Sampling Reality: Exploring Evidence Accumulation Mechanisms in the Psychotic Phenotype

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Thesis submitted in fulfilment of the degree of Doctor of Philosophy

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September 2023
Declaration of Authorship

I, Francesco Scaramozzino, hereby declare that this thesis and the work presented in it is entirely my own. Where I have consulted the work of others, this is always clearly stated.

Signed: [Signature]

Date: ___22/09/2023___________
Abstract

The way the brain samples evidence could be crucial in shaping our experience of reality. Predictive coding accounts hypothesise that increased sensory precision might bias sampling and impact inferences of reality. In a predictive coding framework integrated with the use of sequential sampling models, we investigated the relationship between evidence accumulation mechanisms and psychotic phenotypes in the general population.

Study 1 explored the association of psychotic phenotypes with alterations of evidence accumulation in perceptual inference. We fitted drift-diffusion models (DDM) to behavioural data and evaluated the relation between psychotic phenotype and DDM parameters using the drift rate as a proxy of precision of sensory evidence. Additionally, we sought to replicate findings linking reduced data-gathering in probabilistic reasoning with delusion-like experiences, a bias known as the Jumping to Conclusions bias (JTC). Results showed that both hallucination- and delusion-like experiences were associated with increased sensory precision in perceptual inference. Only hallucination-like experiences predicted lower decision thresholds, while we did not find JTC in the psychotic phenotypes.

Study 2 aimed to modulate evidence accumulation by applying inhibitory transcranial magnetic stimulation (TMS) to the posterior parietal cortex (PPC) and examining its effects along the psychotic phenotype continuum. PPC activity has been correlated with sampling behaviour and might be involved in alterations of evidence accumulation associated with psychosis. We replicated results from Study 1 with both psychotic phenotypes showing increased sensory precision. Notably, participants with a higher delusional phenotype undergoing TMS showed decreased sensory precision.

In conclusion, our findings indicate that increased precision of sensory evidence characterises perceptual inference in both delusional and hallucinatory phenotypes. Specifically for the delusional phenotype, PPC activity might be implicated in alterations of precision encoding. Overall, our studies point to evidence accumulation mechanisms potentially influencing our experience of reality and contributing to the psychotic phenotype in the general population.
Acknowledgements

To my mother, who believed in me from the moment I was born.

For providing me with guidance, knowledge and understanding,
I thank my supervisors, Nick Furl and Ryan McKay.

For giving me life, opportunity, love and trust, I thank my mother
and father, Giusi Zaccari and Giuseppe Scaramozzino.

For teaching me caring and the sacred things of life,
I thank my grandmother, Atlanta Argentina Latella.

For sharing with me love, sorrows, laughs and solace,
I thank my sisters and brothers by blood or soul, near and far.
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I. Reality inference

We open the body of the thesis with a review paper that presents an updated theoretical framework for reality testing in cognitive neuroscience. The paper has been thought for publication and although goes beyond the specific focus of the empirical sections of the thesis, it gives the reader our perspective on psychotic phenotype and the mechanisms that can be associated with it. Our approach is based on the idea that psychosis is present in a continuum of symptomatology that goes from psychotic-like experiences in non-clinical individuals to delusions and hallucinations in patients with psychotic disorders (Mennigen & Bearden, 2020; Strauss, 1969; van Os, 2000; van Os et al., 2009). About the idea of a psychosis continuum, van Os et al. remark:

“A psychosis continuum implies that the same symptoms that are seen in patients with psychotic disorders can be measured in non-clinical populations.” (p. 179; van Os et al., 2009)

This has been showed through the validation of psychotic phenotype measures in the non-clinical population, for example, the Peters et al. delusion inventory (Peters et al., 2004) and the Cardiff anomalous perceptions scale (Bell et al., 2006) that we used in our empirical works. Van Os et al. continue:

“The assumption of this approach is that experiencing symptoms of psychosis such as delusions and hallucinations is not inevitably associated with the presence of disorder.” (p. 179; van Os et al., 2009)

Acknowledging that people can have experiences akin to psychosis outside a pathological context seems to imply that the mechanisms associated with the psychotic phenotype can vary in a continuum from aberrant to functional mechanisms. The review paper we are presenting is born from the need to address the study of mechanisms associated with psychotic phenotype outside a clinical perspective. For example, when we identify a specific pattern of information processing varying with the psychotic phenotype in the non-clinical population, to what extent can we talk about maladaptive mechanisms without evidence of maladaptation?

We became interested in the concept of reality testing when considering the definition of psychosis as an "impairment of reality testing"
(Arciniega, 2015). This led us to reflect on the idea that just as amnesia represents an impairment of cognitive function (i.e., memory), psychosis can be seen as a pathological state of a brain function that also exhibits variability in the general population, specifically, reality testing.

Predictive coding is a theoretical background that already represents a unified, cross-diagnosis, approach to psychosis. This is because, we think, outlines general features of brain functioning that can prompt specific hypotheses linking brain mechanisms to changes in experiences of reality. With the purpose of describing reality testing as a general brain function, we integrated predictive coding, the free-energy principle, and insights from attractor network theory and the entropic brain theory and outlined the implications of these theories on our view on judgements about reality. Within this integrated neurocomputational framework, we introduce reality inference as a construct to explore how the brain constructs conscious representations of reality.

Reality inference as a brain function: Reality testing as a neurocomputational construct.

Abstract

This paper proposes reality inference as a theoretical specification of reality testing in the context of cognitive neuroscience. We believe that empirical research can benefit from a unified approach to altered representations of reality, considering them as outcomes of variability in reality inference as a brain function. We review aspects of predictive coding, attractor network and entropic brain theories, and expand on how these theories can inform our perspective on judgments about reality.

Within the predictive coding under the free-energy principle, reality testing can be viewed as an inferential task aimed at minimising entropy (or uncertainty) and aligning internal representations with sensory evidence while evaluating information as probabilistic signals of varying precision. At the
network level, the brain can be thought of as a dynamical system regulated by attractor networks. These networks, characterised by minimal entropy in attractor states, are influenced by changes in precision/synaptic gain, affecting the stability of these attractor states. Such stability may correspond to more or less stable interpretations of reality. This view is in line with the entropic brain theory that predicts increased entropy, corresponding to higher instability of attractor states, would reflect the experience of altered (pathological or non-pathological) interpretations of reality.

The variability of mechanisms involved in entropy minimisation could map out the variability in reality inference along the population. Thus, the modulation of the precision of neural signals (synaptic gain) and the stability of attractor states can be considered respectively as cellular- and network-level mechanisms covarying with experiences of reality. We conclude that the concept of reality inference offers a comprehensive perspective on reality judgments, encompassing both cellular and network-level mechanisms and emphasising the role of entropy minimisation in shaping the variability of experiences of reality in the general population.

1. **Introduction**
2. **What is reality testing? A brief story**
3. **Inferring Reality: The Predictive Coding Framework**
4. **Brain Dynamics And Reality Inference**
5. **Conclusion**

### 1.1 Introduction

This paper proposes an updated theoretical specification of reality testing within contemporary approaches in computational cognitive neuroscience. Historically, reality testing has been described as a cognitive function involving perceptual, attentive and mnemonic processes that
deliberate whether a signal is internally or externally generated (Balint, 1942; Bentall & Slade, 1985; Hurvich, 1970; Hurvich & Bellak, 1968; Freud, 1951; Johnson & Raye, 1981). In the last decades, predictive coding radically changed our understanding of how the human brain processes information and represents instances of reality. This neurocomputational framework challenges the traditional conception of reality testing and prompts our reevaluation of its definition.

According to predictive coding, the brain is constantly engaged in the ongoing process of inferring the underlying causes of neural signals, while accounting for the uncertainty of the source of information. With an emphasis on the inferential nature of predictive coding, we propose reality inference as a theoretical construct upon which to structure the investigation of the mechanisms that constrain conscious representations of reality. From our perspective, the integration of predictive coding under the free-energy principle, coupled with the embrace of attractor network theory and the Entropic Brain Theory (EBT), collectively give a coherent theoretical ground for reality inference.

We propose that two prominent mechanisms emerge from this theoretical background as pivotal in the characterisation of the spectrum of reality inference across individuals: the precision of neural signalling and the stability inherent to attractor states. The interplay between these mechanisms may significantly impact the brain's minimisation of uncertainty (i.e., free-energy) and its subsequent role in constraining phenomenology.

We believe that clinical and non-clinical research can inform each other and delineate a general understanding of the mechanisms associated with experiences of reality. A unified framework bridging typical and pathological functioning would enable us to bring forth testable predictions on a plethora of phenomena comprising altered experiences of reality shown across the population (e.g., psychotic and psychotic-like experiences, effects of psychotomimetic drugs, mystical experiences, dreaming).

Paralleling Fletcher and Frith’s three explanation levels of psychosis (experiential, neural and cognitive level), we propose that the study of reality inference as a neurocognitive function should work on three levels: (1) the first-person experience (or phenomenological) level that deals with: “the
descriptive study of conscious experience, its structure, its flow, and its dynamics” (Ramstead et al., 2022); (2) the neurobiological level that allows us to examine the physical mechanisms that constrain first-person experiences; (3) a cognitive or natural computation level, where behavioural and/or neurobiological data can be fitted into artificial computational models to produce and test hypotheses about the natural computations that produced those data. We specify the cognitive level as the natural computation level because neurocomputational approaches, such as predictive coding, assume that cognitive processes are carried on by natural computations implemented in biological structures (Ballard, 1999). We think that when working in this theoretical context, cognitive descriptions can be reduced to the natural computations implemented to solve specific cognitive tasks (e.g., decision-making, information storage, signal detection).

In Section 1, we present a brief overview of the concept of reality testing and we justify the need for the re-elaboration of the construct. In Section 2, we present an overview of the core principles of predictive coding, forming the grounding ideas for comprehending reality inference as a neurocomputational function. In Section 3, we introduce the attractor network theory and outline the features of neural connectivity that may play a crucial role in the empirical investigation of inferences about reality; specifically, taking into account the attractor network theory and the EBT, we argue for the relevance of the segregation between Default-Mode Network (DMN) and Task-Positive Network (TPN) for reality inference.

1.2 What is reality testing? A brief story

As with other concepts inherited from psychoanalysis, the term reality testing finds limited popularity in cognitive neuroscience but it is in use in psychiatric research and practice (Arciniega, 2015) as well as in animal models of psychosis (Fry et al., 2020; Kim & Koh, 2016; McDannald & Schoenbaum, 2009).

Sigmund Freud introduced reality testing as the process through which the Ego is able to distinguish between ideas and perceptions
Paraphrasing Freud, Hurvich (1970) describes it as: “a learned procedure of deliberate direction of attention and suitable motor action for the differentiation of internal from external.” (p. 300)- depicting an attentive process whose main task is a classification (internal vs. external). In psychodynamic literature, authors developed and speculated on the concept that took on the features of a complex mind-body function aimed at determining the origin of “sensations” (Balint, 1942; Hurvich, 1970; Hurvich & Bellak, 1968). An interesting example from these works is Balint (1942) who described reality testing as a process in four steps: (1) deciding if the sensation is coming from internally or externally generated signals; (2) inferring the cause of a sensation; (3) evaluating the “significance” of the sensation for the agent; and (4) finding the correct response.

From these early conceptualisations of reality testing, cognitive sciences have extracted the notion that reality testing is a fundamental cognitive function encompassing perceptual, attentive, and mnemonic processes. This function would involve deliberating on the reality of a given piece of information (Bentall & Slade, 1985; Johnson & Raye, 1981). In this transit of reality testing into cognitive sciences, the construct of reality monitoring appeared as a re-working of Hart’s (1967) concept of memory monitoring which was more concerned about the formation and retrieval of false memories and confabulation (Johnson & Raye, 1981). Today, there exists ambiguity between reality testing and reality monitoring. Originally, reality monitoring was specific to memory discrimination and relevant for confabulation, but it has now been referred to more broadly as: “the ability to distinguish internally from externally generated information.” (Simons et al., 2017), a definition that would make it indistinguishable from reality testing.

From this brief excursus, two main ideas emerge about reality testing: (1) reality testing is a fundamental task of human cognition; and (2) this task is about the binary classification of signals as externally or internally generated. We believe that empirical research can benefit from considering the point (1). The idea that conscious representation of reality is a fundamental function of the animal nervous system and that
this function can vary in the population in adaptive and maladaptive ways can give a common research ground to animal, clinical and non-clinical research for investigating the faculty human and non-human animals use to represent reality. At the same time, we think that the reality testing construct as described by (2) needs to be reformulated in order to work as a tool for contemporary accounts of brain functioning. In fact, although distinguishing neural signals as internally or externally generated is fundamental for the nervous system (e.g., corollary discharge) (Carpse & Sommer, 2008), we think that reducing reality testing to a binary classification task limits the description of how the nervous system represents instances of reality.

Predictive coding under the free-energy principle posits that the brain’s main function is to continuously generate predictions about the world, update them based on incoming sensory evidence and reduce uncertainty about reality. Integrated with attractor network theory, these neurocomputation perspectives challenge the traditional binary approach of reality testing and call for a more multifaceted conceptualisation that incorporates our understanding of neurobiological mechanisms and possible natural computations involved in the inference of reality.

1.3 Inferring Reality: The Predictive Coding Framework

The idea that the representation of reality by human cognition is an active constructive process is ancient and could be traced back to the Upanishads or Plato’s dialogues (Friston, 2018; Phillips, 2021; Silverman, 2022). Predictive coding is a contemporary attempt to explain how the brain represents instances of reality and has garnered substantial support from empirical research during the last two decades (Aitchison & Lengyel, 2017; Bastos et al., 2012; Ficco et al., 2021; Friston, 2018). Predictive coding was first suggested as a model of visual processing but soon became a versatile framework for
investigating general features of information processing in the brain (Clark, 2013; Friston & Kiebel, 2009; Rao & Ballard, 1999).

The fundamental idea in predictive coding is that the brain filters out the information that it can predict and processes only the information coming from prediction error (PE). PEs represent residual data that remain unexplained and need further processing. For the implementation of this filtering, the brain would rely on a hierarchical organization where each level generates predictions for the level below and relays sensory information and PE to the level above. Higher levels would adjust their internal representations based on PEs and generate updated predictions reducing PE in the future. Over time, the brain would tend to minimise unexpected information and maximise its explanations of the environment.

**Inference And Precision Modulation.**

Bayesian predictive coding could serve as a natural computation algorithm allowing the brain to minimise PE. Prediction and PE signals could be represented in Bayesian terms by the probability distributions of, respectively, prior beliefs and the likelihood of sensory evidence/PE. Information from prior/predictions and likelihood/PE would be integrated through Bayesian inference to produce newly updated posterior beliefs.

This neurocomputational framework assumes that neural signals are encoded as probability distributions, each with its own precision. Precision is the inverse of variance and informs about the uncertainty ascribed to a stochastic signal (i.e., a signal in the form of a probability distribution). When a signal has higher precision, the values transmitted are less dispersed around a central value. The information conveyed by the signal is more “specific”, as there is less uncertainty about the exact value or meaning of the signal. On the other hand, signals with lower precision have more variability and dispersion, resulting in a broader range of possible values or interpretations. This leads to a higher degree of uncertainty or ambiguity in the conveyed information.
When the precision of a signal (either priors/predictions or likelihoods/PEs) is higher, its influence on the posterior becomes more pronounced. From the agent's point of view, more precise priors/predictions would produce more “conservative” (i.e., relying on predictions) posterior beliefs, while more precise evidence likelihoods/PEs would make posterior beliefs more sensitive to changes in sensory data (Adams et al., 2013; Friston et al., 2016; Stephan et al., 2009; Sterzer et al., 2018). On the neurobiological level, the precision of neural signalling is thought to be implemented by synaptic gain (Feldman & Friston, 2010; Friston & Kiebel, 2009). Synaptic gain quantifies the presynaptic activity's impact on the postsynaptic neuron. From this hypothetical identification of precision with synaptic gain follows that all mechanisms implicated in synaptic gain control (e.g., receptor migration and insertion; synchronised neural activity) affect the modulation of precision of the neural signal.

The modulation of the precision could affect inferences about reality, in adaptive and maladaptive ways. Precision modulation would allow inference to adapt to subjective goals and to the volatility of the environment (Brown & Friston, 2012; Feldman & Friston, 2010; Friston & Kiebel, 2009). In fact, salience and attention neuromodulatory systems could work as precision-weight modulators that “tune” the signals coming from the sensorium increasing the efficacy of information processing for goal-directed behaviours (Brown & Friston, 2012; Feldman & Friston, 2010; Friston & Kiebel, 2009). When precision is not modulated adaptively, it could lead to inferences of reality that are not shared with other individuals, such as delusions and hallucinations (Adams et al., 2013; Friston et al., 2016; Stephan et al., 2009; Sterzer et al., 2018).

**Reality Testing As Inference**

Within this framework, reality testing becomes a neural inferential process, where information is evaluated as probability signals with varying degrees of precision. This probabilistic perspective on representations of reality contrasts classical reality testing from being a
deterministic process, where information is simply classified into fixed categories based on given conditions. For example, when we consider judgements about reality as discrete (classical reality testing), we would need neural signals to be tagged as “external” or “internal” in order to distinguish between imaginative and perceptual representations. However, there is no clear evidence of a neural signature that could implement the “tagging” representations as coming from visual imagination or perception (Dijkstra et al. 2022). Instead, evidence shows that imagined representations evoke weaker neural activity than percepts (Dijkstra et al. 2022; Dijkstra & Fleming, 2023). When we approach judgments about reality from a probabilistic perspective (that is as inferences about reality), the strength of sensory signals could be interpreted in terms of a continuous variable as the degree of precision of sensory signals (synaptic gain). The lower the precision of bottom-up sensory signals, the higher the likelihood that those signals are not coming from the sensorium, and hence are being imagined.

Reality testing conceptualised as reality inference becomes a stochastic process that takes into account the uncertainty inherent in information sources and judgments about reality. The stochastic nature of reality inference allows for an explanation of evidence about delusion- and hallucination-like experiences that can be experienced by the non-clinical population with different degrees of conviction (Bell et al., 2006; Peters et al., 2004). Theorising that the brain adopts a probabilistic approach to reality testing can better explain the complex and nuanced nature of how individuals interpret and perceive the world around them. By acknowledging the role of uncertainty and variability in the inferential process, this framework can provide a more comprehensive understanding of both neurotypical and clinical experiences of reality.

Studying reality inference within the context of predictive coding offers the possibility of formulating hypotheses that encompass the phenomenological, computational, and neurobiological levels. The modulation of precision/synaptic gain represents a fundamental mechanism of reality inference at the cellular level. Such modulation
can lead to macroscopic functional alterations, detectable through neurophysiological and neuroimaging techniques (Friston et al., 2016; Stephan et al., 2009).

**Entropy Minimisation And Reality Inference**

Overall, predictive coding offers a cost-efficient information processing algorithm. It suppresses the redundant processing of predictable information and enables the brain to prioritise the processing of unexpected information, which could potentially disrupt or promote the organism’s homeostasis. The hierarchical processing of unpredicted information implemented in predictive coding implies the optimisation of predictions over time and the minimisation of uncertainty. In this regard, predictive coding is an algorithm complying with the free-energy principle. According to the free-energy principle, a self-organising system must minimise the entropy (or uncertainty) of its internal states over time in order to maintain its homeostasis and allostasis (Friston, 2009, 2010). In this view, the minimisation of entropy is the fundamental task that allows all biological systems to sustain their existence. In this section, we expose the idea that entropy minimisation could also represent a key neurocomputational mechanism constraining experiences of reality.

In relation to probability, entropy can be considered a measure of uncertainty. The entropy \( H \) associated with a variable \( Y \) is described by *Equation 1* as the negative sum of the log-probabilities \( p_j \) for all \( n \) values of \( Y \) (Applebaum, 2008; Ballard, 1999).

\[
(1) \quad H(Y) = - \sum_{j=1}^{n} p_j \ln(p_j)
\]
**Fig. 1 Entropy and uncertainty.** The relationship between entropy and the probability of getting a head or a tail with a rigged coin. Entropy is calculated for each probability value ranging from 0 (bias towards the head) to 1 (bias towards the tail). The solid line depicts the entropy curve, showing how entropy changes as the probability of heads or tails varies. The dashed line at probability \( P=0.5 \) (i.e., when the coin is fair) divides the plot into two symmetric regions, highlighting the point of maximum uncertainty (\( P=0.5 \)), that is the point of maximum entropy (\( E=1 \)).

*Equation 1* describes entropy as a measure of uncertainty. As an example, let’s consider \( Y \) representing several flips of a coin that has been rigged to sometimes show more heads (coded as 0) or more tails (coded as 1) (example reworked from Applebaum, 2008). As shown in *Figure 1*, when the coin is fair, that is when the probability of getting heads or tails is 0.5, our uncertainty on the outcome is at its highest and entropy reaches its maximum value. In information theory and the predictive coding framework, entropy can also be understood as a quantification of information. In fact, if we are equipped with generative models predicting future data, the more an event is unpredictable the higher the quantity of information (or entropy) it carries.
By minimising entropy, the brain maximises the predictability of its internal states, favouring the maintenance of its homeostatic state. However, the brain does not have direct knowledge of what caused its internal states, hence it cannot minimise entropy directly. Given the information available, namely sensory inputs $s$, internal states $\mu$ and a probabilistic representation of the causes that generated those states in the past $q(\theta|\mu)$, the brain can minimise free energy and, as a result, indirectly reduce entropy (Friston & Kiebel, 2009). Equation 2 shows that free-energy ($F$) is equal to a Kullback-Leibler divergence (the first term of the equation) between the probability of the causes given the internal states and the probability of the causes given the sampled sensory data $s$, plus entropy (the second term of the equation).

$$\text{(2) } F = D(q(\theta; \mu) || p(\theta|s)) - \ln p(s|m)$$

The agent can minimise the divergence in the first term of Equation 2, and since $F$ is always a positive difference, the minimisation of the divergence would also result in a minimisation of entropy (the second term of the equation). Hence, an organism can minimise entropy by updating its internal model or beliefs to better match the observed reality (i.e. minimising the divergence in Equation 2), which is equivalent to maximising the conditional probability of the brain's model of the world given sensory data, following an optimal Bayesian approach.

Under the free-energy principle, reality inference as a cognitive function seems to assume the biological aim of minimising uncertainty of internal states and maximising predictions. However, we must specify that the core of reality inference as a theoretical construct is the experience of reality (i.e., phenomenology). Natural computations can be coupled with conscious experience (e.g., perceptions and beliefs) or not (e.g., processing of baroreceptor signals responding to changes in blood pressure; Ramstead et al., 2022). When reality is consciously represented in this process, we live a first-person experience: we perceive, feel, think or believe something. Reality inference refers to
only those processes that are coupled with conscious experience. Now, what could be the relation between entropy in brain information processing and phenomenology?

