folk kan kommunisere telepatisk?				
Føler du noen gang at du ikke har noen interesse av å være sammen med andre?				
Har du noen gang følelsen av at elektriske apparater, for eksempel datamaskiner, kan påvirke tankene dine?				
Har du noen gang følelsen av at du mangler motivasjon for å gjøre ting?				
Hender det at du gråter helt uten grunn?				
Tror du på hekseri, voodoo eller overnaturlige ting?				
Har du noen gang følelsen av at du er en berømt, historisk personlighet?				
Har du noen gang følelsen av at du mangler energi?				
Har du noen gang følelsen av at folk ser rart på deg på grunn av utseendet ditt?				
Har du noen gang følelsen av at hodet ditt er helt tomt for tanker?				
Har du noen gang følelsen av at tankene dine blir tatt fra deg?				
Har du noen gang følelsen av at du bruker alle dagene dine til ikke å gjøre noen ting?				
Føler du noen gang at tankene i hodet ditt ikke er dine egne?				
Føler du noen gang at følelsene dine mangler intensitet?				
Har tankene dine noen gang vært så livaktige at du var redd andre skulle høre dem?				
Føler du noen gang at du mangler spontanitet?				
Hører du noen gang dine egne tanker, som et ekko?				
Har du noen gang følelsen av å være under kontroll av en kraft eller makt utenom deg selv?				
Kjennes det noen gang som følelsene dine er avstumpede?				
Hender det at du hører stemmer når du er alene?				
Hender det at du hører stemmer som snakker sammen når du er alene?				
Har du noen gang følelsen av at du neglisjerer utseendet ditt, eller din personlige hygiene?				
Har du noen gang følelsen av at du aldri får ting gjort?				
Har du noen gang følelsen av at du bare har få hobbyer eller interesser?				
Hender det at du føler deg skyldig?				
Føler du noen ganger som en taper?				
Hender det at du føler deg anspent?				

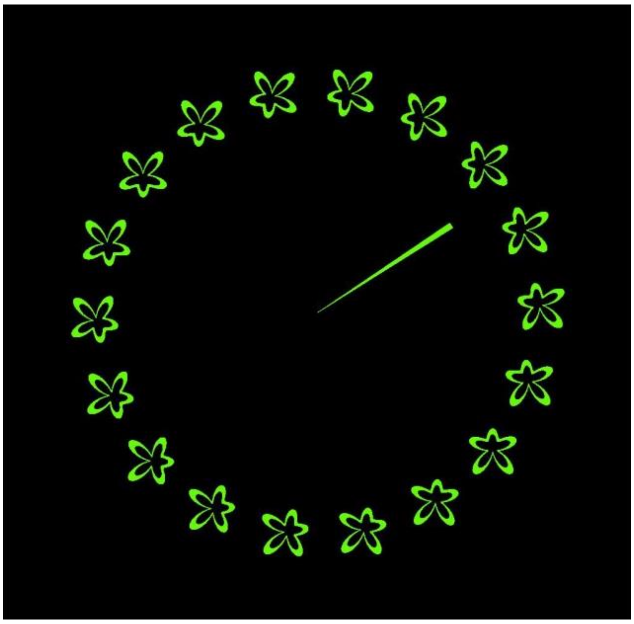
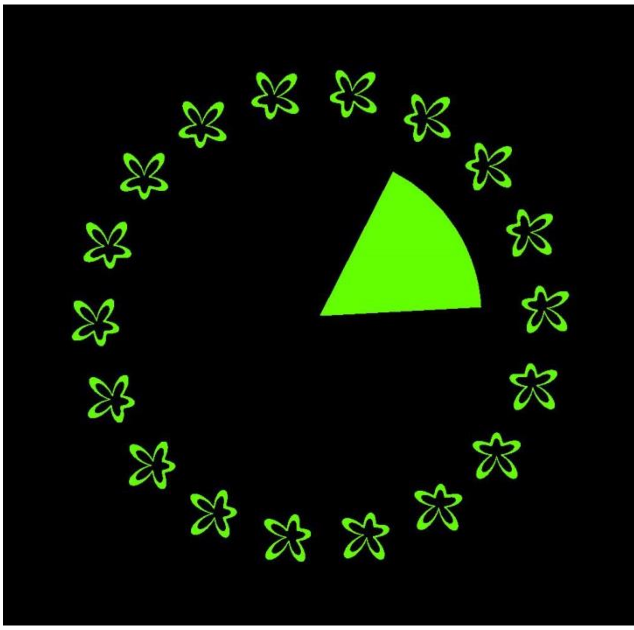
Har du noen gang følelsen av at et familiemedlem, en venn, eller en bekjent har blitt erstattet av en dobbeltgjenger?				
Har du noensinne opplevd et mental kollaps, der du blir en annen person?				
Hender det at du ser gjenstander, folk eller dyr som andre ikke kan se?				