The Entropic Brain Theory (EBT) proposes that the entropy of brain states might be associated with qualitative changes in first-person experiences. More specifically, EBT hypothesises that: “the richness of its [of the experience] content can be indexed by a quantitative measure of the magnitude of entropy (in the information theoretic sense) in a given parameter of spontaneous brain activity” (p. 167; Carhart-Harris, 2018). Supporting EBT, entropy indexes of spontaneous brain activity are decreased in states where individuals show minimal or no conscious experience (for a review, Carhart-Harris, 2018), such as under anaesthetics and in minimal conscious states (Casali et al., 2013; Olofsen et al., 2008; Schartner et al., 2015). Analogously, increased entropy indexes have been associated with altered states of consciousness induced by 5-HT2A receptor agonists and N-methyl-D-aspartate receptor antagonists (Ort et al., 2023; Schartner et al., 2017; Viol et al., 2017).

Hence, the minimisation of entropy/uncertainty by the brain could represent a mechanism of primal impact on first-person experiences. The brain dynamics associated with entropy-minimisation could be mechanisms affecting reality inference and constraining the conscious representations of reality. If precision modulation is a mechanism crucial for reality inference on a cellular level, entropy-minimisation might be a mechanism impacting reality inference that can be investigated on the more macroscopic level of wide brain networks. In the next section, we present the idea that reality inference might be largely affected by the organisation of extrinsic connectivity. The organisation of extrinsic connectivity can be described by non-linear dynamics producing attractor states on a network level. The stability of attractor networks would be a fundamental feature for the maintenance of healthy reality inference (Adams, 2019; Rolls et al., 2008).
Summary

Within the predictive coding framework, reality inference is a task dealing with reducing uncertainty and increasing the agreement between internal representations and the observed reality. It involves evaluating information as probability signals with varying degrees of precision. This probabilistic approach contrasts with the classical views on reality testing as a discrete classification of information sources as internally or externally generated. By considering uncertainty and variability in the inferential process, reality inference may offer a comprehensive understanding of how individuals interpret and perceive reality, both in neurotypical and clinical experiences. The modulation of signal precision largely affects reality inference, potentially increasing or decreasing the entropy of internal states. By minimising entropy and maximising evidence, the brain refines its understanding of reality and makes predictions based on available information. We emphasise precision modulation and entropy minimization as two main mechanisms affecting conscious representations of reality on both the cellular and macroscopic network levels, making them crucial for pathological drifts of reality inference.

1.4 Brain Dynamics And Reality Inference

In the previous section, we described reality inference as an uncertainty-minimisation task. In general terms, predictive coding under the free-energy principle implies that the brain fluctuates between states of high entropy (or uncertainty) when the representation of reality changes through the acquisition of new information; and states of low entropy where precise predictions enable stable representations of reality.

In this section, we will discuss how, on a network level, states of reality inference (i.e., perceptions and beliefs) may stabilise in low entropy states and provide consistent representations of reality, or on the other hand, go through perturbations and potentially induce anomalous experiences of reality. Fluctuations in entropy would be dictated by
non-linear dynamics present in the environment, and non-linear modulations of neural signals (Friston & Kiebel, 2009). Complying with the free-energy principle, this dynamical self-organising system would tend to move toward states of low entropy. On a phenomenological level, low-entropy states would correspond to stable interpretations of reality. Considering predictive coding as an inferential algorithm embedded in non-linear dynamics, the states of the system can be described in terms of attractor networks (Friston & Kiebel, 2009).

Attractor Networks

In a dynamical system, the states of the system at any given time are described by a set of variables and parameters. A non-linear dynamical system can show through time recurrent patterns or sets of values called attractor states (Khona & Fiete, 2022). Attractors represent the values toward which the states of a dynamical system tend to converge over time (Ballard, 1999; Khona & Fiete, 2022; Rolls, 2010). The behaviour of a system with attractors can be described in terms of the stability of its attractors. The system can show stability when its values eventually converge to an attractor state (also referred to as asymptotic stability), instability when its values move away from the attractor state and marginal stability when its values oscillate around the attractor state (Ballard, 1999).

In the cortex, the recruitment of a set of interconnected neurons in response to a specific input might implement an attractor network (Ballard, 1999; Khona & Fiete, 2022; Rolls, 2010). One key feature of attractor networks is recurrent positive feedback. Recurrent positive feedback sustains the recruitment of the neural ensemble elicited by an input (e.g. a visual stimulus) after the input is extinguished. The sustained activation of the neural ensembles enables the circuit to hold a “memory” of the past inputs and to integrate additional signals within a larger window of time. Inhibition would also play a crucial role in the formation of attractor patterns in the brain. In fact, by selectively suppressing the activation of competing neural populations, neurons that fire together can delimit the configuration of the neural ensemble. This
interplay of recurrent positive feedback and selective inhibition contributes to establishing a stable and self-sustaining pattern of neural activity, which might represent specific conceptual or perceptual states (Khona & Fiete, 2022; Rolls, 2010; Rolls et al., 2008).

Attractor networks following predictive coding specifications have been implemented in simulation models of stimulus perception since the first formulations of predictive coding under the free-energy principle (Friston & Kiebel, 2009). Bayesian generative models can be organised in hierarchically connected attractor networks. In this context, hierarchical attractor networks can be thought of as representing different levels of the predictive coding hierarchy (Adams et al., 2013; Friston & Kiebel, 2009). The attractor state would represent the point where the system's internal uncertainty (free-energy) is minimised given the available sensory input and the system's dynamics. In other words, at a given level of the hierarchy, each attractor state would represent the best explanation for sensory evidence given the neural population’s predictions. The convergence towards an attractor state could represent the accumulation of evidence for a specific hypothesis or interpretation of the sensory input. On a neurobiological level, attractor networks are thought to be shaped by Hebbian learning mechanisms (e.g., long-term potentiation and depression) that determine synaptic plasticity and, consequently, synaptic gain (Rolls, 2010; Rolls et al., 2008). In turn, changes in synaptic gain would impact synaptic plasticity and shape the recruitment of the cohort of neurons belonging to an attractor network.

Attractor state stability has been proposed to reflect the stability of conscious experiences such as perceptions and beliefs (Adams, 2019; Rolls et al., 2008). The predictive coding framework integrated with attractor networks can link mechanisms of reality inference at the cellular level (i.e., synaptic gain modulation and synaptic plasticity) to the neural network level (attractor network dynamics). Precision alterations could impact the recruitment of neuronal populations and hijack the free-energy minimisation performed by attractor dynamics, making representations of reality unstable and sensible to change.
Linking Network Dynamics To Reality Inference

In the previous section, we described attractor networks as neural architectures characterised by stable states or "attractors" that the network's activity converges to over time. These states would represent distinct cognitive or perceptual patterns, and transitions between them could be driven by changes in synaptic gain and in general, by interactions between neural populations. The recruitment of different attractor networks could be modulated by overarching brain dynamics detectable on a macroscopic level. Two candidate patterns resulting from these dynamics could be the Default-Mode Network (DMN) and the Task-Positive Network (TPN).

The DMN is known to be a brain-wide neurofunctional pattern associated with resting states and more specifically with selfward thoughts (Carhart-Harris et al., 2013; Dosenbach et al., 2007; Fox et al., 2005). The DMN has been shown to be orthogonal (negatively correlated) to the activation of the TPN, a network that can include frontal, parietal and temporal attentional networks active during goal-directed behaviours (Carhart-Harris et al., 2013; Dosenbach et al., 2007; Fox et al., 2005). DMN-TPN orthogonality could reflect the stability of attractor networks and be associated with mechanisms that constrain conscious representation of reality (Adams et al., 2013, 2018; Carhart-Harris et al., 2013; Rolls et al., 2008).

Neuroimaging studies on perceptual bistability can give insights into the brain dynamics involved in the stability of reality inference. Perceptual bistability is a well-known phenomenon that occurs when ambiguous sensory data elicit two prominent interpretations experienceable only one at a time. Notably, perceptual bistability could be explained by a network with two attractor states, one for each perceptual interpretation (Khona & Fiete, 2022). The experience of one perceptual interpretation or the other would be coupled with the convergence of the network to one attractor state or the other.

Using ambiguous images (mooney images), González-García et al. (2018) found that disambiguation of the stimulus through prior information was associated with the activity of frontoparietal regions.
within the DMN, prompting the hypothesis that DMN activity encodes predictions involved in visual processing. Lyu et al. (2022) supported this hypothesis using the simultaneous presentation of dissimilar stimuli to the two eyes (binocular rivalry). They found that changing perceptual experience from one type of stimulus to the other is associated with coupled activity in V1 and precuneus (DMN posterior-medial parietal area). Interestingly, combining EEG and fMRI, they found evidence for precuneus activity to precede V1 activation during perceptual transitions. The authors suggested that precuneus might serve as a bridging region coupling DMN activity to V1, implicating a causal role in DMN activity in determining perceptual experience via modulation of the primary visual cortex. Perceptual transition in perceptual bistability has also been associated with the activity of TPN regions. A meta-analysis using data from 10 studies contrasting spontaneous vs. experiment-induced perceptual transitions in binocular rivalry showed that spontaneous transitions were associated with TPN areas in the right hemisphere including the dorsolateral prefrontal cortex (DLPFC), inferior frontal cortex, frontal eye field, temporoparietal junction and intraparietal sulcus (IPS) (Brascamp et al., 2018).

Given the known orthogonality between these two networks (Dosenbach et al., 2007; Fox et al., 2005), the involvement of both DMN and TPN in stimulus disambiguation might seem puzzling. One possible explanation for these data could be that, although the activation of these two wide brain networks is temporally distant, they might interact indirectly during perceptual bistability via other brain networks. There is, in fact, evidence showing that DMN and TPN regions may interact with the salience network promoting perceptual stability given ambiguous sensory data (Mao et al., 2020). Mao et al. found that participants’ longer perceptual stability was associated with lower functional connectivity between the whole brain and regions in DMN (including precuneus and dorsomedial prefrontal cortex) and TPN (including DLPFC, cortex around the IPS and anterior cingulate cortex), while functional connectivity between the salience network respectively to the TPN and DMN was associated with longer perceptual stability.
Firstly, this evidence may indicate that DMN-TPN segregation is, in fact, important to maintain perceptual stability so that a higher degree of segregation leads to a more stable percept given conflicting sensory data. Secondly, given that greater connectivity of the salience network with TPN and DMN promoted perceptual stability, it is possible that these two networks interact with the salience network while both impacting perceptual interpretation.

From the evidence we presented here, it can be hypothesised that DMN and TPN supramodal regions, especially in the frontal and parietal hemispheres, exercise predictions about sensory signals. In the case of perceptual bistability, these predictions would give prior information about sensory evidence that would prompt the emergence of one perceptual interpretation over the other. DMN and TPN supramodal regions could hence affect reality inference by promoting, through top-down predictions, the stability of one attractor state over others. Changes in the precision weight of these regions would play a key role in the signalling to areas lower in the hierarchy and could potentially impact reality inference. Theoretically, changes in the precision of higher levels in the hierarchy can have a dramatic impact on perceptual inference, as shown in Adams et al. (2013) where they simulated bird song perception through generative models nested in hierarchical attractor networks and demonstrated that lowering the precision of priors would induce anomalous inference in the simulated percepts.

Overall, from studies on perceptual bistability, we propose that the connectivity between DMN, TPN and the salience network play a crucial role in constraining the phenomenology of reality inference. We can hypothesise that changes in functional connectivity within and between these large networks (e.g., precuneus and VI) can possibly be initiated at the synaptic level by precision alterations. In the next section, we show evidence suggesting that the functional connectivity of these networks, and specifically the degree of orthogonality between DMN and TPN, might represent a mechanism associated with the variability of reality inference in the general population.
**DMN-TPN Connectivity and Altered Reality Inference**

Alteration of functional connectivity of DMN and TPN might disrupt predictions of sensory data at a network level and induce altered inference of reality. In this section, we show that altered experiences of reality are associated with evidence from patients with schizophrenia-spectrum disorders and pharmacological studies supporting alterations of functional connectivity between and within brain-wide networks.

During the performance of decision-making tasks involving the sequential sampling of evidence, patients with schizophrenia-spectrum disorders compared to controls show lower deactivation of DMN (Andreou et al., 2018; Krug et al., 2014; Lavigne et al., 2020) and decreased activation of TPN frontoparietal regions (Andreou et al., 2018; Krug et al., 2014). Specifically for frontal regions, a reduced anticorrelation between Medial Prefrontal Cortex (MPC; in the DMN) and the DLPFC (in the TPN) has been found during working memory tasks in patients as well as in first relatives (Whitfield-Gabrieli et al., 2009). In resting-state fMRI data, Mana et al. (2023) found that patients with schizophrenia compared to controls showed increased global synchronisation of hemodynamic responses. In line with this evidence, resting-state data of participants with high-risk or ultra-high risk for psychosis compared to controls showed decreased anticorrelation between TPN and DMN responses (Shim et al., 2010; Wotruba et al., 2014).

Given the evidence discussed above, lower DMN-TPN segregation and possibly increased whole-brain connectivity seem to be associated with individuals experiencing altered reality inference. One limitation of the studies presented is that the data were not collected directly during the alteration of reality inference (i.e., psychotic episodes) and those patterns of neural activity may not be specifically associated with changes in experience. Pharmacological models on healthy participants can help address this gap by inducing altered experiences mimicking psychosis in experimental conditions.
Studies using 5-HT2A receptor agonists associated with alterations of reality inference showed increased DMN-TPN functional connectivity and increased brain global connectivity during resting states (Carhart-Harris et al., 2013; Tagliazucchi et al., 2016). While others showed reduced functional connectivity within DMN following administration (Gattuso et al., 2023; Palhano-Fontes et al., 2015). The effect of 5-HT2A receptor agonists on brain dynamics elicited the formulation of the Entropic Brain Theory (EBT) (Carhart-Harris, 2018). The central idea of the EBT is based on the principle that the conscious experience is reflected by the level of entropy in brain activity.

One hypothesis of EBT is that higher levels of entropy would contribute to “enriched” first-person experiences of reality. We believe that this prediction is in line with the ideas presented here about the relationship between the stability of attractor states and reality inference (Adams, 2019; Rolls et al., 2008). In fact, increased entropy can result from unstable attractor networks, and this would determine frequent transitions from one attractor state to the other. At the phenomenological level, this would correspond to increased uncertainty on the possible interpretations of reality, and possibly to the experience of anomalous perceptions and beliefs. This hypothesis can be operationalised in the context of reality inference as we presented here. One way would be to test whether the upregulation of the 5-HT2A receptor increases the rate of perceptual transitions. On the neural level, the hypothesis would predict increased functional connectivity between DMN and TPN.

Summary

We propose that DMN and TPN dynamics hold a key role in shaping reality inference by affecting the stability of attractor states. The disruption of DMN-TPN segregation, observed in patients with schizophrenia-spectrum disorders, emerges as a potential mechanism leading to altered predictions of sensory data and subsequent changes in reality inference. This breakdown of segregation has been associated with individuals in both clinical and high-risk populations, emphasising its relevance for alterations of reality inference along the general
population. The evidence from decision-making tasks and resting-state fMRI data showed that decreased DMN-TPN segregation and heightened global brain connectivity are linked to individuals experiencing altered reality inference. The use of pharmacological models employing 5-HT2A receptor agonists shows that altering synaptic signalling results in changes in functional connectivity across wide brain networks, opening possibilities for investigating the influence of signal precision (as reflected by synaptic gain) alterations on attractor states' instability associated with phenomenological changes.

1.5 Conclusion

In this paper, we introduced a conceptualisation of reality testing within the predictive coding framework. In this context, we proposed reality inference as a theoretical construct around which to organise the investigation of the mechanisms constraining the conscious representations of reality. We propose that a research project investigating reality inference should account for data from (1) first-person experience, (2) physical mechanisms and (3) cognition or natural computation.

In our view, predictive coding under the free-energy principle, coupled with attractor network theory and the Entropic Brain Theory (EBT), collectively offer a cohesive theoretical foundation for understanding reality inference. From the extensive literature we've examined, two key mechanisms stand out as crucial for understanding how reality inference varies across individuals: the precision of neural signals and the stability of attractor states. Both of these mechanisms would influence how the brain minimises free-energy and shapes phenomenology in accordance with predictions from EBT.

A significant challenge to the study of reality inference is mapping the relation of the neurocomputational mechanisms we described with first-person experiences. This limit deals with the naturalistic description of experience, which is a major and general limitation of modern science. Despite this challenge, we think that a
research project proposing possible mechanisms constraining conscious representations of reality must, or at least attempt to, address this issue to the best of its ability.

In the context of reality inference, the problem of the relation between neurocomputational mechanisms and phenomenology can be reduced to the question of how the neural processes we have discussed here —such as changes in synaptic strength or the stability of attractor networks— might "encode" reality in a meaningful way, carrying semantic content (Ramstead et al., 2020, 2022). This philosophical and neuroscientific inquiry goes beyond the scope of this paper, yet we want to emphasise its importance as a central area of focus for possible future developments of reality inference as a scientific research project.

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https://doi.org/10.1016/j.cub.2016.02.010


II. Perceptual and cognitive inference in the psychosis continuum

The review article in the previous chapter proposed to investigate reality testing as a brain function varying in the population and reducible to the inferential processes that underpin decision-making. Here, we go more into the details of the literature that motivate the specific hypotheses of the empirical chapters that follow. We first offer the reader an overview summarising the literature and highlighting the gaps our empirical works intend to address. Following the overview, this introduction is composed of three sections: in section 1, we detail the predictive coding account of psychosis; in section 2, we discuss the evidence that links the psychotic phenotype to the Beads Task; in section 3, we introduce the sequential sampling models approach to decision-making and look at the evidence linking abnormal posterior parietal cortex activity and psychosis.

Overview of the chapter

Psychotic symptomatology is thought to be present and detectable at a subclinical level as a continuous phenotype in the general population (Mennigen & Bearden, 2020; Strauss, 1969; van Os, 2000; van Os et al., 2009). In this chapter, we will discuss evidence showing a variety of behavioural, neurophysiological and genetic patterns present in schizophrenia-spectrum patients (Scz) that vary in this continuum along with reported psychotic-like experiences. The study of these biological and behavioural measurements can complement self-reported measures by helping to identify early predictors of diagnosis as well as in eliciting insights on aetiology and treatments.

One behavioural pattern observed along the psychosis continuum is the Jumping to Conclusions bias (JTC) (Dudley et al., 2016; Fine et al., 2007; McLean et al., 2017; Ross et al., 2015). JTC has been studied using various versions of the beads task (BT), a probabilistic reasoning task measuring the quantity of data that participants sample for making a probabilistic estimation. Participants making a probabilistic estimation by sampling a few data show
JTC. The deficits of sampling behaviour and probabilistic inference highlighted by JTC could reflect altered inferential processes possibly underlying delusion formation; however, its role and relation to the psychotic phenotype in the general population are yet unclear. One aim of our empirical work was to confirm the presence of JTC in the general population with higher delusional ideation and to investigate if BT performance may vary with other psychotic phenotypes, i.e. anomalous perceptions and aberrant salience.

One framework that explains JTC in relation to psychosis is predictive coding. Predictive coding is a general theoretical approach to brain functioning that views perception and belief formation as inferential processes, and consequently hallucinations and delusions as aberrant inferences about reality. Inferences are thought to be carried out by hierarchically-structured neural circuits that predict sensory signals and optimise explanations by adjusting prior predictions according to a prediction error (PE), which is the computed mismatch between predictions and actual evidence (Bastos et al., 2012; Friston, 2010). Prior predictions and sensory evidence/PE signals are thought to be computed as probability distributions with their own precision (i.e., the inverse of the variance) that reflects their reliability. Precision weight is thought to be implemented in the brain by synaptic gain, i.e. the magnitude of synaptic efficacy in signal transmission.

Pharmacological and neurophysiological studies show alterations of cortical synaptic gain in Scz, consistent with the idea that altered modulation of sensory precision could underpin psychotic symptoms (Adams et al., 2013; Friston et al., 2016; Stephan et al., 2009; Sterzer et al., 2018). Aberrant modulation of precision weight in Scz would bias the inferential processes involved in perception and belief formation, producing unlikely inferences about reality, i.e. hallucinations and delusions. The canonical predictive coding account of psychosis (PCA) (Sterzer et al., 2018) hypothesises that increased sensory precision could contribute to the formation of abnormal beliefs. JTC in the BT could be a reflection of increased precision of sensory evidence. Predictive coding gives a “skeletal understanding” (Sterzer et al., 2018) of the possible neurocomputational alterations underpinning psychosis. This means that the specificities of precision imbalances can vary in the schizophrenia continuum according to the type of symptoms (hallucinations,
delusions, negative symptoms, etc.), the stage of the information processing considered (e.g., perceptual vs. cognitive) and the progression of the illness (e.g., preclinical vs. clinical) (Sterzer et al., 2018).

Can distinctive neurocomputational and behavioural patterns be related in perceptual inference to psychotic phenotypes? To answer this question, we focused on a classic perceptual evidence-accumulation paradigm rarely studied in schizophrenia research: the Random Dot Motion Task (RDM). In RDM, participants have to correctly discriminate a coherent movement in a noisy environment as soon as possible. Through drift-diffusion models (DDMs), RDM performance can be characterised in terms of precision of signal detection (drift rate) and quantity of accumulated evidence (decision threshold). To our knowledge, only Stuke et al. (2019) and Valton et al. (2019) explored RDM performance in relation to psychotic symptomatology, respectively in the general population and in patients, both applying Bayesian modelling but not DDMs. In the first empirical section of our project, we applied a hierarchical DDM (HDDM) to RDM performance to investigate the variability of drift rate and decision threshold in relation to delusional ideation, anomalous perceptions and aberrant salience in a large sample of the general population.

Interestingly, neurofunctional findings show that posterior parietal cortex (PPC) activity encodes the representation of gathered information and is associated with the decision to end data-gathering in BT and BT-like tasks (Furl & Averbeck, 2011; Evans et al., 2015; Kopp et al. 2016; Tickle et al., 2016) as well as in RDM (Yang & Shadlen, 2009; Kelly & O’Connell, 2013). The implication of the same neural correlates hints that analogous neurocomputational and behavioural patterns may be associated with psychosis on both cognitive and perceptual levels. PPC is an associative brain area involved in attention, the integration of motor and sensorial information (Bear et al., 2007), the conscious experience of stimuli (Pereira et al., 2020) and the accumulation of evidence towards perceptual (Shadlen & Newsome, 1996; O’Connell et al., 2012) and probabilistic judgements (Andreou, Steinmann, Kolbeck, et al., 2018; Furl & Averbeck, 2011; Krug et al., 2014). The relevance of PPC for conscious experiences and the accumulation of sensory evidence makes it a good candidate area for
mechanisms that might relate evidence accumulation to anomalous experiences.