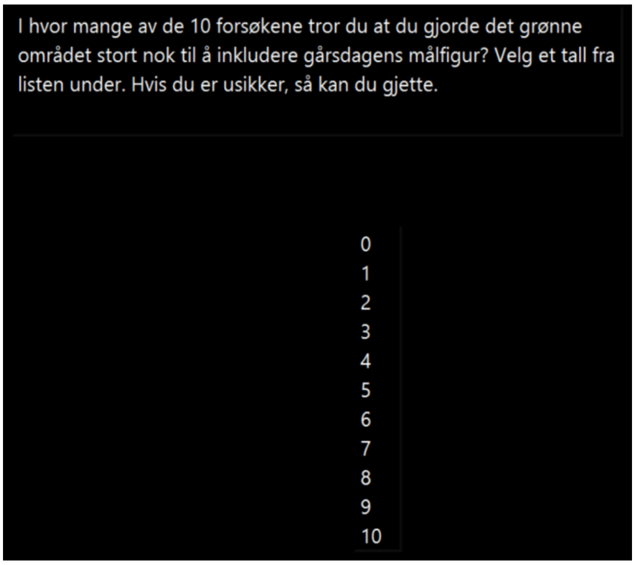
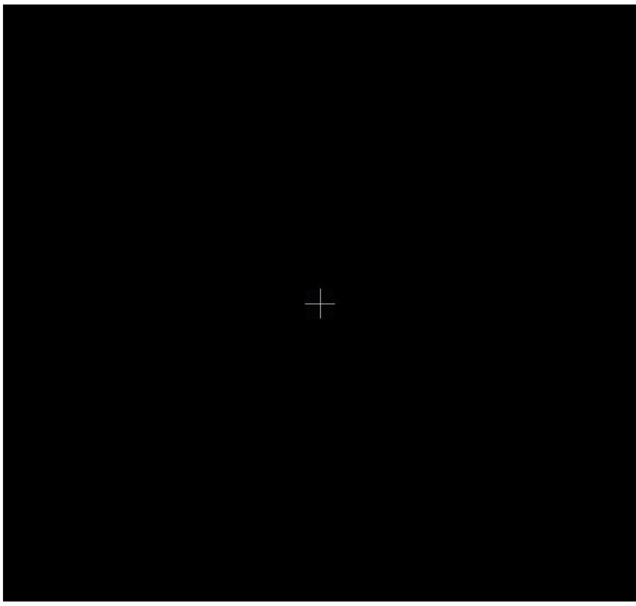
Appendix F: Day 2 Precision task instructions