In RDM, neurophysiological studies demonstrated in human and non-human primates that PPC neuronal activity is modulated by the quality of stimulus information (i.e., more or less noisy) and evidence-accumulation behaviour (i.e., stimulus onset and action) (Shadlen & Newsome, 1996; Kelly & O’Connell, 2013). In BT, higher blood oxygen level-dependent imaging (BOLD) responses in PPC have been associated with greater and more efficient evidence accumulation (Furl & Averbeck, 2011). Abnormal sampling in probabilistic reasoning in Scz has been associated with reduced activation of PPC, suggesting a key role of the parietal cortex in JTC (Andreou, Steinmann, Leicht, et al., 2018; Krug et al., 2014; Lavigne et al., 2020). In perceptual decisions, Scz showed altered PPC activity (Bramon et al., 2004, 2005; Qiu et al., 2014; Yildiz et al., 2011). This evidence suggests that alteration in PPC activity can contribute to the emergence of psychotic symptoms. We modulated PPC superficial cell excitability through repetitive low-frequency transcranial magnetic stimulation (TMS) in order to investigate the role of PPC in inferential processes and detect performance variability along with subclinical psychotic symptoms.

### 2.1 Misperceiving And Misbelieving: The Predictive Coding Account Of Psychosis

Predictive coding develops from the assumption that the brain predicts new incoming data from past experiences. To complete this task, the brain could approximate Bayesian inference and employ it to reduce uncertainty in future predictions. Within this framework, our brain considers to “know” what is real when it can provide precise predictions, or make sense, of the information coming from the environment.

Hierarchically structured microcircuits identified in the cortex are considered to perform the computational tasks required for predictive coding. A circuit’s connectivity can be intrinsic, i.e. between layers of the same cortical column; or extrinsic, i.e. between layers of different cortical columns.
At each level of the hierarchy, intrinsic and extrinsic circuits optimise their predictive performance by minimising the difference between predictions and new evidence, i.e. the prediction error (PE) (Bastos et al., 2012). PE represents what the model still cannot explain and gives a measure of how much a sensorial event is unpredicted. The circuits assume a hierarchical loop-dynamic: new sensory/PE signals reach higher levels yielding a feedback response that in turn influences the generations of new PE signals. A strong inhibiting top-down feedback would result in the dampening or extinction of upcoming PE signals and consequently in a partial or complete explanation of stimuli. Thus, up through the hierarchy, the model works towards the minimization of PE and maximisation of the internal model explanation (Bastos et al., 2012; Friston et al., 2016).

Critically, predictive coding within a Bayesian framework involves computations of information encoded as probability distributions with their own precision (i.e., the inverse of the variance). Prior beliefs (predictions) are updated by new evidence/PE through Bayesian inference to form posterior beliefs that would serve as new (updated) predictions. Encoded as probability distributions, these components are weighted according to a coefficient of precision that encodes the noise, and hence the reliability, of the signal.

Sensory precision determines the weighting of PE: the higher the precision of sensory evidence, the stronger would be the impact of PE on belief. Belief updating is also influenced by precision ascribed to prior belief itself: a weaker precision of prior makes posterior belief more sensitive to changes in sensory data, increasing belief instability (Adams et al., 2018; Friston et al., 2016; Sterzer et al., 2018).

In this view, reality testing becomes an inferential process where the dispersion of the prior and likelihood distributions play a fundamental role. The predictive coding account of psychosis (PCA) hypothesises that psychosis would arise from anomalously increased precision of sensory evidence and/or decreased precision of prior (Adams et al., 2013; Sterzer et al., 2018). In this scenario, strong PE signals in response to otherwise irrelevant stimuli would make the model sensitive to random fluctuations of data that would be treated as meaningful information, making everything equally surprising and unexplained. Psychologically, this would firstly result in the state of sensorial
over-salience and of “strange coincidences” typical of the prodromal phase (Kapur, 2003) and that is observed in the general population prone to psychosis (Roiser et al., 2013). Since the hierarchical computational structure of the brain tends towards minimisation of uncertainty, intensified PE signals over time would induce the formation of strong (very precise) priors that act to reduce the ramping PE signals. This would result in the emergence of steady beliefs made-up to explain the continuously surprising information coming from the environment or from the body itself, giving rise to what we call delusional ideation (Adams et al., 2013).

The synaptic gain of superficial pyramidal cells is thought to encode the precision of PE signals (Adams et al., 2013; Friston et al., 2016). Synaptic gain quantifies the probability that a presynaptic input produces a postsynaptic output (e.g. depolarization at the soma; Adams et al., 2013; Friston et al., 2016). Hence, the more synapses are functionally “wired”, the greater the precision of the encoded information. N-Methyl-D-aspartate receptor (NMDAR)-dependent activity, modulatory neurotransmission, and gamma-aminobutyric acidergic (GABAergic) interneurons activity are all elements that impact synaptic gain and that are thought to be dysregulated in Scz.

NMDAR hypofunction seems to be a key-aberrant mechanism involved in schizophrenia-spectrum disorders. Evidence from pharmacological (Corlett et al., 2009), genetic (Balu, 2016) and post-mortem (Catts et al., 2016) studies suggests NMDAR hypofunction in Scz. Corroborating this idea, NMDAR-inhibitors in healthy individuals induce psychotic-like symptoms and neurophysiological deficits specific to Scz and worsen the symptoms in Scz (Balu et al., 2016). Interestingly, patients with anti-NMDAR encephalitis, an autoimmune disease in which antibodies attack NMDARs, manifest pseudo-schizophrenic symptomatology with psychotic, cognitive and negative symptoms (Stein et al., 2020).

Besides NMDAR hypofunction, profound dysregulations of neuromodulatory systems also seem to contribute greatly to psychotic symptomatology. In fact, typical antipsychotics are antagonists of dopamine receptor D2 (D2R); while atypical antipsychotics can interact with serotonergic, adrenergic and cholinergic receptors (Aringhieri et al., 2018).
Like NMDAR-blockers, the administration of facilitators of dopaminergic or serotonergic neurotransmissions worsens psychosis in patients and mimics it in healthy individuals (Corlett et al., 2009; Stephan et al., 2009; Balu, 2016). Furthermore, the NMDAR and dopaminergic aberrant mechanisms seem to be interlinked in schizophrenia-spectrum disorders. The activation of dopaminergic receptors can in fact modulate NMDAR functionality. As an example, Dopamine D1 receptor (D1R) activation can change NMDAR functionality in a non-linear fashion through numerous molecular mechanisms (e.g. NMDAR membrane trafficking triggered by D1R activation) ( Arnsten et al., 2017; Wang et al., 2012). At the same time, NMDAR-dependent activity regulates neuromodulatory transmission. Hypofunction of NMDARs located on cortical GABAergic interneurons can increase glutamatergic signalling of pyramidal neurons towards subcortical areas. This increase can possibly cause two well-known dopaminergic abnormalities in Scz: the blunting of dopaminergic transmission in the mesocortical pathway that leads to D1Rs hypofunction in the frontal lobes; and the dopaminergic up-regulation in the mesolimbic pathway that leads to over-activation of D2Rs (Stephan et al., 2009; Balu et al., 2016).

Overall, the NMDAR hypo-function, the abnormal activity of neuromodulatory systems and GABAergic interneurons suggest an aberrant control of synaptic gain in Scz, which computationally would correspond to an imbalance of precision encoding. Aberrant synaptic gain modulation might be reflected in macroscopic neurophysiological abnormalities present in Scz: deficits of fast synchronous gamma-range activity (possibly due to alterations of GABAergic interneurons transmission; Shin et al., 2011); larger P50 in the electroencephalographic (EEG) response to stimulus detection; reduced mismatch negativity (MMN) in EEG oddball paradigms; and reduced amplitude of P300a (frontal component) and P300b (parietal component) in attention and decision-making EEG tasks ( Adams et al., 2013; Bramon et al., 2004; Rissling et al., 2010). P300b deficits are specifically relevant to this project since they could reflect reduced synaptic gain in PPC superficial pyramidal cells. In computational terms, this would correspond to a reduction of the precision encoded by those neurons which would implicate abnormal behavioural patterns in the evidence accumulation tasks that we investigated.
2.2 Delusion And The Jumping To Conclusions Bias

Psychotic detachment from community-shared representations of reality becomes impressively evident in patients with delusions. Delusions can be defined as pervasive and fixed beliefs, not shared by the members of a community and that typically defy credibility (Coltheart et al., 2011). Delusion formation has been associated with alterations of probabilistic reasoning and data-gathering in Scz. The classical paradigm used to study probabilistic reasoning in Scz is the BT. In BT, participants are shown two jars both containing beads of two different colours but in inverse proportions (e.g., jar A: 80% blue and 20% green; jar B: 80% green and 20% blue). In the “draws to decision” (DTD) version of BT, participants draw beads from one hidden jar and, as soon as they believe they have seen enough beads, they can guess from which jar (A or B) the sequence has been drawn. Guessing the jar after only 1 or 2 draws is usually considered in the literature as evidence of Jumping to Conclusions bias (JTC)(Evans et al., 2015).

Is there any JTC?

The relevance of JTC for delusions aetiology is largely debated. Rather than giving to the bias *per se* any specific aetiological role, we want to highlight in this paragraph that JTC reflects at least a behavioural manifestation of aberrant cognitive and neural mechanisms that could be linked to delusion formation. The literature mostly agrees with the idea that patients with schizophrenia with current delusions need less evidence to guess the jar than both the general population and patients affected by non-psychotic psychiatric disorders (Dudley et al., 2016; Fine et al., 2007; McLean et al., 2017; Ross et al., 2015).

Nonetheless, the specificity of JTC to delusion symptomatology is debated: some studies reported that JTC can be detected only in currently deluded patients and that there is no difference in BT performance between Scz without current delusions and healthy control (Dudley et al., 2016; McLean et al., 2017); while others have found no relation between delusion symptomatology scores and JTC, and no difference between delusional
disorder patients (a rare disorder which presents only delusion as a symptom) and healthy control (Fine et al., 2007). Moritz et al. (2007) found metacognitive therapy targeting reasoning biases (e.g., JTC) to dampen delusion symptomatology alongside a reduction of JTC compared to a control cognitive-behavioural therapy. This evidence suggests that cognitive alterations underlying JTC could be key elements for delusion formation and persistence. Conversely, pharmacological therapy with neuroleptics showed stationarity of JTC after remission from symptoms (Menon et al., 2008; Peters & Garety, 2006). Nonetheless, Menon et al. (2008) found a reduction of JTC together with the overall psychotic symptomatology in an emotionally salient version of BT.

In line with the view of a continuum between clinical and subclinical psychotic symptoms, JTC has been observed in the population at high risk of developing a schizophrenia-spectrum disorder (Broome et al., 2007), as well as in first-degree relatives of psychotic patients (Van Dael et al., 2006; van Os et al., 2020). Remarkably, Van Os et al. (2020) demonstrated, in a large sample (N=2219) composed of Sez’ siblings and healthy controls, that a higher level of genetic risk for schizophrenia is associated with fewer DTD in BT, linking schizophrenia genetic patterns to aberrant evidence accumulation.

The association between JTC and delusional ideation in the general population is much debated. In a meta-analysis, Ross et al. (2015) showed that delusional ideation, measured through the Peters et al. Delusion Inventory, PDI, (Peters et al., 2004), is associated with JTC, although with a smaller effect size compared to patients. However, Ross et al. (2016) failed to replicate this correlation in a large sample (N=558) of the general population. In an online study using a larger sample (N=1002), Sulik et al. (2023) showed that the association of delusional ideation to JTC might be due to low-quality data. They observed a negative correlation between delusional ideation and DTD but that was no longer significant after removing participants who did not pass attention checks during the task. This evidence suggests that JTC is not present in relation to psychotic phenotype.

In conclusion, JTC has been observed in the clinical population, with higher consistency in patients with schizophrenia experiencing delusions. While it might reflect aberrant cognitive and neural mechanisms potentially
linked to delusion formation, its specificity to delusional symptomatology remains debatable. Evidence accumulation mechanisms represented by JTC appear crucial in understanding the continuum between clinical and subclinical psychotic symptoms, with JTC being observed in high-risk individuals and first-degree relatives of psychotic patients. However, in the general population, the association between JTC and delusional ideation is largely subject to debate.

**Cognitive mechanisms underpinning JTC.**

Although the literature is not consistent about the extent of the relationship between JTC and delusions, three main proposals supported by empirical evidence have been made about potential cognitive mechanisms underpinning JTC. We will consider here three possible accounts of cognitive mechanisms underpinning JTC that are not necessarily mutually exclusive. These accounts can be summarised in the following hypotheses: (1) JTC might be driven by higher perceived costs of sampling and/or lower costs of making a wrong decision (i.e., disregard for the task outcome) (van der Leer et al., 2017); (2) higher levels of noise in inferential processes would increase the difficulty of distinguishing between the values of choices (drawing another bead vs. guessing the jar) (Moutoussis et al., 2011); and (3) the overweighting of sensory evidence might lead to assigning higher decisional value to each piece of evidence, reducing, in turn, the need for sampling (Adams, 2018; Adams et al., 2018; Stuke et al., 2017).

To possibly rule out the (1) hypothesis, Van der Leer et al. (2017) developed a nonserial version of BT where participants decided upfront how many pieces of evidence they wanted to see, knowing that they would incur a cost for each piece. This version of BT presented all the requested beads at once so that the optimal performance was not affected by sequential sampling, eliminating both sampling costs and the possible link between draws and participants’ negligence of the task (i.e. lower wrong decision costs). People with higher PDI scores persisted anyway in JTC, leading the authors to exclude altered perceived costs as a possible cause.

Moutoussis et al. (2011) reached the same conclusion by fitting two different models to behavioural data. One model was a Bayesian generative
model taking into account future draws (accounting for perceived sampling costs), while the other was a simpler model that based decisions solely on the log-likelihood ratio of already collected beads. Interestingly, the performance of patients with paranoia was better explained by the simpler log-likelihood model, leading the authors to reject hypothesis (1). Furthermore, both models included a parameter $\tau$ to capture inference noise. As the $\tau$ parameter increased, it could reproduce the observed JTC in the paranoid group, leading the authors to formulate hypothesis (2). The association of JTC to increased inference noise could indicate that the patients were assigning values to choices more randomly, resulting in suboptimal decision strategies, such as stopping sampling earlier than controls (JTC). However, as pointed out by Adams (2018), the model showing increasing inference noise ($\tau$ values) in patients with paranoia could have not been able to capture the cause of the noise.

One possible mechanism that could explain the inference noise identified by Moutoussis et al. is increased weight of sensory evidence (3). Stuke et al. (2017) tested whether the overweighting of surprising events (i.e. PE) could be correlated with JTC, PDI or proneness to hallucinations measured through the Cardiff Anomalous Perception Scale (CAPS). They induced expectations in BT by making specific tone pitches predict the two different draw types (e.g. green or blue bead) in 80% of the cases. They applied two different models to BT performance of non-clinical participants: in one model, PE was weighted by a parameter $\alpha$ so as to have a linear impact on the updating of belief (i.e. the jar-choice); in the other model, PE was weighted by a non-linear coefficient $\zeta$ that flattened high sporadic (surprising) PEs, making the model more resistant to occasional fluctuations; $\zeta$ was hence taken as a proxy of resilience to irrelevant information. In general, the “$\zeta$-model” explained participants’ performance better than the “$\alpha$-model”, suggesting a non-linear dynamic of the precision weighing of PE in healthy participants, in line with the neurobiological evidence about modulation of cortical pyramidal cells excitability (see Section 1 of the current chapter).

Interestingly, $\zeta$ values positively correlated with DTD, and negatively with PDI and CAPS scores, meaning that participants with lower DTD and higher subclinical psychotic symptoms were more sensitive to irrelevant
information. Although the authors did not parameterise noise as done in Moutoussis et al. (2011), the minor resilience to irrelevant information could reasonably be considered a source of noise in the decision-making of participants with higher psychotic phenotypes. Indeed, treating random fluctuations as relevant can cause the agent to overfit their model of the world, adding unnecessary variability and interference to the average signal. This, in turn, hinders the agent's ability to make reliable predictions. From this perspective, the findings of Stuke et al. can be seen as consistent with Moutoussis et al. In these terms, hypothesis (3) about increased sensory precision (3) can be seen as a specification of hypothesis (2) about inference noise, as (2) can be considered a computational mechanism leading to (3).

Additional evidence consistent with hypotheses (2) and (3) comes from studies using the “graded estimates” (GE) version BT. In GE-BT, participants do not decide when to stop, they are instead asked to estimate (e.g., from 0% to 100%) the likelihood that the sequence is being drawn from one or the other jar at each draw until the sequence ends. This variation of the paradigm allows the monitoring of belief stability throughout the task. The tracking of participants’ belief updates has been used to shed light on JTC. In GE-BT, Scz show higher estimates for one jar at the first bead, together with a particular pattern of belief adjustment: they make extreme estimates at the first draw, but they do not stick to this first judgement and shift their belief when confronted with a bead of a different colour, responding to disconfirmatory evidence more drastically than controls (Langdon et al., 2010; Moritz & Woodward, 2005).

This behavioural pattern has been formalised in Bayesian model-fitting studies as prior belief instability (Adams et al., 2018; Jardri et al., 2017) and is rather surprising with respect to the extremely rigid nature of delusional belief. Jardri et al. (2017) applied a weighted Bayesian model to GE performance, adding extra parameters that accounted for “reverberation”, i.e. the over-counting of either sensory evidence or prior belief. Patients with schizophrenia were found to over-count sensory evidence and underestimate prior information relatively to healthy control, consistently with the PCA.

In Bayesian terms, a stronger influence of new evidence over posterior beliefs can also result from weaker prior beliefs. In this regard, Adams et al. (2018) tested the stability of beliefs in GE-BT in the context of the “unstable
attractor network” hypothesis of schizophrenia. Briefly, an attractor network shows stable patterns of firing neurons when elicited by familiar (not surprising) stimuli; these ensembles of neurons would be the correlates of perceptual and conceptual representations, such as beliefs (Rolls, 2010; Rolls et al., 2008). In this framework, the instability of attractor networks in Scz, as a possible consequence of recurrent surprising events, could explain the drastic adjustment of beliefs in GE-BT. Fitting behavioural data to a hierarchical Bayesian model, Adams et al. found that Scz patients present higher belief instability and high response stochasticity in GE-BT compared to healthy controls, supporting both hypotheses (2) and (3). Attractor-network and Bayesian frameworks can indeed conceive hypotheses (2) and (3) as complementary in explaining the BT performance of Scz patients. In fact, a higher sensibility to random fluctuations of data (increased precision of PE; hypothesis 3) would destabilise attractor-networks. The failed activation of stable attractor-networks would increase the noise (hypothesis 2) in the decisional network, eventually leading to JTC and drastic estimate adjustments. As we will show later in the next section, fMRI studies are consistent with this view, showing a stochastic activation of the task-positive network in Scz.

**Neurobiological mechanisms underpinning BT performance in Scz**

Pharmacological models of psychosis could give insights into the molecular mechanisms underpinning decision-making patterns in Scz. Although administrations of NMDAR antagonists or D2R agonists can induce psychotic-like symptomatology in healthy subjects, both drug models mostly failed in reproducing the JTC and the belief adjustment pattern observed in Scz patients (for a review: Evans et al., 2015).

Strube et al. (2020) recently confirmed that agonists of D2R have no effect on BT performance of healthy participants, but they observed JTC in DTD-BT and increased probability estimates in GE-BT when healthy participants were administrated dextromethorphan, an NDMAR inhibitor. While the authors attribute this effect solely to NMDAR blocking, the inconsistency of these results with previous literature (Evans et al., 2015) could be explained by the different pharmacokinetics of dextromethorphan compared to the NMDAR inhibitors used in other studies: dextromethorphan.
is, in fact, a potent inhibitor of serotonin reuptake and thus upregulates serotonergic transmission (Taylor et al., 2016).

We can speculate that the unprecedented effect observed by Strube et al. in BT could be explained by the dampening of NMDAR-dependent activity together with the up-regulation of serotonergic transmission both exerted by dextromethorphan. This would suggest that only together can NMDAR hypo-activation and alterations of neuromodulatory systems produce the Scz-related decision-making patterns and that the serotonergic system could play a critical role in these patterns, also given the specific link between serotonergic up-regulation and attention deficits (Mirjana et al., 2004; Wingen et al., 2007).

At the level of functional anatomy, fMRI studies on the healthy population showed with good consistency that a network including the parietal cortex, prefrontal cortex (PFC), anterior insula and striatum is implicated in BT performance. Specifically, the event of urn-choice (vs. draw-choice) has been associated with high BOLD responses in PPC, dorsolateral PFC (DLPFC) and anterior insula (Evans et al., 2015; Furl & Averbeck, 2011). Furl & Averbeck (2011) demonstrated that the decision to end evidence-seeking together with the willingness to collect more evidence when needed correlated with strong BOLD responses in the region near the right Intraparietal Sulcus (rIPS). These findings have been corroborated by fMRI results from the box task, a data-gathering task similar to BT (Andreou, Steinmann, Kolbeck, et al., 2018), and are consistent with ERP studies on BT, which associate central parietal activity, i.e. P300b, to evidence-accumulation (Kopp et al., 2016; Tickle et al., 2016). This evidence supports the idea that the PPC around IPS might encode the value of evidence collected and drive the decision to end data-gathering in probabilistic decisions.

Are JTC and belief instability associated with aberrant PPC activity? The fMRI studies investigating BT performance in Scz consistently report alterations in connectivity and reduced BOLD responses in dorsal frontal, posterior parietal and subcortical reward-related regions (Andreou, Steinmann, Leicht, et al., 2018; Krug et al., 2014; Rausch et al., 2015). In BT, Krug et al. (2014) demonstrated that Scz compared to healthy controls presented a right-lateralized reduction of the task-induced hemodynamic response in
posterior parietal and dorsal frontal regions during urn-choice. The authors contrasted BOLD responses between BT (decision-positive condition) and a control task where participants just needed to count beads without making any decision (decision-negative condition). In all participants, a greater difference in responses between decision-positive and decision-negative conditions correlated with higher scores of executive functions and working memory measures, implying that greater functional segregation supports more efficient processing of information. Interestingly, the authors found Scz compared to controls showed a lower difference in frontoparietal activation between decision-positive and decision-negative conditions. This reduced functional segregation observed in Scz could be interpreted as a failure to activate a task-specific attractor network as a consequence of stochastic connectivity between the frontoparietal regions. Although patients did not show JTC in the scanner, making it impossible to link this neural pattern to the bias, they were less accurate than healthy control in guessing the jar corresponding to the dominant colour of the draws-sequence.

As in Krug et al. (2014), Andreou, Steinmann, Leicht, et al. (2018) also observed a pattern of higher activation and lower deactivation of BT-associated regions. In this study, JTC was associated with lower activation of subcortical reward-network regions during choice and increased connectivity between a task-positive network (inferior parietal lobules and dorsal anterior cingulate cortex (dACC)) and the default-mode network. Interestingly, after metacognitive training that targeted reasoning biases (as in Moritz et al., 2007), patients showed improvement in psychotic symptomatology together with increased connectivity of PPC to occipital areas, task-positive, default-mode and reward networks during BT, suggesting a link between PPC connectivity and improvement of psychotic symptoms.