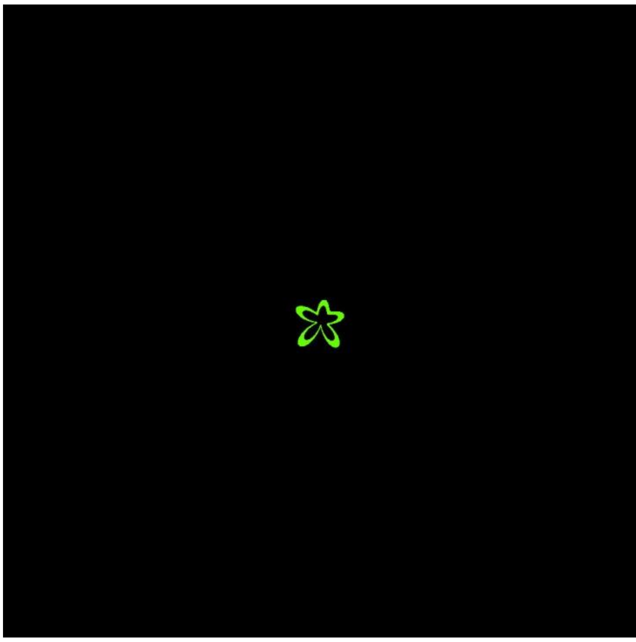
I dag tester vi hvor godt du husker figurer. To av disse testene vil involvere de same figurene du lærte i går. For å forhindre påvirkning under testingen, viser alle illustrasjonene av prosedyrene et annet sett med figurer.

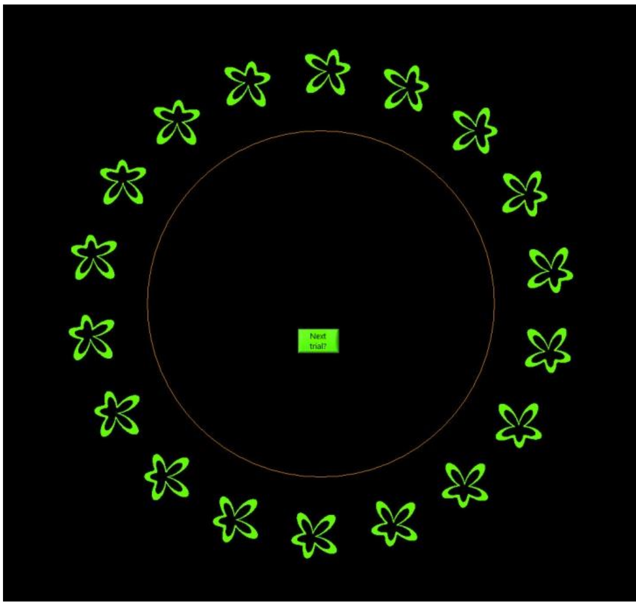
Først tester vi hvor godt du husker figuren du lærte å identifisere i går. Deretter tester vi korttidshukommelsen med et nytt sett figurer. Til slutt tester vi korttidshukommelsen med figurene du lærte å identifisere i går.

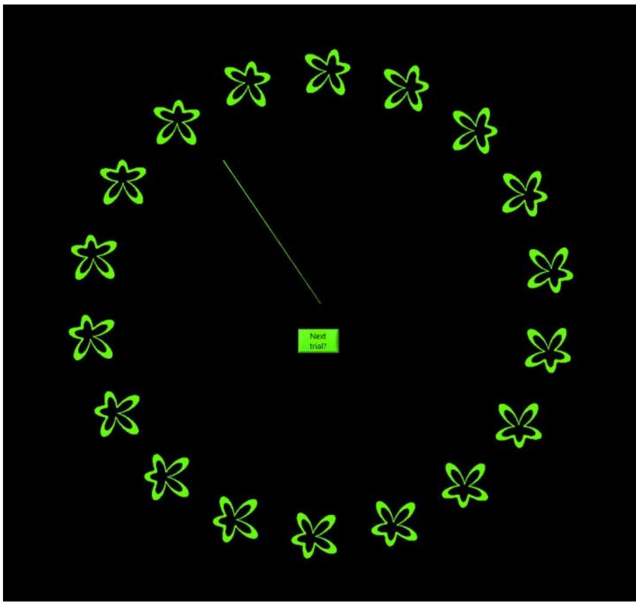
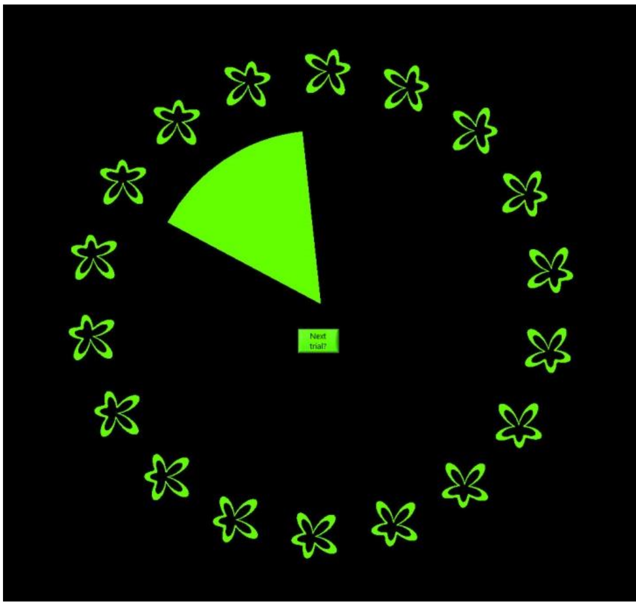
Hvis frontpanelet i programmet viser verktøylinjen på toppen, klikk på den hvite pilen oppe til venstre. Legg inn den sekssifrede IDen fra i går inn i den blå boksen på toppen, så alder og kjønn. Bryteren i midten skal være slått på mot venstre. Klikk på den grønne «Continue» knappen for å gå gjennom en demonstrasjon av den første oppgaven. Det vil være ett demoforsøk. Les beskrivelsen av den andre oppgaven, som vil bestå av tre forsøk. Så les beskrivelsen av den tredje oppgaven, og gå gjennom forsøket.	
Den første oppgaven tester din **langtidshukommelse** for den målfiguren du lærte å identifisere i går. En ring med figurer vil dukke opp. I det faktiske eksperimentet vil du se settet med figurer du øvde med i går, og oppgaven vil være å identifisere målfiguren. Den eksakte figuren befinner seg kanskje ikke i ringen, så da må du klikke mellom de to figurene du tror målfiguren hadde befunnet seg mellom hvis det hadde vært nok plass til å vise alle figurene. Flytt musepekeren til den oransje sirkelen, og venstreklikk der du tror figuren befinner seg, *men hold deg innenfor den oransje sirkelen.*	

I demoforsøket ser du kun de grønne figurene til høyre, som du ikke øvde med i går. Derfor kan du i demoforsøkene kun velge en tilfeldig figur. Når du har valgt en figur og venstreklikket, så vil du se en tynn, grønn linje.	
Deretter vil vi at du velger et intervall/område du er sikker figuren befinner seg innenfor. Intervallet vil være sentrert rundt figuren du allerede har valgt. Velg intervall ved å flytte musen i en retning (det spiller ingen rolle hvilken), til du finner grensen for området du er sikker på at figuren befinner seg innenfor. For å sette intervallet, press Ctrl-tasten på tastaturet. Du får poeng for å lage intervallet akkurat stort nok til at figuren befinner seg innenfor området, men ikke større enn nødvendig. Dette forklares nærmere i neste oppgave, fordi det er enklere, men det samme gjelder for alle oppgavene. I det faktiske eksperimentet vil du ha fem av disse testene av langtidshukommelsen for gårsdagens figur.	

Etter de ti første forsøkene, spør vi deg hvor mange ganger du tror du gjorde intervallet stort nok til å inkludere målfiguren. Klikk på ett av alternativene fra 0 til 10.	
Den neste oppgaven er en test av **korttidshukommelsen**. I eksperimentforsøkene vil vi bruke et annet figursett, men i demoforsøkene bruker vi de samme grønne figurene igjen. Du begynner forsøket ved å klikke på det hvite krysset. Du må være ganske nøyaktig når du klikker på korset.	