Aberrant connectivity of task-specific networks in Scz is also supported by an fMRI study by Lavigne et al. (2020). Lavigne et al. used an evidence integration task where participants are presented with a partial line drawing in which more lines are progressively added, and at each addition of evidence, the participants are asked to judge if the forming shape can be described by a word displayed below. Delusional patients with schizophrenia compared to healthy controls were slower and less accurate and showed a
higher response of a visual attention network (dACC, insula, and occipital regions), lower deactivation of default-mode network and lower activation of a frontoparietal cognitive evaluation network.

To summarise, at the molecular level, the administration of NMDAR antagonists or D2R agonists in healthy subjects has not replicated the JTC and belief adjustment patterns observed in Scz. Recent research by Strube et al. (2020) revealed interesting findings when using dextromethorphan, an NMDAR inhibitor upregulating serotonergic transmission, that could produce the Scz-related decision-making patterns. This might suggest that glutamatergic and serotonergic disregulations together may play a role in JTC.

The evidence from fMRI studies shows a general decrease in the segregation between task-on and task-off networks in Scz compared to controls. An imbalance of signal precision encoding can lead to the macroscopic differences seen in brain dynamics during decision-making (Adams et al., 2018). Regarding specifically JTC, the neurofunctional data from Scz performing various decision-making tasks requiring sequential sampling (Andreou, Steinmann, Leicht, et al., 2018; Krug et al., 2014; Lavigne et al., 2020) are compatible with the idea that JTC might be driven by increased precision of sensory evidence (hypothesis 3; e.g. the higher response of visual attention regions shown in Lavigne et al.) coupled with noisy information processing (hypothesis 2).

In the next section, we will discuss evidence suggesting that activity in PPC might play a crucial role in evidence accumulation. Aberrant PPC activity or aberrant connectivity to PPC might be prominent factors involved in evidence accumulation and neurocomputational patterns associated with psychosis and the psychotic phenotype.

2.3 Posterior Parietal Cortex And Sequential Sampling In The Psychosis Continuum

Physical stimuli are fuzzy sources of information out of which the brain must recognise precise signals to take actions potentially crucial for survival. For instance, imagine walking down a deserted street late at night. In
this scenario, we encounter a figure approaching us from a distance. The challenge lies in determining whether the person is holding a potentially dangerous weapon, like a gun, or if it's just a harmless individual with a professional camera. This situation requires us to process various sources of information and make a clear decision between these two distinct possibilities. Sequential sampling models assume that the brain faces this challenge by accumulating evidence supporting one hypothesis or the other overcoming this state of uncertainty only when a threshold in favour of one is reached, triggering the commitment to action (Ratcliff et al., 2016; Smith, 2000).

The Drift Diffusion Model

The drift-diffusion model (DDM) is a stochastic sampling process that simulates this mechanism by accumulating evidence over time that is randomly pooled from a Gaussian distribution of values, whose mean indicates the “signal” in the data. Progressively, the build-up of accumulated evidence will necessarily reach values near the mean of the Gaussian, as they are the values with the highest probability of being drawn. The decision in favour of one option will be taken when the build-up reaches a stereotypical quantity, a decision threshold usually indicated with the letter $a$. The slope of the build-up is the drift rate ($v$), which indicates how precise (vs. noisy) the sampling process is. For low-noise stimuli, the model assumes that the data are drawn from a Gaussian with a low standard deviation. Having higher chances to pick values close to the mean, the model will give higher drift rates than for high-noise stimuli. In other words, when sensory evidence is less ambiguous, we can decide faster and with more confidence.

The DDM was originally implemented as an approach to analyse reaction time (RT) paradigms by computing a trade-off between time and accuracy which is represented by the drift rate (Ratcliff 1985). So, it is intended here (and in the literature in general) as both a tool for analysing RT decision-making paradigms and a model of cognitive and neural processes (Forstmann et al. 2016). Given as inputs only the outcome of the decision (usually accuracy) and the RT, the problem that DDM attempts to solve is to model the time-dependent evidence accumulation process that led to that decision.
On the Cartesian axes, this problem translates into estimating the position of a decision-variable \( X \) (on the y-axis) at a given time \( t \) (on the x-axis). Taking a starting point \( z \) for \( X(t=0) \), and assuming \( z \geq 0 \), we need to estimate the increment of \( X \) over time to know the values of \( X \) for \( T \), \( >0 \). We can estimate the increment \( \frac{d}{dt}X(t) \) as a Wiener diffusion process with drift, which is a stochastic differential equation of the form

\[
\frac{d}{dt}X(t) \sim \text{Normal}(v, \sigma^2),
\]

where \( \frac{d}{dt}X(t) \) denotes the increment of \( X \) from one time point \( t \) to another. What makes it stochastic is that the values of the increment are drawn from a Gaussian with mean mean \( v \) and variance \( \sigma^2 \). Because of the nature of the Gaussian distribution, the values of the increment \( \frac{d}{dt}X(t) \) resulting from this sampling process will more likely lay around its mean. This means that the values of \( X \) over time (i.e., the marginal distribution of \( X \) over \( t \)) are also distributed on a normal distribution with mean \( vt + z \) and variance \( \sigma^2 t \). We can further assume that the accumulation of evidence ends when \( X \) reaches a decision-threshold value \( a \), so that the value of \( X(t=0) \), the starting point \( z \), lies in the range \( 0 \leq z \leq a \), where \( a \) represents one of the two possible choices (the upper-boundary) and \( 0 \) the other choice (the lower boundary). For \( \sigma^2 = 1 \) and given a choice \( c \) (usually the accuracy) and a decision time \( t \), the model can be described by what is called the Wiener first-passage time (WFPT) distribution, denoted as \( c,t \sim \text{WFPT}(v, a, z) \) (see Navarro & Fuss, 2009), for the solution of the WFPT distribution. Bogacz et al. (2006) showed that, given the limit of time, the DDM can be considered an optimal decision-maker if we posit a given level of acceptable accuracy (our decision threshold). In this sense, the DDM seems to simulate an adaptive approach to decision in real environments.

**PPC activity and evidence accumulation.**

The DDM accumulation process has been qualitatively compared to patterns of neuronal activation in the parietal cortex of human and non-human primates. A classic paradigm studied in this research context is the RDM.

In RDM, participants are presented to a cloud of moving dots (see Figure 1) in which a percentage of the dots moves coherently either to the left
or to the right, while the others move randomly. Participants have to recognise, as soon as they can, the direction of the coherently moving dots, indicating their decision with a finger (button press) or eye movement.

Numerous animal and human studies showed that PPC activity correlates with the quality and quantity of evidence accumulated. Notably, single neuron recordings in monkeys showed that during RDM, firing rates of neurons in the lateral intraparietal cortex (LIP) ramp with evidence accrual until they reach a peak and dampen after the decision is taken (Shadlen & Newsome, 1996; Roitman & Shadlen, 2002; Hanks & Summerfield, 2017).

![Random Dot Motion Task (RDM)](image)

*Fig. 1 Graphical example of Random Dot Motion task (RDM).* Participants view a cloud of moving dots where some dots move randomly (usually the majority; e.g. 85%) and some move coherently in one direction (e.g. left). They are required to indicate as quickly as possible the direction of the dots moving coherently.

In monkeys, electrical and optogenetic stimulation of LIP neurons modulate accuracy and RT in RDM (Hanks et al., 2006; Dai et al., 2014), suggesting a causal role of LIP in choice selection. LIP is thought to accumulate spatial-visual inputs from the near mid-temporal cortical area (MT), constructing what has been called a “saliency map” (Hanks et al., 2006) on which motor action can be properly selected. Importantly, pharmacological inhibition of LIP neurons does not prevent or disrupt movement, but it seems to bias the choice towards target contralateral to the intervention (Cristopoulos et al., 2018; Hanks et al., 2017); this suggests that modulation of LIP affects decision and not motor functions.
Neurons in LIP seem to behave as evidence accumulators showing higher slopes of the build-up of firing rates for more precise stimuli as if they were accumulating evidence according to a drift rate, and irrespective of the stimuli quality or reaction time (RT). The build-ups reach the same level just before the decision as if the accumulation process had a stereotypical decision-threshold value (Shadlen & Newsome, 1996; Roitman & Shadlen, 2002; Hanks & Summerfield, 2017). Consistent with the idea that DDM can approximate this neuronal behaviour, neurons in LIP seem to accumulate evidence for all options in units of log probabilities (Yang & Shadlen, 2009; Kira et al., 2015). This neural activity can in fact be explained by a sequential probability ratio test (SPRT), an optimal decision-making model where the evidence is accumulated in discrete units (log probabilities). Increasing the frequency of the discrete samples, the sampling can be approximated by a time-dependent continuous variable which makes SPRT converge to DDM (Bogacz et al., 2006).

In humans, a parietal ERP, the central parietal positivity (CPP), has been identified as a neural correlate of evidence accumulation that shows characteristics analogous to neuronal activity in LIP of monkeys: CPP progressively ramps from stimulus onset and reaches its highest peak after around 300 msec, just before the decision (O’Connell et al., 2012). Like LIP neurons’ firing rates, CPP amplitude is higher for more precise stimuli and its latency reflects RTs. CPP has been recorded in auditory and visual tasks independently of motor execution (O’Connell et al., 2012; Kelly & O’Connell, 2013), in a face recognition memory task (Van Vugt et al., 2019) and in a taste-preference decision task (Pisauro et al., 2016).

CPP seems to reflect not merely the accumulation of perceptual information but also memory and subjective reward value. Indeed, CPP relates more strictly to the variability of reported subjective precision of stimuli (participant’s confidence) than the physical stimulus (e.g., dots movement coherence) (Tagliabue et al., 2019). Thanks to an epileptic patient’s microelectrode implant into the junction between the postcentral and intraparietal sulcus, Pereira et al. (2020) were recently able to study more closely the relation between PPC activity and subjective reports of confidence by measuring single neuron activity during a tactile stimulus-detection task.
Reports of detected stimuli were anticipated by the typical ramping activity of PPC neurons that mirrored RTs and intensity of stimuli, analogous to EEG and animal studies. Interestingly, the same PPC neurons showed flatter firing rates for stimuli that did not trigger a conscious experience, as if they were accumulating evidence but not reaching a threshold of activity necessary for the stimulus to be consciously perceived. Supporting this idea, TMS pulses over the IPS were demonstrated to promote the fading of visual stimuli presented in the periphery of the visual field (Kanai et al., 2008). Moreover, Pereira et al. observed that the stimulus-induced firing rates were modulated by participants’ confidence, showing, consistently with Tagliaabue et al. (2019), that PPC activity reflects not only the noise of the physical stimuli but also the precision ascribed to the sensory signal. Superficial neurons in PPC seem to behave as evidence accumulators, encode conscious detection, and reflect the subjective precision ascribed to sensory evidence.

Alongside sequential sampling models, studies using Bayesian models also represent an influential neurocomputational approach to investigating PPC activity during decision-making. As seen in the previous section, Furl & Averback (2011) showed that PPC BOLD responses increased in participants who sought more evidence when facing greater uncertainty in BT conditions. O’Reilly et al. (2013) confirmed this role of PPC showing that IPS activation correlated with task uncertainty (quantified by Shannon information). In ERP research, Kopp et al. (2015) showed that P300b (homologue of CPP) amplitudes were larger for lower likelihoods in the Bayesian formulation of the BT. From this evidence, PPC seems to process information about the uncertainty or precision of sensory evidence. Further bringing this body of evidence closer to the predictive coding framework, the slope of cumulative activity of PPC neurons recorded with magneto-encephalography (MEG) during RDM has been correlated with the synaptic gain of superficial pyramidal cells as simulated by a dynamic causal model (Fitzgerald et al., 2015). The whole of this evidence leaves space to formulate the hypothesis that PPC superficial cells encode the precision of PE.

We think we can consider the findings presented here from the sequential sampling models and Bayesian approaches as a consistent body of evidence. In fact, it has been shown that the drift rate in sequential sampling
models can approximate the precision of evidence/PE in a predictive coding framework (Hesselman et al., 2010; Fitzgerald et al., 2015; Bitzer et al., 2014; Fard et al. 2017). Specifically, Bitzer et al. have shown that the DDM can be considered equivalent to a hierarchical Bayesian generative model. They demonstrated that the drift rate is equivalent to the precision of sensory evidence, while the starting point $z$ is equivalent to the prior, and that the decision-threshold can be considered as a boundary on the posterior value that, if crossed, can trigger a specific action. This equivalence allows us to relate the PCA to the whole of neurocomputational findings on PPC activity and decision-making. In the next section, we are going to overview the evidence on abnormal PPC morphology and neurophysiology associated with Scz.

**PPC abnormalities in the psychosis continuum**

For the topography, the polarity, and the peak just before response execution, CPP is considered a homologue of the P300b (O’Connell et al., 2012). P300b is a parietal ERP component that shows reduced amplitude and latency in chronic schizophrenia and first-psychotic episode patients (Bramon et al., 2004; Bramon et al., 2005; Devrim-Üçok et al., 2006), in healthy relatives of Scz (Qiu et al., 2014), and in people at risk of psychosis (Nuchpongsai et al., 1999).

A substantial amount of evidence implicates aberrant PPC activity in Scz. Anatomically, PPC of chronic and first psychotic episode patients showed reduced grey matter and abnormal organisation of white matter compared to controls, and these morphological measures correlated with the severity of symptoms (Yildiz et al., 2011). fMRI studies in patients and people at risk of psychosis indicate abnormal activity of PPC in response to perceptual and cognitive tasks, and these PPC functional patterns were often predictors of future diagnosis of psychotic disorders or correlated with psychotic symptoms. Using MEG, Sanfratello et al. (2018) observed a lower activation of PPC in schizophrenia patients compared to controls during a visual-auditory decision task and interestingly, a higher IPS activation was negatively correlated to psychotic symptomatology.

However, it is hard to identify a precise pathophysiological pattern in PPC. In fact, abnormal PPC activation in the clinical population seems to vary according to the task, being higher or lower compared to controls (Yilidiz et
al., 2011). PPC seems to be over-activated compared to controls in non- or low cognitive demanding contexts, such as resting states (Franck et al., 2002) and Go/No go (Arce et al., 2006) or simple motor tasks (Spence et al., 1997). On the other hand, as discussed previously, the fMRI studies using BT or other cognitive evidence accumulation tasks suggest consistently a hypo-activation of PPC during the performance in Scz (Andreou et al., 2018b; Lavigne et al., 2020). This abnormal recruitment of PPC was paradigmatically observed by Krug et al. (2014) in BT with patients showing over-activation in task-off and hypo-activation in task-on conditions.

From this evidence, we could posit that the abnormal physiological and morphological changes found in the schizophrenia continuum should be reflected in perceptual decision-making by alterations of the typical evidence accumulation process. We will now examine behavioural computational studies confirming that behavioural patterns mirror indeed these neurobiological alterations.

The psychosis continuum and computational modelling of perceptual decisions

In schizophrenia, only relatively recently, computational modelling started to be applied in the study of perceptual decisions. By fitting a DDM to performance on a reward-and-punishment perceptual decision task, Moustafa et al. (2015) showed for the first time that Scz presented lower drift rates and higher decision thresholds than controls. These results were partially replicated with an oddball-stimuli task in Fish et al. (2018), where Scz and their siblings showed lower drift rates compared to controls.

Limongi et al. (2018) fitted a hierarchical Bayesian DDM (HDDM) to patients’ and controls’ performance in a task where they had to push a button at the timing of a virtual billiard-balls collision; the participants had also to inhibit their action if the first moving ball was red coloured. The best-fit HDDM suggested that the starting point bias parameter ($\xi$) was higher in patients, interpretable as a higher influence of colour prior on decisions. This evidence from perceptual decision-making modelled with DDM supports the idea of weak sensory evidence/strong priors in Scz compared to controls.
Valton et al. (2019) tested this idea using a modified RDM version that included trials where dots moved with full coherence in five different directions against a low background contrast alternated with trials where no dots were presented (zero contrast). The participants had to align a red bar to the motion direction and decide if they had actually seen or not the dots. They induced prior belief by presenting more trials of dots moving in one chosen direction than the others. Their best-fit model showed no difference between patients and controls in perceptual prior belief influence on direction choice. The authors contrasted this conclusion with the fact that patients compared to controls were significantly less prone to see the dots when they were not actually visible (zero contrast), suggesting a lower prior of previous dots images on the no-stimulus trials compared to controls, supporting the idea that low perceptual prior precision is involved in the well-known resistance of schizophrenic patients to visual illusions (Adams et al., 2013).

At the subclinical level, testing a sample from the general population on a paradigm where participants made decisions between competing representations in ambiguous corrupted images, Davies et al. (2018) found that delusional phenotype predicted lower differences in drift rate between naive trials and non-naive trials where the uncorrupted images where presented before the ambiguous image decisions; the hallucinatory phenotype showed the opposing effect predicting higher drift rate differences between conditions. The authors’ account for these findings was that people with higher hallucinatory phenotype made heavier use of prior knowledge in the non-naive trials that resulted in higher gain of evidence (drift rate) compared to naive trials. For the effect of PDI on drift rate differences, the authors proposed the idea that more delusion-prone individuals might have encoded prior knowledge (the viewing of uncorrupted images) as more “belief-like” information resulting in not being accessible in the perceptual decision-making of non-naive trials. The authors did recognise that these conclusions need to be supported by further evidence.

In the general population, Stuke et al. (2018) analysed RDM performance in the frame of Bayesian inference in the psychosis continuum. Stuke et al. induced prior information using tones predicting the direction of dot movement in 80% of the trials; people with higher PDI scores resulted to
rely less on prior belief. They concluded that low prior belief precision at a low level of the processing (i.e., perception) could promote delusional ideation by increasing the influence of sensory evidence on perceptual inferences.

Overall, the evidence on Scz seems to suggest a higher influence of prior on perceptual decisions. At the subclinical level, the evidence in perceptual decision-making is scarce for a characterisation of the neurocomputational specifics in the psychotic phenotype.

Our project aims to contribute to the existing literature by examining behavioural, neural and computational aspects of both cognitive (BT performance) and perceptual (RDM performance) inferences within the same population samples. We will utilise HDDMs to analyse RDM data and assess, within a predictive coding framework, how neurocomputational quantities correlate with subclinical psychotic symptomatology in the general population.

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III. Methods

In this chapter, we are going to present the methods we used with common relevance across our empirical chapters of this project and discuss their relevance to our project. This chapter is structured in three paragraphs, one for each level of investigation: behavioural, computational and neurophysiological. In section (1), we will describe the two behavioural paradigms at the focus of our investigation: the Beads Task (BT) and the Random Dot Motion task (RDM). In section (2), we will describe the specific package used in our empirical works, the hierarchical DDM (HDDM). In section (3), we will give some notions about the transcranial magnetic stimulation (TMS) protocol we used in this project's second empirical section. In each section, we will also explain why we decided to adopt that particular method for this project.

3.1 Behaviour: The Beads Task And The Random Dot Motion Task

We investigated data-gathering in support of decision-making in relation to psychotic traits focusing on the BT and the RDM. Here, we are going to briefly describe these paradigms (for a more detailed description see the Methods sections of the articles in Chapter IV and Chapter VI) and discuss why we chose to focus on BT and RDM.

3.1.1 The Beads Task

The BT is one of the main paradigms used in the psychosis literature on decision-making. The BT is a probabilistic reasoning task used to evaluate the variability in the quantity of evidence needed for the formation of a probabilistic belief in a noisy environment. In the classic BT, the participants are presented with two urns containing beads of two different colours in a different ratio. For example, urn A would contain 60 green and 40 blue beads, while urn B has 60 blue and 40 green beads. The participants are then
presented with a hidden urn and asked to draw beads until they feel ready to
guess if the hidden urn is the A or the B. After each draw, the participants can
decide to guess the urn or see one bead more.

In BT, the pattern associated with psychosis, specifically with
delusions, is the Jumping to Conclusions bias (JTC), which can be identified
in trials where no more than three beads were drawn or by taking the count of
drawn beads, the draws to decision (DTD), as a continuous score where lower
DTD indicate a higher propensity to JTC (Evans et al., 2015).

The Graded Estimate version of BT (GE-BT) allows the evaluation of belief
updating of participants. In GE-BT, they do not choose when to stop,
instead at each bead presented, they rate how confident they are that the
hidden urn is A or B. In GE-BT, patients with schizophrenia compared to
healthy controls seem to change their confidence rating more when presented
with a bead of a different colour (Langdon et al., 2010; Moritz & Woodward,
2005). This pattern has been called over-adjustment and has been evaluated by
averaging the difference in ratings between consecutive draws of different
colours (Langdon et al., 2010).

As seen in Chapter II, the BT has been considered a standard paradigm
for testing decision-making and data-gathering in relation to psychosis. In our
studies, the use of the BT in parallel with the RDM allowed us to address the
long-standing debate about the link between JTC and delusional ideation (see
Chapter II) while exploring the relationship of psychotic phenotypes to other
types of evidence accumulation, namely perceptual decision-making.

3.1.2 The Random Dot Motion Task

In the classic version of RDM, participants are presented with a cloud
of moving dots where some dots (usually the majority) move randomly while
a subset of dots move coherently in one direction (either left or right
depending on the trial). The participant is asked to guess as soon as possible
the direction of the coherently moving dots. The measurements taken from the
task are the response time (RT) and the accuracy, which are commonly
analysed using DDMs.

As seen in the introductory Chapter II, few studies investigated this
paradigm in psychosis and even fewer in the subclinical context. We chose to
focus on RDM for several reasons. We wanted to investigate perceptual inference in subclinical psychosis and RDM seemed to us a good analogous to BT in a perceptual context. In fact, in BT as in RDM, participants are asked to infer a hidden state of the world (the urn in BT and the direction of coherent movement in RDM) in an environment with quantifiable noise (the colour ration in BT and the percentage of coherently moving dots in RDM).

Moreover, evidence on both BT (Andreou, Steinmann, Kolbeck, et al., 2018; Furl & Averbeck, 2011; Krug et al., 2014) and RDM (Hanks & Summerfield, 2017; Kelly & O’Connell, 2015a) showed the recruitment of the posterior parietal cortex (PPC) correlated to the accumulation of evidence in both tasks. Specifically for RDM, neural data approximated the behaviour of a decision variable that accumulates evidence over time until it reaches a decision threshold, a sequential sampling process such as the one described by a DDM (Forstmann et al., 2016) (see Chapter II for a more detailed discussion). In fact, the DDM can be used to characterise participants’ performance in terms of DDM parameters but it can also be used as a tool to formulate hypotheses about underlying cognitive and neural processes. In the next session, we describe the hierarchical DDM (HDDM), the tool we used to fit DDMs to our data.
3.2 Modelling and statistical analysis: The Hierarchical Drift Diffusion Model package

In this section, we will describe the use we made of the HDDM package developed in Python by Wiecki et al. (2013) for the modelling of our data. We refer the reader to the Drift Diffusion Model section in Chapter II for a more comprehensive description of the model.