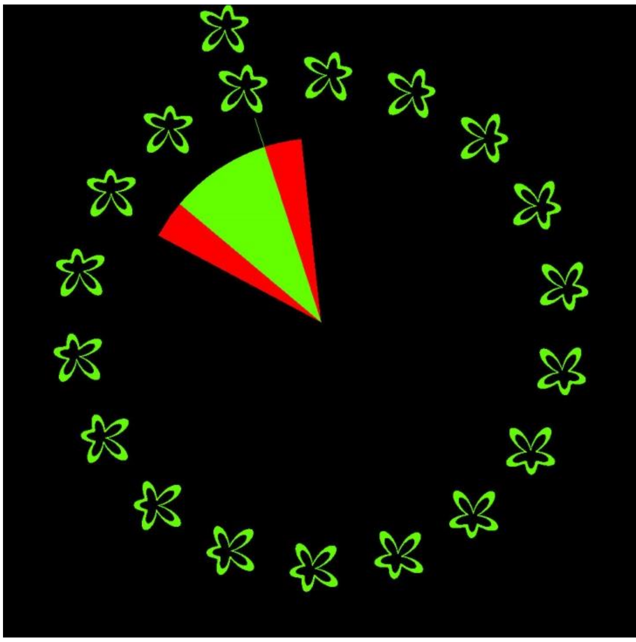
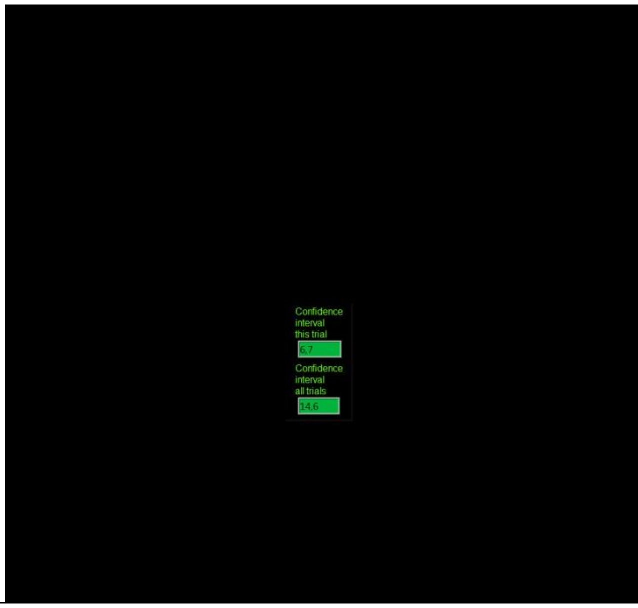
<table>
<tr>
<td>Du vil se en figur, som vil være den figuren du skal huske.</td>
<td></td>
</tr>
<tr>
<td>Etter kort tid vil du se en ring av figurer, akkurat som i den forrige oppgaven. Prøv å identifisere den figuren du akkurat ble vist, og hvis den figuren ikke blir vist, hvor den hadde vært hvis vi hadde hatt plass til alle figurene.

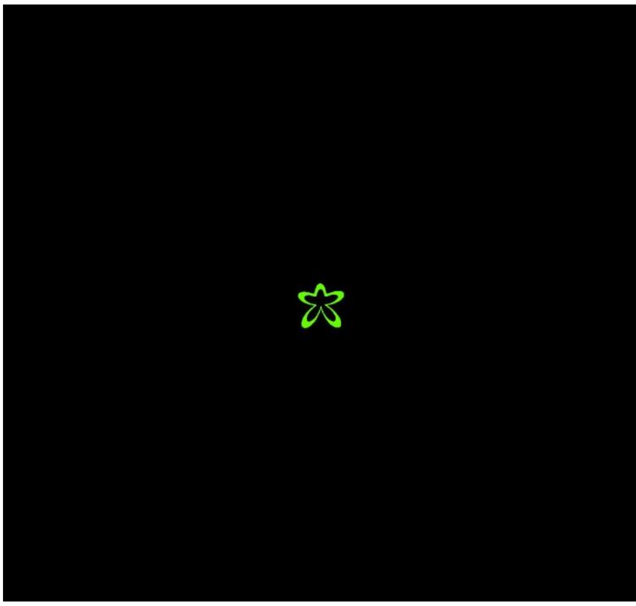
Har du helt glemt hvordan figuren så ut, så har du muligheten til å hoppe til neste forsøk, ved å trykke «Next trial» i midten av sirkelen.</td>
<td>
</td>
</tr>
</table>

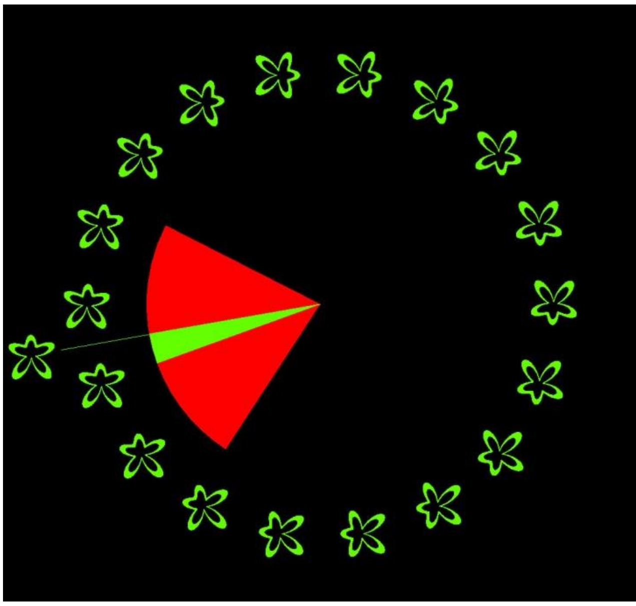
For å velge figur, trykk på det passende stedet i sirkelen, innenfor den oransje sirkelen og klikk venstre museknapp. I eksempelet til høyre, var beste gjetning at figuren ville befinne seg litt til høyre for en av de figurene som er vist.	
Nå kommer hovedpoenget: kan du bedømme hvor godt du husker? Det er lite sannsynlig at hukommelsen din er så god/presis at du kan peke på eksakt riktig sted i sirkelen. For å indikere intervallet som burde inneholde figuren, beveg musepekeren slik at den danner et område som er akkurat så stort at du er sikker på figuren kommer til å være innenfor. Du får 8 poeng hvis du klarer å inkludere figuren i intervallet, men mister poeng tilsvarende overflødig område, som vist i neste bilde. Når du tror intervallet har nådd den riktige størrelsen, press Ctrl-tasten	

<table>
<tr>
<td>I disse oppgavene som tester korttidshukommelsen vil du få tilbakemelding/feedback. Den første delen av tilbakemeldingen er vist til høyre.

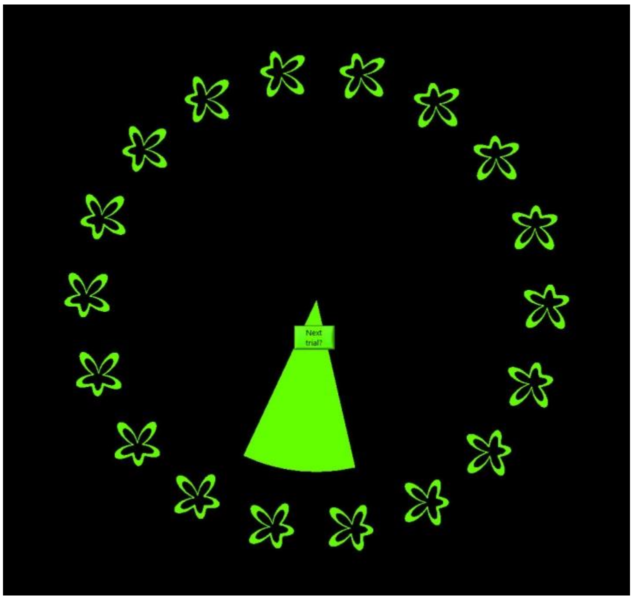
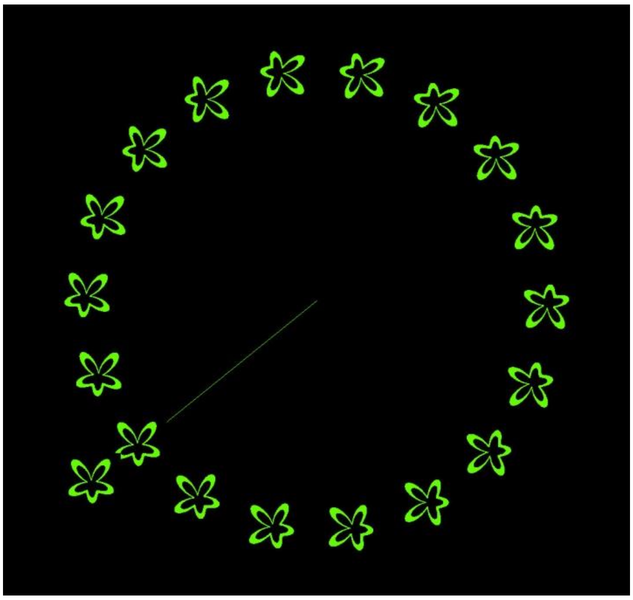
Målfiguren vil dukke opp over den riktige figuren utenfor sirkelen av figurer.