Among other implementations of the DDM in the literature (such as DMAT and fast-ddm), we chose to use the HDDM, precisely because of its hierarchical structure that allows more robust parameter estimations (Wiecki et al., 2013). The HDDM uses the solution to the Wiener first-passage time distribution given by Navarro & Fuss (2009) to estimate the DDM parameters while embedding the estimation in a hierarchical Bayesian framework.

In fact, differently from other packages, the HDDM is designed to deal with the kind of hierarchical structure of data we often encounter in behavioural testing, where the degrees of freedom at the trials’ level are tied to the individual variability and in turn, individual degrees of freedom to the group variability. This hierarchy is operationalised in the HDDM by using hierarchical Bayesian inference: parameter distributions on the subject level are posterior distributions estimated from trials’ data (likelihood) and constrained by prior distributions with the group level’s mean and variance. Thus, for example, in the case where there is substantial variability in participants’ performance within the group, the high variance of distributions on the group level would exercise smaller constraints on estimates on the subject level. Estimating posterior distributions of parameters at different nodes of the data hierarchy allows us to directly use Bayesian statistics to test hypotheses across different levels of the data structure. Within the HDDM 0.8.0 (the version used in this project), we have two main approaches to data analysis: Bayesian hypothesis testing and Bayesian regression.

3.2.1 Group comparison through Bayesian hypothesis testing

In HDDM, we can compare posterior parameter distributions between groups/conditions. The depends_on() argument allows the estimation of one or more parameters with means and variances varying between
groups/conditions. We can compare the resulting distributions (one per each group/condition) and evaluate, for example, whether the values of a parameter’s posterior probability distribution $A$ for a given condition are significantly higher than the values of a distribution $B$ for another condition. We can do so by computing the proportion $P(A>B)$ in which the values of one posterior distribution are greater than the other. Since the distributions are posterior probability distributions, this proportion indicates the effective probability of the values of one group being higher than the other. $P(A>B)$ lies in the range $0<P<1$ where $P=0$ would indicate that no value of $A$ is greater than any value of $B$, while $P=1$ that all values of $A$ are greater than any value of $B$.

In Figure 1, we show examples of Bayesian hypothesis testing from our analysis. In Figure 1-A, we can see that the distribution of drift rates for high coherence is clearly higher on the y-axis compared to low coherence. The probability ($Q$) of the drift rate values in high coherence to be higher than low coherence values is $Q=1$, indicating that 100% of the values in the high coherence posterior probability distribution are greater than the values in low coherence. To accommodate the presentation of this result to a frequentist eye, Wieckie et al. proposed to report the complement probability of $Q$, that is $(P=1-Q)$ and to consider the result significant when $P<0.05$. 


**Fig. 1 HDDM between-group comparison.** Examples of drift rate posterior distribution comparison between motion coherence conditions from HDDM-C in Study 1 (A; significant difference) and between TMS sessions from HDDM-TMS in Study 2 (B; non-significant difference).

TMS = Transcranial Magnetic Stimulation
3.2.2 Bayesian Regression

In HDDM, the hddm_regressor() class allows the DDM parameters to vary with the response-dependent variable of a linear regression model. In this way, we can test linear relationships between experimental variables and DDM parameters. Where a standard linear regression estimates the value of the regression coefficient $\beta$ that optimises the prediction of the data (the least squares solution), a Bayesian regression estimates a posterior probability distribution of values of $\beta$ giving us information about the uncertainty of $\beta$. We can then compute the probability that the values of $\beta$ are higher or lower than zero ($P(\beta>0)$ or $P(\beta<0)$).

In Figure 2, we show an example of results from an HDDM regression model, taken from Study 2 for illustrative purposes. We plotted the distributions for the $\beta$ of three different predictors: PDI, TMS and their interaction. The dotted lines represent the 95% credible interval of the distribution. We consider the results significant when the zero is not included in the 95% interval, which is equivalent to saying that we have a 95% probability that the values of $\beta$ are either greater than zero (positive relationship) or lower than zero (negative relationship). For example, in the case of the TMS effect over the drift rate (shown in magenta in Figure 2), the credible interval includes zero, meaning that the probability $Q(\beta<0)$ is lower than 0.95 and that the effect does not reach significance. Similarly to what we do for the Bayesian hypothesis testing, we can report the complement probability $P$ of $Q$, so that $P=1-Q$, and consider a result significant when $P<0.05$ (as shown in Figure 2).
**Fig. 2 HDDM Bayesian regression.** Examples of significant and non-significant effects evaluated by considering the $\beta$ posterior distribution from HDDM regression models. $\beta$ for different predictors from HDDM-PDI-TMS in Study 2.

TMS= Transcranial Magnetic Stimulation  
PDI= Peters et al. Delusion Inventory

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### 3.3 Neurostimulation: Transcranial Magnetic Stimulation

Transcranial Magnetic Stimulation (TMS) is a non-invasive brain stimulation technique that can modulate neurons’ membrane potential. TMS is used in research to investigate causal relationships between brain activity and behaviour, and for the treatment of different psychiatric and neurological conditions (Rotenberg et al., 2014). TMS functioning is based on Faraday's electromagnetic induction principle according to which the electric current passing through a wire loop generates a magnetic field. For the same principle,
the generated magnetic field induces an electric current in a conductor placed in the magnetic field. In TMS devices, the electric current flows through a coil of wire loops in pulses creating small magnetic fields in discrete time points. When placed over the scalp, the TMS coil induces electric currents flowing parallel to the brain surface. What neural mechanisms are affected by the TMS is still a matter of debate. Authors in TMS literature seem to agree that TMS pulses primarily interact with myelinated axons inducing the depolarization of the cell (Siebner et al., 2022).

Different protocols can be applied in TMS research for different purposes. As mentioned, TMS can be used to manipulate neuronal activity and evaluate the effect of this modulation on behavioural and neurophysiological measurements. TMS can be applied “online” or “offline”. In online protocols, the stimulation occurs during the execution of the task at a specific moment to perturb or facilitate neuronal activity. Offline protocols utilise the long-lasting effect of repetitive TMS (rTMS) and test the effect of the manipulation after stimulation. Modulating the frequency of the pulses changes the effect of rTMS on the brain tissues in a non-linear fashion (Siebner et al., 2022).

In Study 2 of our project (Chapter VI and Chapter VII), we employed low-frequency (1 Hz) rTMS (lrTMS) as an inhibitory TMS protocol. When applied for several minutes, lrTMS can decrease cortical excitability for a period that varies depending on the duration of the stimulation (Casula et al., 2014; Rotenberg et al., 2014). The mechanisms underlying this inhibitory effect remain unclear. However, from studies on lrTMS over the primary motor cortex (Casula et al., 2014; Siebner et al., 2022), it seems plausible that the lrTMS suppressive effect might be mediated by TMS-induced depolarisation of gamma-aminobutyric acid (GABA)-ergic interneurons. GABAergic interneurons may be depolarised directly by a single TMS pulse or indirectly via the activation of axonal branches of pyramidal cells terminating on GABAergic interneurons (Siebner et al., 2022).

Although lrTMS must be considered a less precise manipulation compared to the invasive techniques used to suppress neuronal activity in animal research, it is a valuable and safe technique for this purpose in humans. Through lrTMS, we were able to test in a large sample the impact of lowered excitability of the posterior parietal cortex (PPC) on inference. Largely
because of time limitations pending on this project partially disrupted by the Covid-19 pandemic, we could not use magnetic resonance imaging to target the area around the rIPS for each participant. We overcame the time limitations by using the 10-20 system and target P4 which reliably showed to lay over the cortical region surrounding the rIPS (Okamoto et al., 2004). We applied 15 minutes of lrTMS over P4 which should induce a suppressive effect lasting approximately 20 minutes (Rotenberg et al., 2014), a longer time than the duration of the behavioural testing part of our second experiment (approximately 15 minutes).

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IV. Evidence Accumulation in the Psychotic Phenotype

In this chapter, we present in the form of a research article the first empirical part of this PhD project. The primary objective of this paper is to explore evidence accumulation in perceptual inference in relation to subclinical psychosis.

Specifically, we tested the hypotheses that in perceptual inference, participants reporting more psychotic-like experiences show (1) increased precision of sensory evidence and (2) accumulate lower quantities of evidence to make perceptual decisions. Secondarily, we sought to replicate sampling biases in cognitive inference that have been associated with the psychotic phenotype in previous literature.

Focusing on perceptual inference, this study represents an effort to characterise information processing in subclinical psychosis and to untangle the relationships between experiences resembling psychosis in the general population and neurocomputational mechanisms of perceptual inference.

Hallucination- and delusion-like experiences are associated with increased precision of sensory evidence in perceptual inference

Abstract

AIMS. Predictive coding accounts theorise that increased sensory precision may characterise subclinical psychosis. Moreover, there is suggestive evidence that increased precision of sensory evidence associated with psychotic-like experiences might lead to impulsive inference in probabilistic reasoning. In perceptual inference, the relationship between psychotic-like experiences, data-gathering and sensory precision encoding remains underexplored. In this study, we investigated whether increased
sensory precision and poor data-gathering relate to psychotic-like experiences in perceptual inference.

**METHODS.** We fitted drift-diffusion models to performance on a perceptual decision-making task, the Random Dot Motion task (RDM), for 191 participants from the general population. Drift rate (a proxy for precision of sensory evidence) and decision threshold parameters could vary: 1) between groups with higher vs. lower levels of subclinical psychotic symptoms; 2) as dependent variables in a regression model having subclinical psychotic symptoms as predictors. Using the Beads Task (BT), we also attempted to replicate the finding that impulsivity is associated with delusional ideation in probabilistic reasoning.

**RESULTS.** In perceptual inference (RDM), both delusion- and hallucination-like experiences were associated with higher precision of sensory evidence (higher drift rates). Hallucination-like experiences were also associated with lower decision thresholds. In contrast, in probabilistic reasoning (BT), we did not find that impulsive inference was associated with any psychotic-like experiences.

**CONCLUSION.** Our findings suggest that subclinical alterations of inference might be more prominent for perceptual than for probabilistic inference. Increased precision of sensory evidence in perceptual inference may represent a candidate neurocomputational mechanism contributing to the psychotic phenotype in the general population.

**4.1 Introduction**

A profound transformation of how one perceives oneself and the world typically precedes the onset of schizophrenia-spectrum disorders. In this prodromal phase, the emergence of anomalous perceptual experiences often accompanies the progressive alteration of the belief system. Both perceptual and cognitive disturbances precede and predict the first episode of psychosis
At the neurophysiological level, abnormalities in event-related potentials associated with information processing seem to be already present in this preclinical phase (Bodatsch et al., 2015). Computational modelling can potentially link behaviour, neurobiological evidence and phenomenology and outline the mechanisms that predispose to psychotic experiences (Sterzer et al., 2019). Psychotic symptomatology is thought to be present in a continuum along the general population from psychotic-like experiences in healthy individuals to psychotic disorders (Mennigen & Bearden, 2020; Strauss, 1969; van Os, 2000; van Os et al., 2009). The mechanisms that predispose to psychotic symptomatology could be also detectable in the non-clinical extreme of this continuum. In this study, we aimed to identify the neurocomputational mechanisms implicated in the emergence of psychotic phenotype in the general population. We investigated whether an imbalance of precision of sensory evidence and poor data-gathering characterise subclinical psychosis in perceptual inference and probabilistic reasoning.

The predictive coding account of psychosis (PCA) (Sterzer et al., 2018) hypothesises that imbalances in the encoding of precision can explain perceptual and cognitive disturbances associated with psychotic traits and comprise the core of reality-testing alterations. The concept of precision weight of neuronal signals can be understood in light of the free-energy principle and predictive coding (Friston, 2010; Bastos et al. 2012). This framework considers the cortex to be hierarchically structured in canonical microcircuits, where neuronal signals are computed as probability distributions with their own precision (i.e., the inverse of variance). Cortical regions higher in the hierarchy would encode expectations (or prior beliefs) and predict the activity of lower regions encoding new sensory inputs and prediction error (PE). PE is the mismatch between predictions and actual evidence and represents something striking and unexpected in the environment. At each level of the hierarchy, the neural circuits would implement Bayesian inference to minimise uncertainty (i.e., PE) and generate optimised estimations of reality. Crucially, the precisions ascribed to prior or PE/new sensory evidence determine their impact on posterior estimates, with
more precise signals having larger leverage on inferences. The precision weighting would be implemented in the brain by synaptic gain, which is the likelihood of a post-synaptic output given a pre-synaptic input (Adams et al., 2013; Friston et al., 2016; Sterzer et al., 2018).

The excitatory/inhibitory imbalance and the neuromodulatory dysregulations (Stephan et al., 2009; Sterzer et al., 2018) in schizophrenia-spectrum patients (Scz) have been understood as disturbances in precision encoding. Specifically for the incipient phase of psychosis, PCA hypothesises that these synaptic dysregulations may be consistent with a scenario of weak priors and/or increased precision of sensory signalling which results in increased unpredictability of new stimuli (Corlett et al., 2009; Stephan et al., 2009; Adams et al., 2013; Friston et al., 2016; Sterzer et al., 2018). The persistent experience of unexplained stimuli/events produced by highly precise PE/sensory signals would weaken the stability of the belief system potentially inducing a “hyper-plastic” mind and brain state, which can mediate the profound psychological transformation typical of schizophrenia-spectrum disorders (a construct recently defined as “pivotal mental state”; Brouwer & Carhart-Harris, 2021). At the phenomenological level, these neurocomputational alterations would result in a pervasive sense that reality is uncertain and inexplicable. This sense of inexplicability could be mitigated by creating fixed explanations in the form of delusional beliefs (Carhart-Harris & Friston, 2019). These neurocomputational mechanisms might underpin the experience of subclinical psychosis in the general population and, in some individuals, could predispose the development of psychotic disorders.

The hypothesis of weak prior/ strong sensory evidence signals in psychosis has found support in the context of the Beads Task (BT). The BT is a probabilistic reasoning task where participants have to infer an unknown state of the world (e.g., the dominant colour of beads in a jar) by sequentially sampling pieces of information (e.g., coloured beads). In the classic version of BT, which we will refer to as Draws to Decision BT (DTD-BT), delusional Scz make inferences based on little evidence (fewer beads drawn) compared to healthy controls, a phenomenon called “jumping to conclusions bias” (JTC) (Fine et al., 2007; Evans et al., 2015; Dudley et al., 2016; McLean et al.,
2017). Delusional ideation in the general population has also been associated with JTC (Ross et al., 2015), suggesting the relevance of JTC in the predisposition to form delusions.

Extrapolating from Kapur’s (2003) account of psychosis, it has been proposed that aberrant salience might arise from unduly strong dopamine-encoded PE signals, which might underlie JTC (Evans et al., 2015; Sterzer et al., 2019). Strong dopamine-encoded PE signalling in response to stimuli would exacerbate the salience ascribed to collected evidence. This would increase the leverage of each piece of evidence in decision-making and lower the threshold of evidence needed to commit to a probabilistic belief, resulting in JTC. In line with this view, probabilistic estimates in Scz seem to be particularly sensitive to newly collected evidence (Moritz & Woodward, 2005; Langdon et al., 2010; Adams et al., 2018; Speechley et al., 2010; Strube et al., 2021). This has been shown using a version of BT known as graded-estimates BT (GE-BT), where participants give estimates about the probability of two unknown states after gathering each piece of evidence (e.g., “What are the chances so far that the dominant bead colour of the jar is red or green?”).

In GE-BT, Scz compared to controls shift their probability estimates more drastically when faced with new evidence that confirms (Speechley et al., 2010) or disconfirms previous evidence (Moritz & Woodward, 2005; Langdon et al., 2010; Adams et al., 2018; Strube et al., 2021). Studies using DTD-BT and GE-BT in both clinical and non-clinical populations indicate that a higher influence of sensory information might mediate belief instability and the premature adoption of beliefs (Jardri et al., 2017; Stuke et al., 2017; Adams et al., 2018). In the general population, Stuke et al. (2017) found that sensitivity to sensory evidence in DTD-BT was positively associated with delusional ideation; while in Scz, studies focusing on GE-BT have associated drastic shifts in estimates with the increased influence of sensory signalling (Jardri et al., 2017) and unstable prior beliefs (Adams et al., 2018).

These findings on BT endorse the PCA and suggest that increased precision of sensory evidence might impact inferential processes on a cognitive level in a way that generates impulsive sampling (i.e., JTC), possibly contributing to the adoption of abnormal beliefs. Given the evidence just
presented and the perceptual disturbances present alongside delusions (Klosterkötter et al., 2001; Schultze-Lutter et al., 2007; Schultze-Lutter et al., 2008), we could expand the same PCA prediction of increased sensory precision to the perceptual domain, possibly contributing to the formation of both anomalous perceptions and delusional ideation. We sought to investigate this PCA prediction in the general population by focusing on a classic perceptual decision-making task, the Random Dot Motion task (RDM) (Yang & Shadlen, 2009; Kelly & O’Connell, 2013). Like BT, RDM requires participants to collect evidence from a noisy source of information to infer a hidden state. Participants view a cloud of moving dots in which a subset of the dots moves coherently either to the left or to the right, while the others move randomly. As soon as participants accumulate a criterion amount of evidence in favour of a motion direction, they express their choice.

Interestingly, activity in the posterior parietal cortex (PPC) correlates with the evaluation of evidence in probabilistic reasoning tasks including the DTD-BT (Furl & Averbeck, 2011; Kopp et al. 2016; Tickle et al., 2016) as well as in RDM (Yang & Shadlen, 2009; Kelly & O’Connell, 2013), suggesting common mechanisms of evidence accumulation for perceptual and cognitive inferences. The qualitative similarity between the two paradigms and the involvement of the same neural correlates suggested to us the idea that the imbalance in sensory precision implied by the performance of psychosis-prone participants on the BT might also manifest in their performance on the RDM.

Mirroring the JTC findings in DTD-BT (Fine et al., 2007; Ross et al. 2015; Evans et al., 2015; Dudley et al., 2016; McLean et al., 2017), we expected delusional ideation to correlate negatively with sampled evidence in RDM. Moreover, we investigated the role of aberrant salience in perceptual inference and tested if aberrant salience was associated with precision of sensory evidence. We also attempted to replicate probabilistic reasoning biases in DTD-BT and GE-BT found in the population with psychotic traits.

We applied drift-diffusion modelling (DDM) to RDM and tested whether delusional ideation, anomalous perceptions and aberrant salience were associated with higher sensory precision and less accumulated evidence. DDM approximates perceptual decision-making as a stochastic sampling process in which a decision variable accumulates evidence over time as a
function of a signal component (the drift) and a noise component (the diffusion) until a threshold in favour of one of the response options is reached (Ratcliff et al., 2016).

We described participants’ performance in terms of precision of signal detection parameterised as the drift rate ($v$) and quantity of accumulated evidence parameterised as the decision threshold ($a$). Notably, the sequential sampling model and Bayesian approaches (e.g., PCA) have been considered complementary and formally equivalent (Hesselman et al., 2010; Fitzgerald et al., 2015; Bitzer et al., 2014; Fard et al. 2017), and other empirical work has already interpreted DDM parameters within the Bayesian predictive coding framework (Hesselman et al., 2010; Fitzgerald et al., 2015; O’Callaghan, 2019). In particular, Bitzer et al. (2014) showed that when Bayesian updating is construed as the decision component of a two-alternative forced choice, it is equivalent to a DDM. They demonstrated that the drift rate parameter is equivalent to the mean value of the evidence given as input to a Bayesian updating model, approximating the precision of sensory evidence in a predictive coding framework.

Preliminary to the present study, we conducted a pilot study ($N=20$) that showed psychotic phenotypes to be associated with lower drift rates and higher decision thresholds, contradicting the PCA predictions. Based on these data, we preregistered the present study (link to pre-registration: https://osf.io/d7es8 ) with the hypothesis that scores of scales measuring delusional ideation, anomalous perceptions and aberrant salience would be associated with lower drift rates and higher decision thresholds.

### 4.2 Methods

**Participants**

We used Amazon’s Mechanical Turk service to invite a subsample of 200 participants from a larger cohort ($N=1002$) recruited by Sulik et al. (2023) to take part in our online study. Three participants did not complete the whole experiment and six participants were excluded from the analysis because of
partially missing data from their RDM performance. Statistical analyses were hence performed on 191 participants (females=87, males=104; age: M=32.2 yrs, SD=9.8). We limited our invitations only to participants who successfully answered at least two of three attention checks in Sulik et al. (2023). The data from the draws to decision and graded estimates (ADJ) versions of BT (details below) and the PDI were collected by Sulik et al. (2023). Before recruiting participants for the present study, we preregistered our analysis (the pre-registration can be found at this link: https://osf.io/d7es8). In the present study, participants performed the RDM and completed the CAPS and the ASI. RDM, CAPS and ASI were designed and submitted through the Gorilla platform and undertaken on participants’ computers/laptops.

Subclinical psychotic symptoms

We used three measures of subclinical symptoms: the 21-item PDI (Peters et al., 2004), evaluating delusion-like beliefs; the CAPS (Bell et al., 2006), evaluating hallucination-like experiences; and the ASI (Cicero et al., 2010), evaluating experiences and life attitudes related to aberrant salience (Kapur, 2003). For each measure, we used the total score (sum of subscales). For the between-groups Bayesian hypothesis testing, participants were categorised into two groups for each measure of subclinical psychotic symptoms using the median as a cut-off value; each participant was categorised in three ways: high- or low-PDI group, high- or low-CAPS group and high- or low-ASI group.

Random Dot Motion Task (RDM)

The visual stimuli for RDM were created through the open-access Java script made available on Codepen.io by Rajananda et al. (2018). On a black background, we presented a cloud composed of 500 white dots, each with a 3-pixel radius. The dots moved at 1 pixel/frame in a circular aperture with a 600-pixel diameter. The coherency of the display was manipulated by designating “noise” dots moving in randomly assigned directions, and “signal” (coherent) dots moving in one direction which was either left or right. An infinite lifetime was given to the dots, which means that each dot was redrawn only after reaching the aperture edges. At each new video frame, the dots were
randomly designated to be “signal” or “noise” dots, making it impossible for the participant to infer the coherent motion by following a single dot.

Trials of two different motion coherence conditions were presented in random order: 15 trials of high motion coherence with 25% coherently moving dots; and 15 trials of low motion coherence with 15% coherently moving dots. On each trial, the coherent motion was randomly assigned to be left or right. Participants were instructed to place their index fingers ready on the “F” and “J” buttons and to express their preference about the direction by pushing on their keyboard the letter “F” button for left and the letter “J” button for right. Participants were prompted to answer as quickly and accurately as possible. After each trial, a green tick was displayed for correct answers and a red cross for incorrect. Fast and slow outliers were handled using the cut-off method: trials with reaction times (RT) of <200 msec or >6000 msec were excluded (Voss et al., 2013).

“Draws to decision” Beads Task (DTD-BT)

In DTD-BT, participants could draw beads in a predetermined sequence of bead colours in a ratio of 60/40 (sequence: [1- 0- 0- 1- 1- 0- 1- 1- 1- 0- 1- 1- 0- 1- 1- 0- 0- 1- 0- 0- 1- 1]). Participants could decide when to stop sampling and choose the jar the sequence was being drawn from. If participants wanted to draw more beads than those in the predetermined sequence, more draws were randomly generated (up to a maximum of 30), maintaining the same 60/40 colour ratio. We evaluate performance using the Draws To Decision scores (DTD), namely the number of beads the participant needed to decide the jar the beads were drawn from. Participants also gave confidence reports at three stages of DTD-BT: at 0 draws (Conf-0), after the first draw (Conf-1) and after the final draw (Conf-N when they decided to stop data-gathering).

“Graded-estimate” Beads Task (GE-BT)

In GE-BT, participants were shown a predetermined sequence of 10 beads (ratio: 60/40; sequence: [1, 1, 0, 1, 1, 0, 1, 1, 0, 1]). Instead of deciding when to stop, they were asked to estimate (from 0% to 100%) at each draw the likelihood that the sequence was being drawn from the jar of the majority
colour of the sequence. Here, we report ADJ. To compute ADJ, we took participants’ probability estimates from the disconfirmatory draws. These draws (the 3rd, 6th and 9th of each sequence) were disconfirmatory in the sense that they were of a different colour than the majority of preceding draws. From the probability estimates provided in response to these draws, we subtracted the estimates provided in their preceding draws (the 2nd, 5th and 6th of each sequence) and then summed these subtractions per sequence to produce the variable ADJ. If the estimate for the majority colour was lower in the disconfirmatory draw (e.g., 50% on the 3rd) compared to the preceding one (e.g., 70% on the 2nd) the result of the subtraction would be a negative value (e.g., 50-70 = -20) and that would indicate a decrease in belief in the majority colour. If the estimate for the majority colour was higher in the disconfirmatory draw compared to the preceding one, we would have a positive value of the subtraction which would stand for an increase in belief in the majority colour. So, when our total ADJ score (the overall sum of the subtractions) is negative, it indicates an overall adjustment toward disconfirmatory evidence; if positive an adjustment toward the majority colour. Because we discovered later that estimates in response to individual draws were not available from the previous data collected using this paradigm, we diverged from our pre-registered analysis and took as a dependent variable these total ADJ scores instead of estimates at each draw.

Data analysis and computational modelling

Following the data analysis plan we pre-registered, we performed three Ordinary Least Square (OLS) regression models with PDI, CAPS and ASI scores each set as the predictor of an OLS model. The dependent variables for RDM were RT and proportion correct responses for high motion coherence, for low motion coherence and averaged over high motion coherence and low motion coherence. The dependent variables for BT were DTD and total ADJ scores. However, the distributions of residuals lacked constant variance (evaluated through visual inspections of the residuals plotted against predicted values), potentially biasing the standard-error estimations of the regression models. For this reason, we additionally performed quantile (median) regression models to confirm the results from the pre-registered OLS models.
These statistical analyses were performed in an Anaconda Python 3.6 environment using the statsmodels 12.2 toolbox (https://www.statsmodels.org/dev/index.html). Using the Tableone package for Python (Pollard et al., 2018), we evaluated between-groups differences in distributions of demographic and psychometric variables. We applied the hierarchical DDM (HDDM) to RDM performance using the HDDM 0.8.0 toolbox (http://ski.clps.brown.edu/hddm_docs/index.html; Wiecki et al., 2013) in an Anaconda Python 3.6 environment. HDDM uses hierarchical Bayesian inference to estimate the posterior distributions of DDM parameters for each participant, allowing them to vary according to condition, group or defined linear regression models. The DDM (Wiecki et al., 2013; Ratcliff et al., 2016) simulates a stochastic sampling process accumulating evidence in favour of two choices over time. The two choices are represented by two boundaries and the distance between them is quantified in the decision threshold parameter \( a \), which gives a measure of how much evidence is needed to reach a decision boundary. The starting point of the sampling is represented by a parameter \( z \), which we set at 0, simulating unbiased decisions. In DDM, evidence is accumulated by randomly extracting values from the distributions of the information sources (Ratcliff et al., 2016). The precision (or inverse variance) of the distributions determines the drift rate parameter \( \nu \), i.e. the slope of the evidence accumulation process, which we take here as a proxy for sensory evidence precision. The more precise the extraction of information, the higher the drift rate. In all the models we performed, the two choices were coded as correct or incorrect answers (the correct answer being left or right depending on the trial), hence \( \nu \) can also be considered as an indicator of the RT-accuracy trade-off.

We analysed the effects of subclinical psychotic symptoms on DDM parameters using two approaches: a between-groups approach and a regression model approach, both using Bayesian statistics. For the between-group approach, HDDMs in which \( \nu \) and \( a \) parameters could vary between conditions and groups (see Table 1 for details). We report here HDDMs in which we estimated parameters for the psychotic trait and motion coherence condition within the same models. This analysis simplifies the analyses proposed in our pre-registration; specifically, we run the models named (in Table 1)
HDDM-PDI, HDDM-CAPS, HDDM-ASI instead of those named EC-HDDM 1, 2, 3 and HC-HDDM 1, 2, 3 (See preregistration). For the regression model approach, we used the *HDDMRegressor* class of the HDDM package to run DDMs in which \(\nu\) and \(a\) parameters varied according to a Bayesian linear regression model specified as in *Table 1*. We \(z\)-scored the values of all predictors that varied between subjects (i.e., the psychosis trait variables) and not between trials (i.e., the motion coherence conditions) before running the models with *HDDMRegressor*

For the between-group/condition models, we compared posterior probability parameter distributions between conditions and groups, computing the probability that a parameter is higher or lower in one condition/group than in the other. For the Bayesian regressions, we evaluated whether the probability \(P\) of the posterior probability distribution of the regression coefficient \(\beta\) was significantly different from 0, meaning that at least 95% of the distribution was either >0 (positive \(\beta\)) or <0 (negative \(\beta\)) (Wiecki et al., 2013). To maintain a notation familiar with a frequentist approach, we considered our results “statistically significant” when the probability of the disconfirming hypothesis was <0.05 (Wiecki et al., 2013).

We evaluated model fit using the Deviance Information Criterion (DIC). Since DIC penalises models for complexity, lower DIC values indicate better model fit. We compared the DIC of models taking into account subclinical psychosis measures to a model where parameters did not vary according to any variable (*Null-model*) and to models taking into account only motion coherence conditions for RDM (*HDDM-C, HDDM-LR-C*). In comparing the models, we considered significant a difference (\(\Delta\)) of 10 DIC points (Spiegelhalter et al., 2002). For each DDM, Markov chain Monte Carlo simulations were used to generate 20,000 samples. The first 2,000 samples were discarded as burn-in, a thinning factor of 5 was used and outliers were set at 10%. The convergence of Markov chains was assessed by visual inspection and by computing the Gelman-Rubin statistic and verifying values ranging between 0.9 and 1.1.
Table 1. HDDM specifications. Conditions/groups according to which drift rate and decision threshold parameters were free to vary.

HC=High coherence
LC=Low coherence
LR=Linear Regression

<table>
<thead>
<tr>
<th>Between-group Models</th>
<th>Conditions/Groups</th>
<th>Regression Models</th>
<th>Predictors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null-model</td>
<td>None</td>
<td>Null-model</td>
<td>None</td>
</tr>
<tr>
<td>HDDM-C</td>
<td>HC vs. LC</td>
<td>HDDM-LR-C</td>
<td>HC vs. LC</td>
</tr>
<tr>
<td>HDDM-PDI</td>
<td>Low-PDI vs. High-PDI</td>
<td>HDDM-LR-PDI</td>
<td>PDI</td>
</tr>
<tr>
<td>HDDM-CAPS</td>
<td>Low-CAPS vs. High-CAPS</td>
<td>HDDM-LR-CAPS</td>
<td>CAPS</td>
</tr>
<tr>
<td>HDDM-ASI</td>
<td>Low-ASI vs. High-ASI</td>
<td>HDDM-LR-ASI</td>
<td>ASI</td>
</tr>
<tr>
<td>HDDM-PDI-C</td>
<td>Low-PDI vs. High-PDI</td>
<td>HDDM-LR-PDI-C</td>
<td>PSI</td>
</tr>
<tr>
<td>HDDM-CAPS-C</td>
<td>Low-CAPS vs. High-CAPS</td>
<td>HDDM-LR-CAPS-C</td>
<td>CAPS</td>
</tr>
<tr>
<td>HDDM-ASI-C</td>
<td>Low-ASI vs. High-ASI</td>
<td>HDDM-LR-ASI-C</td>
<td>ASI</td>
</tr>
</tbody>
</table>

4.3 Results

RDM RTs and accuracy

Figure 1-A shows that the OLS models did not show any effect of PDI, CAPS or ASI on RT or accuracy in any motion coherence condition. On the other hand, the quantile regressions (Figure 1-B) revealed positive effects of PDI and CAPS on RT mainly for high motion coherence.
**Fig. 1 OLS and quantile regression models.** (A) Results from ordinary least squares models, each with PDI, CAPS and ASI as the predictor. (B) Results from quantile (median) regression models with PDI, CAPS and ASI as predictors. Vertical dashes indicate the estimates for $\beta$ and coloured points the upper and lower bounds.

<table>
<thead>
<tr>
<th>HC</th>
<th>LC</th>
<th>RT</th>
<th>DTD</th>
</tr>
</thead>
<tbody>
<tr>
<td>High motion coherence</td>
<td>Low motion coherence</td>
<td>Reaction time</td>
<td>Draws to decisions</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Conf-0</th>
<th>Conf-1</th>
<th>Conf-N</th>
<th>ADJ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Confidence at 0 draws</td>
<td>Confidence at the first draw</td>
<td>Confidence at the last draw</td>
<td>Belief adjustment</td>
</tr>
</tbody>
</table>

* $p < 0.05$
** $p < 0.01$
HDDM modelling: Effects on drift rate and decision threshold

Convergence. All models showed evidence of convergence from visual inspection and the Gelman-Rubin diagnostic, the values of which ranged between 0.9 and 1.

Between-group analysis. As shown in Table 2, models that took subclinical psychotic traits into account showed a significantly lower DIC when compared with models that did not. Hence, accounting for subclinical psychotic traits increased the fit of HDDMs to our data. Models where parameters vary for both motion coherence conditions and median-split groups (PDI, CAPS or ASI groups; $HDDM$-$PDI$-$C$, $HDDM$-$CAPS$-$C$, $HDDM$-$ASI$-$C$) showed significantly lower DIC when compared with the Null-model or the HDDM-C. In the following, therefore, we report the between-group differences in posterior probability estimates from $HDDM$-$PDI$-$C$, $HDDM$-$CAPS$-$C$ and $HDDM$-$ASI$-$C$. 

100
Table 2. DIC between-group HDDMs. Values of Deviance Information Criterion (DIC) for each model in descending order (lower DIC, better fit); differences in DIC (Δ DIC) between each model and the Null-model (parameters not varying for any variable); Δ DIC between each model and the C-model (parameters varying for motion coherence only).

<table>
<thead>
<tr>
<th>Model</th>
<th>DIC</th>
<th>Δ DIC Null-model</th>
<th>Δ DIC HDDM C</th>
</tr>
</thead>
<tbody>
<tr>
<td>HDDM-CAPS-C</td>
<td>17329.78</td>
<td>-219.82</td>
<td>-134.54</td>
</tr>
<tr>
<td>HDDM-ASI-C</td>
<td>17345.5</td>
<td>-204.09</td>
<td>-118.82</td>
</tr>
<tr>
<td>HDDM-FDI-C</td>
<td>17349.19</td>
<td>-200.41</td>
<td>-115.13</td>
</tr>
<tr>
<td>HDDM-CAPS</td>
<td>17416.54</td>
<td>-133.06</td>
<td>-47.78</td>
</tr>
<tr>
<td>HDDM-FDI</td>
<td>17422.22</td>
<td>-127.38</td>
<td>-42.1</td>
</tr>
<tr>
<td>HDDM-ASI</td>
<td>17426.16</td>
<td>-123.44</td>
<td>-38.16</td>
</tr>
<tr>
<td>HDDM-C</td>
<td>17464.32</td>
<td>-85.28</td>
<td>0</td>
</tr>
<tr>
<td>Null-model</td>
<td>17549.6</td>
<td>0</td>
<td>85.28</td>
</tr>
</tbody>
</table>

In all three of these models, drift rates were significantly higher in high motion coherence than in low motion coherence conditions (see Fig. 2-A), reflecting the noise in the physical stimulus (percentage of coherently moving dots), thus empirically confirming the idea that drift rate can be considered a good proxy for precision of sensory evidence. Decision thresholds were lower in low motion coherence than in high motion coherence (see Fig. 2-B), showing a lower quantity of accumulated evidence for less precise stimuli.
Fig. 2 Between-group comparison. Posterior probability density distributions of drift rate (A) and decision threshold (B) for median-split groups of subclinical psychotic symptoms. Bold lines and adjacent annotations indicate the means of the distributions.

In HDDM-PDI-C, the high-PDI group showed significantly higher drift rates compared to the low-PDI group in both motion coherence conditions. In HDDM-CAPS-C, the high-CAPS group showed significantly
higher drift rates compared to the low-CAPS group in low motion coherence and trend-wise in high motion coherence.

We found no significant difference in decision thresholds between high- and low-CAPS groups. In HDDM-ASI-C, the high-ASI group showed significantly lower drift rates compared to the low-ASI group in high motion coherence, but not in low motion coherence. Decision threshold was significantly higher for the high-ASI group in low motion coherence but not in high motion coherence.

Table 3. DIC regression HDDMs. Values of Deviance Information Criterion (DIC) for each model in descending order (lower DIC, better fit); differences in DIC (Δ DIC) between each model and the Null-model (parameters not varying for any variable); Δ DIC between each model and the C-model (parameters varying for motion coherence only).

<table>
<thead>
<tr>
<th>Model</th>
<th>DIC</th>
<th>Δ DIC Null-model</th>
<th>Δ DIC HDDM C</th>
</tr>
</thead>
<tbody>
<tr>
<td>HDDM-LR-CAPS-C</td>
<td>16216.39</td>
<td>-1333.21</td>
<td>-24.83</td>
</tr>
<tr>
<td>HDDM-LR-PDI-C</td>
<td>16229.03</td>
<td>-1320.57</td>
<td>-12.19</td>
</tr>
<tr>
<td>HDDM-LR-C</td>
<td>16241.22</td>
<td>-1308.38</td>
<td>0.0</td>
</tr>
<tr>
<td>HDDM-LR-ASI-C</td>
<td>16248.85</td>
<td>-1300.75</td>
<td>7.63</td>
</tr>
<tr>
<td>HDDM-LR-CAPS</td>
<td>16299.22</td>
<td>-1250.38</td>
<td>58.0</td>
</tr>
<tr>
<td>HDDM-LR-PDI</td>
<td>16310.81</td>
<td>-1238.79</td>
<td>69.59</td>
</tr>
<tr>
<td>HDDM-LR-ASI</td>
<td>16331.88</td>
<td>-1217.72</td>
<td>90.66</td>
</tr>
<tr>
<td>Null-model</td>
<td>17549.6</td>
<td>0.0</td>
<td>1308.38</td>
</tr>
</tbody>
</table>

Bayesian regression analysis. The models where PDI or CAPS were predictors together with motion coherence (HDDM-LR-PDI-C, HDDM-LR-CAPS-C) showed significantly lower DICs compared to the Null-model and the HDDM-LR-C, which included coherence as the only predictor. In contrast, HDDM-LR-ASI-C did not outperform the HDDM-LR-C (Δ DIC= 7.63).

In Figure 3, we show the posterior distributions of β coefficients for PDI, CAPS and ASI from the models that showed the lowest DIC with these predictors (HDDM-LR-PDI-C, HDDM-LR-CAPS-C and HDDM-LR-ASI-C). The regression model analysis confirmed the results from the between-group analysis for PDI; for CAPS, it confirmed the effect on drift rate and showed an
effect on decision threshold that was not present in the between-group analysis; for ASI, it disconfirmed the results from the between-group analysis by showing no effect of ASI on HDDM parameters.

Fig. 3 HDDM regressions. Posterior probability density distributions of $\beta$ coefficients for PDI, CAPS and ASI respectively from HDDM-LR 4, HDDM-LR 5 and HDDM-LR 6.

**Probabilistic reasoning: BT**

Although we found no relationship between psychotic phenotypes and DTD or ADJ (see Fig. 1), the results from OLS models showed a positive effect of CAPS and ASI on Conf-N (i.e., confidence rating at final draw, see
Fig. 1-A). The quantile regressions confirm these results showing a positive effect of all psychotic traits, including PDI, on Conf-N (see Fig. 1-B).

Demographics and Subclinical psychosis

In Table 4, we report the main demographics of our participant sample and the means and quartiles of the distributions for high and low PDI, CAPS, and ASI groups. Only between low-CAPS and high-CAPS groups was there a significant difference in age with participants in the high-CAPS group being older ($t (189) = -0.36$, $p<0.05$). In all group pairs, we see an uneven distribution of the psychotic phenotype measures: CAPS and ASI scores are higher for the high-PDI group, PDI and ASI scores are higher for the high-CAPS group, PDI and CAPS scores are higher for the high-ASI group.

Table 4. Differences between psychotic phenotype groups. Median values of demographic, psychometric and psychotic trait variables with tests of their group differences.

<table>
<thead>
<tr>
<th></th>
<th>Overall</th>
<th>High-PDI</th>
<th>Low-PDI</th>
<th>p value</th>
<th>High-CAPS</th>
<th>Low-CAPS</th>
<th>p value</th>
<th>High-ASI</th>
<th>Low-ASI</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>191</td>
<td>95</td>
<td>96</td>
<td></td>
<td>96</td>
<td>95</td>
<td>90</td>
<td>101</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age, mean (SD)</td>
<td>36.1 (9.9)</td>
<td>36.5 (9.2)</td>
<td>35.6 (10.5)</td>
<td>0.56*</td>
<td>37.8 (10.3)</td>
<td>34.3 (9.1)</td>
<td>&lt;0.05*</td>
<td>36.6 (10.2)</td>
<td>35.6 (9.6)</td>
<td>0.459*</td>
</tr>
<tr>
<td>Gender, n (%) F</td>
<td>97 (45.3)</td>
<td>42 (43.3)</td>
<td>45 (47.9)</td>
<td>0.625†</td>
<td>47 (49.0)</td>
<td>40 (42.1)</td>
<td>0.42†</td>
<td>38 (42.2)</td>
<td>49 (48.5)</td>
<td>0.468†</td>
</tr>
<tr>
<td>Gender, n (%) M</td>
<td>104 (54.5)</td>
<td>55 (56.7)</td>
<td>49 (52.1)</td>
<td></td>
<td>49 (51.0)</td>
<td>55 (57.9)</td>
<td></td>
<td>52 (57.8)</td>
<td>52 (51.5)</td>
<td></td>
</tr>
<tr>
<td>PDI, median [Q1,Q3]</td>
<td>22.5 [6.5,43.0]</td>
<td>43.0 [31.0,60.0]</td>
<td>6.0 [0.0,14.8]</td>
<td>&lt;0.001*</td>
<td>36.5 [18.5,58.0]</td>
<td>10.0 [0.0,27.0]</td>
<td>&lt;0.001*</td>
<td>35.0 [12.2,58.0]</td>
<td>13.0 [0.0,27.0]</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td>CAPS, median [Q1,Q3]</td>
<td>13.0 [0.0,37.5]</td>
<td>30.0 [8.0,56.0]</td>
<td>6.0 [0.0,18.0]</td>
<td>&lt;0.001*</td>
<td>37.5 [20.0,59.0]</td>
<td>0.0 [0.0,6.0]</td>
<td>&lt;0.001*</td>
<td>32.0 [17.2,59.0]</td>
<td>0.0 [0.0,11.0]</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td>ASI, median [Q1,Q3]</td>
<td>6.0 [2.0,12.0]</td>
<td>9.0 [6.0,15.0]</td>
<td>3.0 [1.0,7.0]</td>
<td>&lt;0.001*</td>
<td>10.0 [6.0,26.0]</td>
<td>2.0 [0.0,5.0]</td>
<td>&lt;0.001*</td>
<td>13.0 [9.0,17.0]</td>
<td>2.0 [0.0,4.0]</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td>CNT, median [Q1,Q3]</td>
<td>0.7 [0.4,0.9]</td>
<td>0.7 [0.4,0.9]</td>
<td>0.7 [0.3,0.9]</td>
<td>0.325*</td>
<td>0.7 [0.3,0.9]</td>
<td>0.7 [0.4,0.9]</td>
<td>0.468*</td>
<td>0.7 [0.4,0.9]</td>
<td>0.7 [0.3,0.9]</td>
<td>0.679*</td>
</tr>
</tbody>
</table>
4.4 Discussion

We identified increased precision of sensory evidence in perceptual inference as a candidate neurocomputational mechanism contributing to the emergence of both delusion-like and hallucination-like experiences in the general population. Both delusional ideation and anomalous perceptions predicted higher drift rates (i.e., precision of sensory evidence) in perceptual inference (i.e., RDM); while psychotic traits were not associated with probabilistic reasoning (i.e., DTD-BT and GE-BT). From a psychosis-continuum perspective (Strauss, 1969; Van Os et al., 2000; Van Os et al., 2009; Mennigen & Bearden., 2019), our findings support the idea of altered information processing in perceptual inference (i.e., RDM performance) associated with anomalous reality-testing at the perceptual (i.e., CAPS) and belief (i.e., PDI) levels.

Taking drift rate as a proxy for precision of sensory evidence (Hesselman et al., 2010; Fitzgerald et al., 2015; Bitzer et al., 2014; Fard et al. 2017), and decision threshold as a quantification of accumulated evidence, we tested in a classic RDM task if and how these DDM parameters varied with measures of psychotic phenotype. In our non-clinical sample, both anomalous perceptions and delusional ideation were associated with higher precision of sensory evidence in RDM (i.e., drift rate), while only anomalous perceptions predicted lower decision thresholds. We also attempted to replicate previous studies showing impulsive sampling (e.g., fewer draws of evidence samples) in probabilistic reasoning, namely in the BT, associated with delusional ideation. After controlling for performance attentiveness, we found no evidence of impulsive sampling in probabilistic reasoning for participants higher in delusional ideation. This suggests that in subclinical psychosis, alterations of inferential processes might be more prominent and detectable in the perceptual rather than in the cognitive domain.

Psychotic-like experiences and perceptual inference

We showed that delusional ideation (i.e., PDI) is associated with higher precision of sensory evidence (i.e. drift rate) in perceptual inference, suggesting a link between perceptual mechanisms and the formation of abnormal beliefs. Alterations of perceptual information processing could
precede and potentially contribute to anomalous perceptions as well as to changes in the belief system. This supports the evidence associating PDI with weaker perceptual priors (Schmack et al., 2013; Stuke et al., 2019) and the idea in the PCA that delusional ideation might be driven by the urgency of explaining persistent PE signals (Corlett et al., 2009; Adams et al., 2013; Sterzer et al., 2018; Carhart-Harris & Friston, 2019). In this view, in a prodromal phase, an overly precise perceptual encoding of otherwise irrelevant stimuli would undermine the stability of prior beliefs, producing a pervasive sense of inexplicability.