Hvis du lagde intervallet for stort, vil det overflødige området på begge sider av hvor du forventet figuren var bli markert rødt. Et beløp proporsjonelt med det røde området vil bli trukket fra de 8 poengene vunnet for å inkludere målfiguren i intervallet.</td>
<td></td>
</tr>
<tr>
<td>I dette tilfellet resulterte det i 6.7 poeng for dette forsøket. Du får ikke poengene for bedømmelsen din av hvor godt du husker. Å være «accurate» gjør det enklere, men det som betyr noe er hvorvidt du vet hvor nøyaktig du er.</td>
<td>
</td>
</tr>
</table>

For å videre illustrere dette, her er et eksempel på et annet forsøk	

Hukommelsen var her faktisk mer nøyaktig, men vurdert til å være mindre nøyaktig, som resulterte i et større overflødig område, og trekk i poeng.	

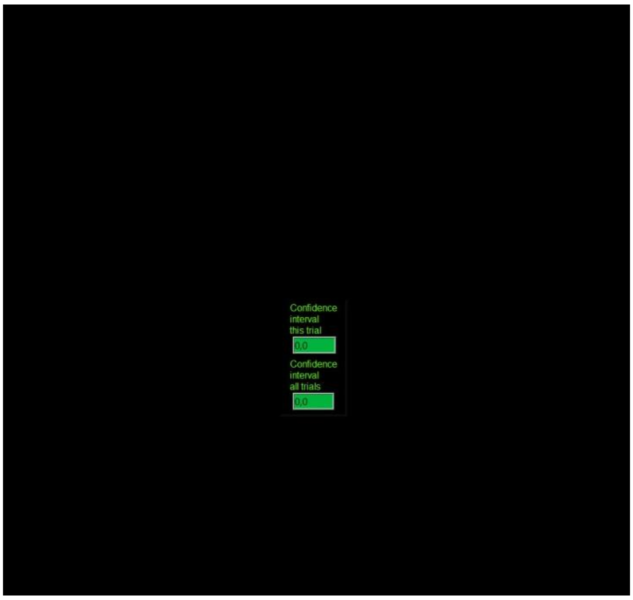
Resultatet er -5.8. poeng for dette forsøket. Det er mulig å gå under 0, og faktisk miste poeng.	
Men på en annen side, hvis dette er figuren…	

Og dette er den beste gjetningen på hvor figuren er og hvor sikker du er på at figuren befinner seg innenfor det grønne området..	
Det viser seg å være en undervurdering, og figuren var ikke inkludert i intervallet, som resulterer i 0 poeng.	