Later, in a pathological phase, the tendency of cortical computing to minimise PE would push top-down processes to form strong prior beliefs able to explain past and future events perceived as odd and which “must mean something”. These accounts of the environment would be biased by increased precision weights representing an underestimation of the uncertainty in the evidence first, and in prior beliefs later. These inaccurate inferences would hence constitute the basis for the development of psychotic symptoms. In line with the PCA (Corlett et al., 2009; Adams et al., 2013; Sterzer et al., 2018; Carhart-Harris & Friston, 2019), we showed that higher influence of sensory evidence (i.e., higher drift rate) in RDM is associated with subclinical psychosis.

At the same time, our work conflicts with previous studies supporting increased influence of prior beliefs (Furl et al., 2022). Teufel et al. (2015) and Davies et al. (2017) reported better performance in association with PDI and CAPS when identifying figures in ambiguous pictures, and interpreted this advantage as a greater and more positive impact of prior knowledge on performance. However, no formal measure of the impact of priors was taken in Davies et al. and the one adopted by Teufel et al. did not vary with CAPS or PDI. We might also trace back this inconsistency in the literature to the different nature of the stimuli employed. In fact, in contrast to the abstract stimuli used in ours and others’ studies supporting a greater influence of sensory evidence in subclinical psychosis (Schmack et al., 2013; Stuke et al., 2019), these studies reporting greater influence of priors used visual stimuli representing concrete scenes which often included living beings.
Interestingly, Stuke et al. (2018) found higher prior weights associated with CAPS and PDI when detecting faces in noise, showing that the processing of socially meaningful stimuli could be characterised by higher priors in people reporting more psychotic-like experiences. The involvement of socio-emotional information, and the consequent recruitment of cortical regions possibly not involved in the processing of abstract stimuli, could result in a variation of prior/sensory evidence influence on inference.

Contrary to PDI and CAPS, aberrant salience as measured by ASI was associated with lower (rather than higher) precision of sensory evidence and lower decision thresholds in the between-group analysis. Like PDI and CAPS, ASI is also considered to measure a psychotic trait (Cicero et al., 2010) and in our study, all three measures were positively associated with each other (see Table 2). This discrepancy in the impact on RDM performance between ASI and other subclinical traits might represent a dissociation between core psychotic-like symptoms (delusional ideation and anomalous perceptions) and aberrant salience of stimuli. However, when ASI is taken as a continuous variable, the regression model did not show any effect of ASI and did not outperform the model taking only motion coherence conditions into account. The inconsistency between group and continuous variable approaches may suggest a false positive effect of ASI grouping on parameters. Alternatively, the ASI-DDM parameters relationship might not be well described by our linear model which could not capture nonlinear effects.

**Subclinical psychosis and cognitive inference**

Although JTC has been found in clinical and general population samples (Fine et al., 2007; Ross et al. 2015; Dudley et al., 2016; McLean et al., 2017), it remains uncertain if this behaviourial pattern is specifically associated with delusional symptomatology. Different studies have pointed out how other factors modulate sampling in BT possibly creating an illusory association between JTC and delusions: miscomprehension of the task (Balzan et al., 2012), motivation (McKay et al., 2006), socio-economic status (Baker et al., 2019) and intelligence quotient (Tripoli et al., 2020). Ross et al. (2016) found that PDI had no effect on DTD, and showed that cognitive style (analytical vs. intuitive) could be considered a more reliable predictor of
sampling behaviour in BT. Sulik et al. (2023) confirmed this view and although in an analysis of their full sample they found a negative relationship between PDI and DTD, the exclusion of low-quality data (i.e., participants who did not pass attention checks during the task) ruled out any effect of PDI on DTD. When we analysed here data from a subsample of attentive participants of Sulik et al.’s cohort, we did not find any JTC in relation to delusional ideation or other subclinical psychosis measures. These results illustrate the sporadic nature of the association between delusion-like beliefs and impulsive sampling in the BT (Ross et al., 2015) and show how alterations of perceptual inference (e.g., on the RDM task) might represent instead a more prominent feature of subclinical psychosis.

We did not find any significant relationship between psychotic-like experiences and ADJ. Although this BT behavioural pattern has been shown in Scz with delusions (Langdon et al., 2010; Speechley et al., 2010; Jardri et al., 2017; Adams et al., 2018), it has repeatedly failed to be replicated in individuals from the general population with high scores for delusional ideation (Colbert & Peters, 2002; Balzan et al., 2012; Sulik et al., 2021). Our study therefore supports the idea that ADJ does not vary with measures of subclinical psychosis.

**Neurofunctional implications**

We identified a computational pattern in RDM task performance, namely increased precision of sensory evidence, that varies along with subclinical psychotic symptoms. Given that RDM is a well-studied paradigm in animal and human neurophysiology, we would like to suggest here some hypotheses about possible neural mechanisms underpinning our findings.

In RDM, neural firing-rates in the lateral intraparietal cortex (LIP) of monkeys (Shadlen & Newsome, 1996; Roitman & Shadlen, 2002; Hanks & Summerfield, 2017) and the central parietal positivity (CPP) in humans (O’Connell et al., 2012; Kelly & O’Connell, 2013) show a similar pattern: they ramp up during evidence accrual until they reach a peak and dampen after the decision is taken. Behaving as a drift rate, the slope of the build-up of LIP firing rates as well as the amplitude of CPP are higher when the precision on the evidence is higher (e.g., higher motion coherence in RDM). Moreover, this
same PPC ramping activity seems to track not merely the noise of the physical stimuli, but to reflect the subjective precision ascribed to the sensory signal (participant’s confidence) (Kiani & Shadlen, 2009; Tagliabue et al., 2019; Pereira et al., 2020). Interestingly, the slope of cumulative activity of PPC neurons recorded with magneto-encephalography during RDM has been correlated to the synaptic gain of superficial pyramidal cells as simulated through dynamic causal modelling (Fitzgerald et al., 2015), suggesting the hypothesis that PPC superficial cells encode the precision ascribed to sampled evidence.

We can hence speculate that altered synaptic gain in PPC superficial pyramidal cells may underpin the information processing specificities we found associated with subclinical psychosis. Acknowledging the association between psychotic-like experiences and higher drift rates in RDM shown here, future studies might aim at describing any distinctive relation of drift rate with PPC activity in psychosis-prone individuals.

In conclusion, our study highlights a significant association of both hallucination- and delusion-like experiences with increased sensory precision in perceptual inference, as observed in the RDM task. This suggests a potential interplay between altered perceptions and the belief system. We did not find any significant behavioural pattern in cognitive inference (i.e., on the draws to decision beads task) associated with psychotic-like experiences.

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Supplementary materials

Distributions of psychotic phenotype measures

For a full display of the psychotic phenotype data in our sample, we report here the medians and the frequency distribution in sample percentage for PDI, CAPS and ASI (Fig 1-A-B-C).

A. PDI (delusion-like experiences)

![Graph showing the distribution of PDI scores with median indicated at 22.00]

B. CAPS (hallucination-like experiences)

![Graph showing the distribution of CAPS scores with median indicated at 13.00]
Fig 1. Frequency distribution of psychotic phenotype measures. Distribution in participant percentage of (A) Peters et al. Delusion Inventory (PDI), (B) Cardiff Anomalous Perceptions Scale (CAPS) and (C) Aberrant Salience Inventory (ASI).
V. Cautious decisions, cautious perceptions

In this chapter, we further present and discuss findings obtained from the data collected in Study 1. Coming from the general population, these data are relevant for drawing conclusions about human decision-making. In this new analysis, we investigated the relationship between perceptual and cognitive decisions outside the general focus on psychosis. Specifically, we tested the hypothesis that a cautious approach to cognitive decision-making would be reflected in more cautious perceptual decisions.

Abstract

AIMS: We examined decision commitment in perceptual and cognitive paradigms. Previous research suggests common neural mechanisms for evidence accumulation and decision commitment across perceptual and cognitive domains. We investigated whether cautiousness in cognitive decisions could predict cautious evidence accumulation in perceptual decisions.

METHODS: 191 participants completed the Random Dot Motion task (RDM), alongside three cognitive tasks: the Draws-To-Decision Beads Task (DTD-BT), the "Graded-Estimate" Beads Task (GE-BT), and the Cognitive Reflection Test (CRT). We operationalised cautiousness in cognitive paradigms through a more analytical approach in CRT, increased draws-to-decision (DTD) in DTD-BT, or reluctance to adjust beliefs in GE-BT. We employed hierarchical drift-diffusion models (HDDMs) to assess how cognitive decision variables (CRT, DTD, ADJ) influenced drift rate and decision threshold in the RDM task.
RESULTS: CRT, DTD, and ADJ scores predicted higher decision thresholds in the Random Dot Motion task (RDM). Additionally, CRT and ADJ scores predicted higher drift rates in RDM.

CONCLUSION: Our findings show that a cautious approach to decisions in the cognitive domain is reflected by cautiousness in perceptual decisions. This supports the notion that shared mechanisms might underpin decision commitment across cognitive and perceptual domains.

5.1 Introduction

Before any informed decision, we decide, more or less consciously, when to stop collecting information. Time is a natural constraint to our search for information, and depending on the type of decisions we need to make, our decisional strategies can vary. For instance, when we have to decide whether a traffic light is green or whether to purchase a house we just viewed, the process of finalising these decisions could vary significantly. The brain mechanisms underpinning the commitment to decisions might also vary between these two very different situations. Nonetheless, evidence shows that perceptual (e.g. “Is the traffic light green?”) and cognitive (e.g., “Is this the best quality-price tradeoff I can find?”) decisions may share the same mechanisms.

The Random Dot Motion task (RDM) represents a classic paradigm in the study of perceptual decisions. In its classic version, participants are presented with a cloud of dots moving randomly while a subset of dots move coherently in one direction (e.g., left or right). Participants need to decide in which direction the coherently moving dots are aimed. Neural correlates in RDM have been studied at single-neuron and neuronal population levels. Neurons in monkeys’ lateral intraparietal cortex (LIP) increase their firing rate with evidence accumulation during RDM performance and decrease steeply just before the commitment to a decision (Hanks & Summerfield, 2017; Roitman & Shadlen, 2002; Shadlen & Newsome, 1996). In humans, this
neuronal behaviour seems to be captured by the amplitude of late (300/400 ms) positive parietal event-related potentials that, analogously to LIP’s firing rates, increases and dampens in conjunction with evidence accumulation and commitment to a decision (Kelly & O’Connell, 2013; O’Connell et al., 2012).

Probabilistic reasoning paradigms have also been shown to have the same parietal neural correlates in both non-human (Kira et al., 2015; Yang & Shadlen, 2007) and human primates (Kelly & O’Connell, 2015; Kopp et al., 2016; Tickle et al., 2016). Concurrently, functional magnetic resonance imaging (fMRI) studies associate the posterior-parietal cortex (PPC) with decision commitment in probabilistic reasoning tasks (Andreou et al., 2018; Furl & Averbeck, 2011). This evidence suggests that activity in the parietal cortex, in PPC in humans, correlates with the accumulation of evidence and subsequent commitment to a decision on both the perceptual and cognitive levels.

If the commitment to perceptual and cognitive decisions is driven by the same mechanisms, we would expect that participants who are more cautious on cognitive decisions would also show more cautious perceptual decisions. In Study 1, 191 participants from the general population completed the Random Dot Motion task (RDM), and three different reasoning paradigms: the Draws-To-Decision Beads Task (DTD-BT), the “Graded-Estimate” Beads Task (GE-BT). Using these data, we can test the idea of shared mechanisms of decision commitment on a behavioural level across perceptual and cognitive paradigms. For this purpose, we included in our analysis a measure present in the data-set of Sulik et al. (2023), the cognitive reflection test (CRT). The CRT is a reasoning task designed to measure an individual’s ability to resist intuitive, incorrect responses and engage in analytical thinking to arrive at correct answers. We tested this hypothesis and operationalised cautiousness in cognitive decisions as a having more analytical approach in CRT (i.e., higher CRT scores), drawing more beads in DTD-BT (i.e., more draws-to-decision; DTD) and being reluctant in adjusting beliefs in GE-BT (i.e., higher ADJ scores). We devised three hierarchical drift-diffusion models (HDDMs) where drift rate and decision threshold varied as outcome variables of a Bayesian linear regression model where CRT, DTD or ADJ were set as the predictor in each together with motion coherence conditions.
5.2 Methods

For details about participants and the RDM, DTD-BT and GE-BT, the reader can consult the Methods section of Study 1 in Chapter 4.

Cognitive Reflection Test (CRT)

In the CRT, participants are asked seven questions which often induce quick intuitive but wrong responses, while an analytical time-taking approach is needed to respond correctly (e.g., “A bat and a ball cost $1.10. The bat costs $1.00 more than the ball. How much does the ball cost?”; the intuitive answer is $0.10, the correct answer is $0.05) (Frederik, 2005).

Data analysis and HDDM modelling.

Here, we constructed HDDM regression models where drift rate and decision threshold parameters could vary as dependent variables of regression models where either CRT scores, DTD or ADJ scores were a predictor, together with trial motion coherence conditions respectively in the following models: HDDM-CRT, HDDM-DTD, HDDM-ADJ. Before running the models, we z-scored the values of all predictors that varied between participants (DTD, ADJ and CRT). We evaluated model fit using the Deviance Information Criterion (DIC). We compared the DIC of models with DTD, ADJ or CRT as predictors to a model where parameters did not vary according to any variable (Null-model) and to models taking into account only motion coherence conditions in RDM (HDDM-LR-C). We considered a difference (Δ) of 10 DIC points (Spiegelhalter et al., 2002) to be significant. For all the DDMs, we used Markov chain Monte Carlo simulations to generate 20,000 samples; for better convergence, we discarded the first 2,000 samples as burn-in and used a thinning factor of 5. Outliers were set at 10%. The convergence of Markov chains was assessed by visual inspection and by computing the Gelman-Rubin statistic and verifying that values ranged between 0.9 and 1.1.
Additionally, we further explored the relationship between cognitive and perceptual decision-making through a Kendall-τ-b correlation map including DTD, CRT, ADJ, raw data from RDM (participant-level averages of accuracy and reaction time; RT) and confidence reports from DTD-BT at zero draws (Conf-0), at the first draw (Conf-1) and the final draw (Conf-N).

5.3 Results

HDDM modelling

Convergence. All models showed evidence of convergence from visual inspection and the Gelman-Rubin diagnostic, the values of which ranged between 0.9 and 1.1.

Bayesian regressions. As shown in Figure 1, the DICs of HDDM-CRT, HDDM-DTD and HDDM-ADJ were all significantly lower (better fit) than the DICs of HDDM-LR-C and Null-model.

Figure 2 shows the results of the Bayesian regressions: CRT scores predicted higher drift rates and higher decision thresholds; DTD in BT predicted higher decision thresholds.; ADJ scores in GE-BT predicted higher drift rates and higher decision thresholds.

Fig. 1 DIC Bar plot. Values of Deviance Information Criterion (DIC) for the Null-model and for HDDMs with parameters varying as response variables of a linear regression model (HDDM-LR-C, HDDM-CRT, HDDM-DTD, HDDM-ADJ).
**Correlations**

In *Figure 3*, we show the *Kendall-τ-b* statistics and *p* values (not corrected for multiple comparisons) of the correlations between the nine variables considered. Participants in the DTD-BT rated their confidence before the first draw (Conf-0), after the first draw (Conf-1) and at the final draw (Conf-N). The confidence reports at the three stages of DTD-BT (Conf-0, Conf-1 and Conf-N) were all correlated with DTD but their effects had different directions. DTD was negatively correlated with Conf-0 and Conf-1, but positively with Conf-N. Moreover, Conf-0 was negatively correlated with CRT and Conf-N; ADJ scores were negatively correlated with Conf-1.

We found accuracy in RDM performance to be correlated positively with CRT scores and age; and negatively with Conf-0 and RT in RDM. The negative correlation between RT and accuracy is a well-known effect in RT research, where faster reaction times are associated with more accurate responses in difficult tasks (Forstmann et al., 2016).
**Fig. 3** Kendall-t-b correlation map. Circle size is proportional to the Kendall-t-b statistic.

- **CRT** = Cognitive Reflection Test scores
- **DTD** = Draws to Decisions
- **Conf-0** = confidence rating at zero
- **Conf-1** = confidence rating at the first draw
- **Conf-N** = confidence rating at the final draw
- **ADJ** = Belief Adjustment scores
- **RT** = Reaction Time averaged per participant
- **Accuracy** = Accuracy of responses averaged per participant

* *p* < 0.05  
** *p* < 0.001
5.4 Discussion

In addition to the pre-registered analyses of Study 1, we tested a second hypothesis, exploring instead the relationship between cognitive and perceptual decisions. Specifically, we tested the hypothesis that cautiousness in cognitive decisions predicts higher decision thresholds in perceptual decisions. To RDM data, we fitted HDDMs where drift rate and decision threshold varied as outcome variables of Bayesian linear regressions with DTD, CRT or ADJ scores as predictors together with motion coherence conditions.

Commitment to perceptual and cognitive decisions

We considered that caution about cognitive decisions was reflected in a more analytical cognitive style in CRT (i.e., higher CRT scores), drawing more beads in DTD-BT or being reluctant to adjust beliefs in GE-BT (i.e., higher ADJ scores). CRT and ADJ are indicative of cautious decisions, but they are not direct measures of the quantity of evidence accumulated, as are DTD and decision threshold. However, the positive correlations of DTD with both CRT and ADJ shown in Figure-3, indicate at least a link between the latter and evidence accumulation in cognitive decisions.

CRT, DTD and ADJ scores predicted higher decision thresholds in RDM. These results depict a general picture where more individuals who are cautious in cognitive decisions also take an analogous cautious approach in perceptual decisions by raising their decision thresholds. In line with evidence from neurophysiological data from monkeys (Hanks & Summerfield, 2017; Kira et al., 2015; Roitman & Shadlen, 2002; Shadlen & Newsome, 1996; Yang & Shadlen, 2007) and humans (Kelly & O’Connell, 2013, 2015; Kopp et al., 2016; O’Connell et al., 2012; Tickle et al., 2016), these results might suggest that common decision-making processes have contributed to produce the behavioural data in the perceptual and reasoning tasks we employed.
Evidence evaluation in perceptual and cognitive decisions

Unlike DTD, CRT and ADJ predicted higher drift rates in addition to
decision thresholds. This pattern of association might be explained by the fact
that the DTD specifically indexes the quantity of evidence accumulated but
not decision accuracy. CRT is reflective of a more cautious approach to
decisions and, at the same time, of accurate reasoning since higher CRT scores
are obtained from answering correctly to CRT items. Although indirectly, ADJ
scores can also be informative about the accuracy of participants’ probabilistic
inference. Throughout the sequence of 10 bead draws in our GE-BT,
participants evaluated disconfirmatory evidence (bead of the minority colour
in the sequence) at the 3rd, 6th and 9th draw, after having seen respectively 2,
4 or 6 beads of another colour (the majority colour). Bigger belief shifts
favouring the minority colour in the sequence (lower ADJ scores especially in
later draws: 6th and 9th) may represent less accurate probabilistic inference.
Hence, ADJ scores, indirectly, captured a component of the accuracy of
probabilistic inference. Hence, a more cautious and accurate analysis of the
evidence in CRT and ADJ was reflected in a higher quantity of evidence
accumulated (decision threshold) and higher gain of information over time
(drift rate) in RDM. It can be argued that the positive associations of CRT and
ADJ with drift rate suggest an underlying trait that gives rise to the same
effects in both perceptual and cognitive decision-making.

Another aspect of this mapping is metacognition. In fact, the
confidence rating before sampling any bead in DTD-BT (conf-0) was
negatively correlated with DTD, CRT and accuracy in RDM, indicating that
participants who were a priori more confident of their probabilistic inferences
drew fewer beads in DTD-BT and were characterised by a less analytical
reasoning style and less accurate perceptual decisions. Interestingly, in RDM,
Olawole-Scott and Yon (2023) found that participants perceived motion
coherence as stronger when they were previously made to overestimate motion
cohere for those trials. They did not find any effect on accuracy but
showed that the manipulation of metacognition can at least affect participants’
phenomenology. We can speculate that in our data, the overconfident-like
approach in DTD-BT reflects a hidden (not measured) metacognitive process
affecting phenomenology and accuracy of performance across perceptual
decision-making and reasoning. To further explore this possibility, future studies might test the impact of prior confidence on phenomenology and accuracy in perceptual and cognitive decision-making tasks.

In conclusion, these supplementary findings suggest that the behavioural data from the perceptual and cognitive paradigms we considered have been generated by common decisional processes. Specifically, the results showed a correspondence of both decision commitment and accuracy between perceptual and cognitive domains. This relation of evidence accumulation and evaluation supports the idea that common neural mechanisms contribute to decision-making independently from the level of information processing. In Chapter VII, we will further discuss this point by looking at how modulation of PPC excitability impacts perceptual and cognitive decisions.

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VI. Psychotic phenotype and modulation of posterior parietal cortex excitability

In this chapter, we introduce Study 2 where we aim to explore evidence accumulation mechanisms specifically in relation to the excitability of the posterior parietal cortex (PPC). We employed offline inhibitory transcranial magnetic stimulation and examined perceptual and cognitive inference in relation to psychotic-like experiences. Our paper sheds light on the impact of reduced PPC excitability on estimations of drift rate and decision threshold. Notably, these effects were shown to vary depending on the specific psychotic phenotype under examination.

Reduced posterior parietal cortex excitability affects perceptual decisions depending on hallucinatory and delusional phenotypes.

Abstract

AIMS. Poor data-gathering and increased precision of sensory evidence in decision-making are hypothesised to be associated with psychotic-like experiences. Impulsivity and precision imbalances might arise from altered synaptic gain in posterior parietal cortex (PPC) where ramping neural activity correlates with the quality and quantity of accumulated evidence in both the random dot motion task (RDM; perceptual inference) and the beads task (BT; probabilistic reasoning). By the use of 1Hz repetitive transcranial magnetic stimulation (TMS), we aimed to evaluate the impact of reduced PPC excitability on neurocomputational and behavioural patterns in RDM and BT.

METHODS. We compared performance on the RDM and BT in two groups of participants (total, $N = 68$) who underwent a 15-minute session of either 1Hz TMS or sham-TMS over the right PPC. By fitting hierarchical drift-diffusion models to RDM data, we estimated drift rates (taken as a proxy
of sensory precision) and decision thresholds at the group level. We evaluated differences between TMS and sham-TMS groups and tested for interactions of these TMS groups with psychotic-like experiences.

RESULTS. In RDM, TMS induced a significant increase in decision thresholds compared to sham-TMS in participants with low psychotic phenotypes. This effect was not present in participants with higher hallucinatory or delusional phenotypes. Only in participants showing higher delusional phenotype, TMS was associated with lower drift rates. We did not find any significant effect on BT performance.