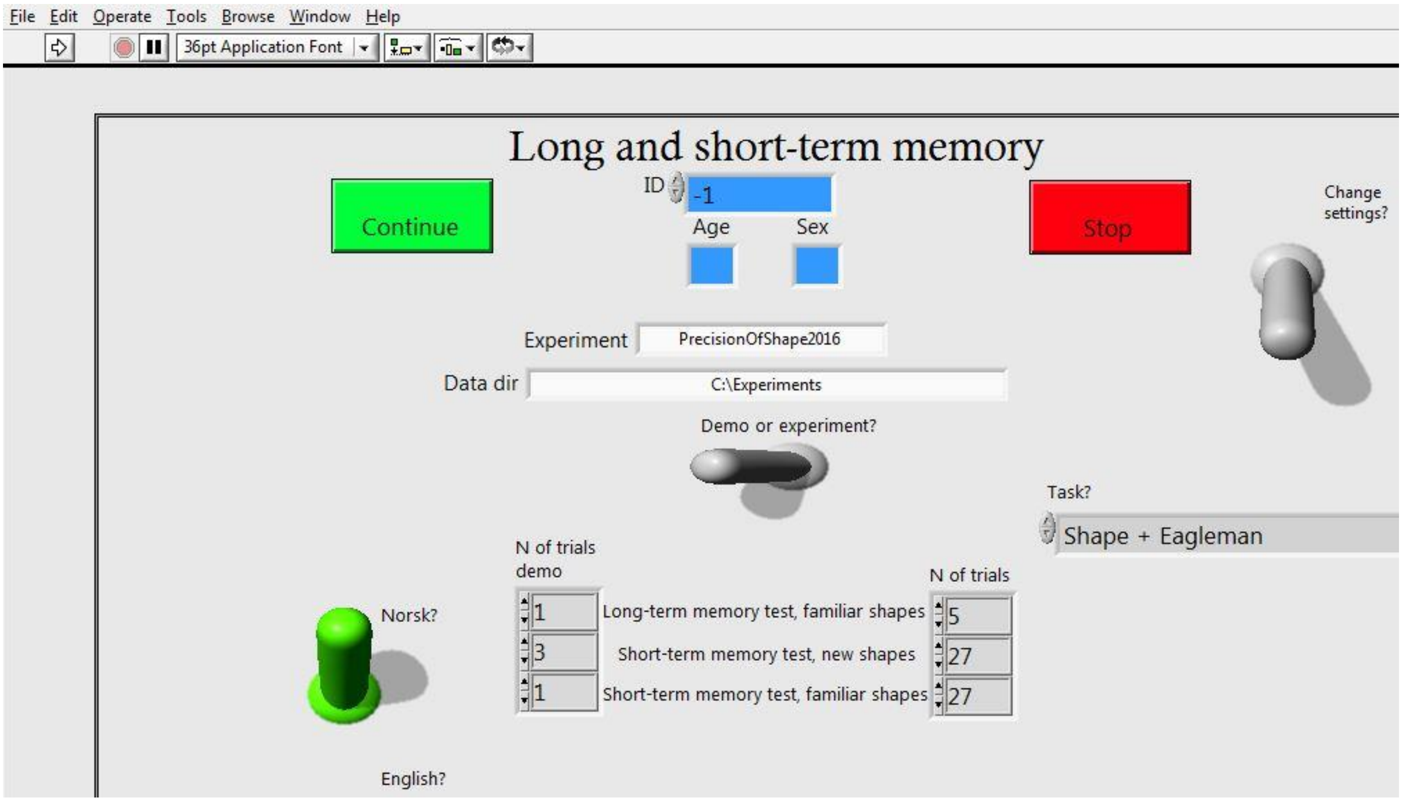
Som dette.

Derfor, prøv å gjøre intervallet akkurat så stort som du tror det burde være, men ikke større. De samme reglene for poeng gjelder for alle de tre oppgavene.

Den tredje oppgaven er igjen en **korttidshukommelse oppgave**, der du skal huske og identifisere figuren du akkurat så. Den eneste forskjellen er at du i denne oppgaven bruker figursettet fra i går, og at du ikke får noen tilbakemeldinger før alle forsøkene er gjennomført



Når du har kjørt ferdig demoforsøkene, så skal du gå tilbake til frontpanelet og se noe som dette:



Flipp den grønne bryteren til ditt foretrukne språk, opp for norsk, ned for engelsk. Forsikre deg om at du tastet inn seks-siffer IDen, alder og kjønn. Flipp bryteren i midten fra «Demo» til venstre, til «Experiment» til høyre, klikk på pilen oppe til høyre igjen, klikk på «Continue», og kjør gjennom de faktiske test forsøkene.

Se ark for lagring av data.

Vi takker deg for din deltakelse

Appendix G: Link to Open Science framework and OSF preregistration.

Open Science Framework: https://osf.io/

Preregistration: https://osf.io/593sz/