CONCLUSIONS. Our findings establish a causal role of PPC in decisions to end data-gathering in perceptual inference. The dissociable effects of PPC disruption depending on psychotic phenotype suggest that PPC excitability is involved in the variability of sensory precision and decision threshold associated with the delusional and hallucinatory phenotypes.

6.1 Introduction

Animals are continuously engaged in more or less conscious decisions about the reality of what surrounds them. Deciding if a stimulus represents a threat, a chance for mating or access to resources can be crucial for survival. Humans are no exception in this: “Is that a weapon or a toy?” – “Is this person following me?” – “Do you think the government is spying on us?” – the answers to such questions are examples of perceptual and doxastic (belief-related) judgements concerning what we perceive as or believe is real.

Theoretical and empirical work of the past decades put forward the idea that our experience of reality emerges from neural inferential processing of “raw data” coming from the sensorium (Ballard, 1999; Clark, 2013; Friston, 2010). A corollary of this is the idea that alterations of these inferential mechanisms produce unlikely inferences about reality, namely hallucinations and delusions. Research on subclinical psychotic traits in the
general and at-risk populations shows that the psychotic phenotype is present in a continuum (Mennigen & Bearden, 2020; Strauss, 1969; van Os et al., 2009, 2020) and that behavioural and computational patterns associated with altered inference also vary along this continuum (Davies et al., 2018; Schmack et al., 2013; Stuke et al., 2017). However, the neural mechanisms underlying this variability in behaviour and phenomenology are still unknown. The predictive coding account of psychosis (PCA) provides a theoretical framework linking phenomenology, computational and neural mechanisms (Sterzer et al., 2018). Within the PCA, in this study, we investigated whether changes in the posterior parietal cortex (PPC) excitability impact the encoding and quantity of accumulated evidence differently in individuals showing high vs. low psychotic phenotypes.

Within the PCA, we can consider psychosis as the phenomenological outcome of inferential alterations in perceptual (hallucinations) or cognitive (delusions) information processing. Predictive coding under the free-energy principle theorises that the nervous system confronts uncertainty about the environment by implementing a hierarchical Bayesian generative model. The brain holds representations of the world based on past experience (prior beliefs) that it uses to generate predictions about newly collected data (likelihood). When predictions fail, the agent-brain must change its representation accordingly. The bottom-up signals that lower levels failed to predict would pass up to higher levels as prediction error (PE) signals. Past representations (prior beliefs) would then be adjusted to new data/PE signals to improve the explanatory power of the newly updated representations (i.e., posterior estimates).

The extent of belief update is dictated by the precision of prior and PE signals. Precision (i.e. inverse of variance) is a quantification of uncertainty and would be implemented in neurons by the synaptic gain, which is the probability of a presynaptic event causing a postsynaptic one (Feldman & Friston, 2010). Very precise predictions would be harder to change by PEs, while precise PEs would more easily impact predictions. In this scheme, alterations of precision encoding can radically impact the agent’s representation of reality. Psychotic distortions of reality arise from imbalances of precision encoding in prior or new evidence signalling. In fact, undue
variations in precision (and so in synaptic gain) of prior or new evidence/PE signalling could produce drastic changes in posterior estimations resulting in psychotic experiences.

The PCA is successful at predicting variability in precision estimations along the psychosis continuum. Using different modelling approaches in perceptual and probabilistic decision-making, numerous studies have shown that parameters that can approximate precision encoding vary with psychotic and psychotic-like symptoms (Adams et al., 2018; Davies et al., 2018; Jardri et al., 2017; Limongi et al., 2018; O’Callaghan et al., 2017; Schmack et al., 2013; Stuke et al., 2017; Weilnhammer et al., 2020). The neural mechanisms that play a role in this variability in information processing are still unclear.

In paradigms requiring sampling of evidence, synaptic gain of PPC superficial pyramidal neurons might be involved in alterations of precision encoding and quantity of accumulated evidence. Firing rates in the lateral intraparietal area (LIP) of monkeys performing the random dot motion task (RDM) increase with the quantity and quality of accumulated evidence until they reach a canonical threshold value just before the decision (Hanks & Summerfield, 2017; Roitman & Shadlen, 2002; Shadlen & Newsome, 1996). In humans, an analogous pattern has been found using electroencephalography (EEG): a positive centroparietal event-related potential known as centroparietal positivity (CPP) whose amplitude increases with the quality and quantity of accumulated information in data-gathering tasks (Kelly & O’Connell, 2015b; O’Connell et al., 2018). CPP seems to occur independent of sensory modality or motor execution and has been replicated in various paradigms including RDM (Kelly & O’Connell, 2013; Pisauro et al., 2017; Tagliabue et al., 2019; van Vugt et al., 2019). Interestingly, Fitzgerald et al. (2015) showed that the slope of source reconstructed PPC ramping activity, as measured using magnetoencephalography during the RDM, correlated with the synaptic gain of PPC superficial pyramidal cells estimated by dynamic causal modelling in Fitzgerald et al. (2015). This evidence supports the hypothesis that neurons within the PPC may encode the precision attributed to accumulated evidence and elicit the decision to terminate data-gathering. In a previous study using RDM in combination with drift-diffusion models (DDMs), we associated delusional and hallucinatory phenotypes in the general
population with increased precision of sensory evidence in perceptual decisions and the hallucinatory phenotype with lower decision thresholds (Scaramozzino et al., in prep). This variability in precision encoding of sensory evidence associated with the psychotic phenotype in RDM could reflect differences in the synaptic gain of PPC superficial pyramidal cells.

In the present work, we explored how neuronal activity in the superficial PPC modulates evidence accumulation in relation to psychotic phenotypes. We reduced excitability in the PPC surrounding the right intraparietal sulcus (rIPS; thought to be the human homologue of LIP in non-human primates) through transcranial magnetic stimulation (TMS). Given the variability in sensory precision encoding we previously found in RDM associated with psychotic phenotypes (Scaramozzino et al., in prep), we expected both delusional and hallucinatory phenotypes to moderate any effect of TMS on sensory precision. Given our previous results on hallucinatory phenotype affecting decision thresholds, we also expected hallucinatory phenotype to moderate any TMS effect on decision thresholds. Because of the uncertainty associated with the effect of 1Hz repetitive TMS on a cortical network level (Beynel et al., 2020), and consequently on behavioural performance, in both cases, we did not have any hypotheses about the direction of the moderation.

We proxied precision of sensory evidence with the drift rate parameter in DDMs fitted on participants’ performance of the RDM. The DDM is a stochastic sampling process in which a decision variable $X$ varies over time until it reaches one of two decision threshold values of parameter $a$ that represents two possible choices. The increment of $X$ toward one of the two thresholds is a Wiener diffusion process as described by the following:

$$\frac{d}{dt} X(t) \sim \text{Normal} (v, \sigma^2)$$

*Equation 1* indicates that the increment of $X$ depends on samples from a Gaussian distribution, which represents the possible values of the information source. The lower the precision of the Gaussian, the noisier the evidence accumulation. By estimating the mean drift rate ($v$), we evaluate the
precision of the accumulation process so that the higher the \( v \), the higher the precision. Notably, it has been demonstrated that the DDM’s drift rate can approximate the precision of sensory evidence of Bayesian models (Bitzer et al., 2014), allowing for generalisations of DDM findings to PCA.

PPC activity has also been correlated with evidence accumulation and evaluation in a classic probabilistic reasoning task popular in psychosis research: the beads task (BT). Furl & Averbeck (2011) found higher BOLD responses in the rIPS in participants who decided to collect more evidence when the task uncertainty increased. This link between PPC and evaluation of evidence uncertainty is supported by O’Reilly et al. (2013) who observed increased BOLD responses in IPS associated with higher trial uncertainty in a saccadic planning task. Overall, this evidence suggests that the neural activity in cortical regions around the rIPS might be involved in the encoding of uncertainty associated with collected evidence in cognitive inference and in the decision to stop data-gathering at the cognitive or doxastic level, as opposed to the perceptual level tested using RDM. Given this evidence linking PPC and BT performance, we also investigated the effect of TMS over rIPS and the quantity of collected evidence in BT and any interaction with psychotic phenotypes.

### 6.2 Methods

**Participants**

Participants were recruited through the Sona Systems platform at Royal Holloway, University of London and were rewarded for participation with a £15 Amazon voucher or 3 university credits. For reasons of TMS safety, we excluded participants who confirmed at least one of the following: a history of neurological or psychiatric conditions; having suffered from epilepsy, febrile convulsions in infancy or had recurrent fainting spells; having relatives suffering from epilepsy; having undergone neurological surgery; a heart pacemaker, cochlear implant, medication pump, surgical clips fitted in their body; taking any unprescribed or prescribed medication; undergoing
anti-malarial treatments. We recruited only right-handed participants in order to control for hemispheric lateralisation.

Participants were invited to complete the first online part of the experiment through a link sent via email. The online part of the study was designed on the Gorilla platform and included: information about the study, the screening questionnaire, demographic questions (age and gender), the Peters et al. Delusion inventory (PDI) (Peters et al., 2004) and the Cardiff Anomalous Perception Scale (CAPS) (Bell et al., 2006). Participants who matched at least one of our exclusion criteria on the screening questionnaire could not continue with the online study. After the completion of the online part, participants were invited to our facilities at Royal Holloway, University of London, where they underwent the in-person part of the study. In the laboratory, participants underwent our TMS protocol and just after the TMS session, performed each of the three behavioural tasks in a randomised order on a computer in the same room. After the screening, the number of participants who took part in the experiment was 70. However, because the online data of two participants were missing due to incompletion, the final total number of participants in our analysis is 68.

**Psychotic phenotype questionnaires**

We used the 21-item PDI (Peters et al., 2004) for evaluating the delusional phenotype and the CAPS (Bell et al., 2006) for the hallucinatory phenotype. For both scales, we used the total score (sum of subscales). Using the median as the cut-off value, participants were categorised into two groups for PDI (high or low PDI; median= 60) and CAPS (High or low CAPS, median= 53).

**Behavioural tasks**

We designed the RDM, BT and a simple reaction time task (SRT) using *PsychoPy3* (v2021.2.3) (Peirce et al., 2019). The tasks were delivered in one *PsychoPy3* experiment randomising the order of the tasks. All participants performed the tasks on the same computer and screen. For every task, each trial began with a white fixation cross (0.2x0.2 degrees of visual angle).
**RDM.** On a grey background, we presented 500 white dots within a 5-pixel radius. The dots were moving at a speed of 3 pixels/frame in a circular aperture with a 600-pixel diameter. Dots had 50 frame lifetimes, after which they were redrawn within the aperture. In all trials, the majority of the dots were moving randomly (noise dots) while a subset of dots moved coherently to the left or to the right depending on the trial (signal dots). The noise dots were set to move in a random direction at each frame. The signal dots moved coherently for their entire lifetime. Participants performed four practice trials where the proportion of signal dots was 25% or 50%. Participants then completed 40 trials of two different coherence conditions in random order: 20 trials of a high coherence precision condition (HP) with 15% of signal dots; and 20 trials of a low coherence precision condition (LP) with 5% of signal dots. On each trial, the coherent motion of the dots was randomly assigned to be left or right. Participants ended the trial by indicating whether the signal dots were moving to the left or to the right. In order to control the effects of the TMS on motor execution, participants were instructed to use only their left hand to respond and to place their index and middle fingers respectively on the “A” and “S” buttons for left and right, respectively. Participants were asked to answer as quickly and accurately as possible. After each trial, participants were asked to report confidence in their response with a slider on a 0-10 continuous scale.

**Simple reaction time task (SRT).** We designed the SRT to control for any effects of TMS on motor execution and side of stimulus presentation (contralateral or not to the TMS stimulation site). On each trial, a green circle of 250 pixels radius was presented randomly on the left or right of a grey background. As for RDM, to examine motor execution of the right hemisphere (targeted by TMS), participants were instructed to use only their left hand and to press the “A” button when the circle appeared on the left and to press the “S” button when the circle appeared on the right. Participants completed 30 trials where the circle could appear with a 50% probability to the left or to the right.
BT. We designed a draws-to-decision BT with an 80/20 colour ratio and a maximum of 10 beads drawable per trial. With the support of on-screen images, participants were encouraged to imagine two urns: a blue urn with 80 blue beads and 20 green beads, and a green urn with 80 green beads and 20 blue beads. At each bead sequence, they were presented with a hidden urn and had to draw beads from it before guessing whether it was the blue or the green urn. At each draw of the sequence, they were instructed to press the “1” button to guess the blue urn, “2” for the green urn and “3” to draw another bead. After the tenth bead was drawn, participants were forced to choose one urn to continue to the next sequence or the end of the study. Before the experimental sequences, participants completed four practice sequences with an 80/20 colour ratio. After practice, participants completed 20 sequences of which 10 were blue urn sequences and 10 were green urn sequences presented in random order. At each draw, the colour of the bead shown on the screen was determined using a function that randomly picked one colour (“green” or “blue”) from a list of 100 strings of colour names where, depending on the trial, “green” and “blue” strings were present according to the 80/20 ratio. After each trial, participants were asked to report confidence in their response with a slider on a 0-10 continuous scale.

TMS protocol

For each participant, we first localised P4 using the 10-20 system which was shown to reliably correspond to the cortical area around the rIPS (Okamoto et al., 2004). Using a Magstim Rapid² machine, we established the individual active motor threshold (AMT) by stimulating the left primary motor cortex. The stimulation for AMT started at 50% of stimulation intensity, we then increased the intensity until a twitch in the participant’s right-hand fingers was induced. Participants were randomly assigned to a session of either 1-Hz-rTMS or the sham-TMS over P4. The intensity was set at 90% of the AMT intensity. During the 1-Hz-rTMS, magnetic pulses were delivered at 1 Hz frequency for 15 minutes. For the sham-TMS session, we reversed the TMS coil and delivered pulses at 1 Hz frequency so that the noise and the touch experience were preserved without the effect of the magnetic stimulation.
Statistical analysis and computational modelling

Demographic group comparisons. We used the Tableone package in Python (Pollard et al., 2018) to compare age (independent T-test), gender (Chi-square), PDI and CAPS scores (Kruskall-Wallis test) respectively between TMS conditions, PDI and CAPS groups.

HDDM. We used the HDDM 0.8.0 toolbox (http://ski.clps.brown.edu/hddm_docs/index.html) (Wiecki et al., 2013) in an Anaconda Python 3.6 environment to fit hierarchical Bayesian DDMs to RDM and SRT data. The DDM models binary decisions as stochastic sampling processes that take place in a continuous time frame. The DDM describes the increment of a decision or “accumulator” variable $X$ on a space of possible values of $X$ over the time $t$. The inputs of the DDM are then the time $t$ that is the RTs, and the value of $X$ that can be either the accuracy (wrong or correct answers) or the binary value of a stimulus property (e.g., left or right). The increment $\frac{d}{dt}X(t)$ is determined by a stochastic process where values are sampled from a Gaussian distribution $N(v, \sigma^2)$. The accumulation process starts at an origin point where $t=0$ and $X$ is equal to a given value $z$. For unbiased decisions, $z=0$; while in biased decisions $z$ can assume positive or negative values if respectively biased towards decision $A$ or $-A$. Depending on the precision of $N$ (i.e., on $\frac{1}{\sigma^2}$), $X$ would reach one of the two value options more or less quickly. The drift rate $v$ quantifies this speed or rate at which the $X$ increases towards $A$ or $-A$. The accumulation process ends for one option or the other when the value of $X$ at time $t$ is equal either to $A$ or $-A$. The distance between $A$ and $-A$ in the $X/t$ space is the decision threshold $a$, which indicates the amount of evidence (or “the space” of the evidence) needed for the accumulation process to reach a decision.

The estimation of DDM parameters in HDDM is embedded in a hierarchical Bayesian scheme where posterior estimates of parameters are obtained by using population-level prior parameter distributions (see supplementary material in Wiecki et al., 2003, for values of informative priors) and estimates of parameter distributions obtained by the Markov Chain Monte Carlo (MCMC) sampling method. We fitted RDM data to six different
HDDMs where the parameters were free to vary for conditions/groups as illustrated in Table 1. We fitted SRT data to two HDDMs: HDDM-SRT-TMS, where parameters were free to vary for the TMS session; and HDDM-SRT-Null where parameters were fixed. For RDM $X$ was coded as accuracy values. As SRT generally gives near-perfectly accurate performance and as we wanted to control evidence accumulation toward stimuli presented contralateral or not to TMS stimulation site rather than toward stimuli representing accurate or inaccurate response, $X$ was coded as left or right choice for SRT.

We ran 20,000 samples of MCMC iterations for each HDDM, discarding the first 2,000 samples as burn-in and using a thinning factor of 5 and a 10% outliers setting. Convergence of MCMC chains was assessed by visual inspection and by computing the Gelman-Rubin statistic and verifying that values ranged between 0.9 and 1.1. We used the HDDM package to estimate and compare at the condition/group level the following DDM parameters: drift rate ($v$), decision threshold ($a$) and non-decision time ($t$). Since no prior bias has been induced in the task, we assumed $z=0$.

<table>
<thead>
<tr>
<th>Model</th>
<th>Conditions/Groups</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null-model</td>
<td>None</td>
</tr>
<tr>
<td>HDDM-C</td>
<td>HC vs. LC</td>
</tr>
<tr>
<td>HDDM-TMS</td>
<td>TMS vs. Sham</td>
</tr>
<tr>
<td>HDDM-TMS-C</td>
<td>HC vs. LC</td>
</tr>
<tr>
<td>HDDM-TMS-PDI</td>
<td>TMS vs. Sham</td>
</tr>
<tr>
<td>HDDM-TMS-CAPS</td>
<td>TMS vs. Sham</td>
</tr>
<tr>
<td>HDDM-TMS-PDI-C</td>
<td>TMS vs. Sham</td>
</tr>
<tr>
<td>HDDM-TMS-CAPS-C</td>
<td>TMS vs. Sham</td>
</tr>
</tbody>
</table>

The best-fitting model was evaluated by comparing the deviance information criterion (DIC) obtained for each model. DIC is a Bayesian measure of fit which trades off the fit of the model and model complexity.
Lower values of DIC suggest a better fit (Spiegelhalter et al., 2002). We considered significant a difference (Δ) of 10 DIC points (Spiegelhalter et al., 2002).

Because HDDM computes the posterior probability distributions of parameters for each condition or group, comparing them and determining the likelihood of a parameter being higher or lower in one condition or group than another is straightforward. We considered a difference between phenotype groups or conditions as statistically significant when the probability (P) of a parameter value being higher or lower in one condition/group compared to the other was >0.95 (Wiecki et al., 2013). For significance to look familiar to a frequentist eye, we reported significant results as the (1-P) probability being <0.05.

Post hoc HDDM-regression analysis. Given that the results from the between-group comparison showed TMS to affect low- and high-psychotic phenotype groups differently, we ran HDDM-regression models to investigate the interaction between TMS and psychotic phenotype as continuous variables. We devised two HDDM models where drift rate, decision threshold and non-decision time could vary as a linear regression. Motion coherence, TMS, PDI and PDIxTMS were predictors of HDDM parameters in model LR-HDDM-PDI; motion coherence, TMS, CAPS and CAPSxTMS in LR-HDDM-CAPS. We considered as significant the effects where 95% of the β coefficient posterior distributions (credible interval) of the regression coefficient lay completely above (positive effect) or below zero (negative effect).

Linear mixed models. We used the Statsmodels 12.2 toolbox (https://www.statsmodels.org/dev/index.html) and evaluated the effect of rTMS on DTD in BT using a mixed linear model where the TMS condition was set as predictor and random slopes and intercepts were estimated for each participant.

We then employed hierarchical Bayesian regression analyses utilising the PyMC3 3.11.2 software package in an Anaconda Python 3.8 environment to examine the effect of TMS, PDI and CAPS on participants' trial-level DTD. We fit three separate generalised mixed models with a Poisson distribution as
a link function with setting predictors specified by Table 2. We assigned to the intercepts’ prior distributions a mean centred on the median value of DTD and a standard deviation of 5. For the β coefficients, we employed relatively weak priors with a centred distribution around 0 and a standard deviation of 10. To account for individual variability in intercept and coefficient, we made these estimates vary for each participant.

Model parameters were estimated using MCMC sampling, with 8000 iterations and 5000 tuning steps. The Bayesian regression yielded posterior distributions for each parameter pertaining to each participant. To evaluate significant effects, we considered 95% highest density intervals (HDI) of the β coefficient posterior distributions. We identified effects as significant when the 95% HDI indicated values either higher or lower than zero (95% HDI > 0 or 95% HDI < 0).

Table 2. Bayesian regression models draws-to-decision. Bayesian regression linear models (LMs) predicting draws-to-decision in the beads task.
x = interaction

<table>
<thead>
<tr>
<th>Model</th>
<th>Predictor</th>
</tr>
</thead>
<tbody>
<tr>
<td>LM-TMS</td>
<td>TMS vs. Sham</td>
</tr>
<tr>
<td>LM-TMSxPDI</td>
<td>TMS, PDI, TMS x PDI</td>
</tr>
<tr>
<td>LM-TMSxCAPS</td>
<td>TMS, CAPS, TMS x CAPS</td>
</tr>
</tbody>
</table>

6.3 Results

Random Dot Motion Task (RDM)

Convergence. We confirmed that all HDDM models converged, using visual inspection of MCMC trace plots and the Gelman-Rubin diagnostic whose values ranged between 0.9 and 1.1.

Model selection. In Table 3, we present the DICs of the HDDM models for RDM and their differences in DIC, compared to the Null-model (fixed parameters) and the HDDM-C (parameters varying for motion coherence). We
performed two parallel model selections: one selection comparing the fits of these two control models with the fits of models including PDI as a predictor; and the other selection comparing the fits of the control models with those of models including CAPS as a predictor.

For the delusional phenotype, the model where parameters varied for the TMS, motion coherence, and PDI groups (i.e., \textit{HDDM-TMS-PDI-C}) was the best model, outperforming the \textit{Null-model}, the \textit{HDDM-C} and the \textit{HDDM-TMS} (parameters varying for TMS session). Similarly, \textit{HDDM-TMS-CAPS-C} (parameter varying for TMS, motion coherence and CAPS groups) was the best model for the hallucinatory phenotype, outperforming the \textit{Null-model}, \textit{HDDM-C} and the \textit{HDDM-TMS}.

\textbf{Table 3. DIC HDDMs.} Deviance Information Criterion (DIC) for each HDDM in descending order; differences in DIC (Δ DIC) between each model and the Null-model (parameters do not vary for any condition/groups); Δ DIC between each model and the C-model (parameters vary only for motion coherence condition)

<table>
<thead>
<tr>
<th></th>
<th>DIC</th>
<th>Δ DIC Null-model</th>
<th>Δ DIC HDDM C</th>
</tr>
</thead>
<tbody>
<tr>
<td>HDDM-TMS-CAPS-C</td>
<td>9591.82</td>
<td>-633.46</td>
<td>-395.11</td>
</tr>
<tr>
<td>HDDM-TMS-PDI-C</td>
<td>9609.01</td>
<td>-614.27</td>
<td>-379.92</td>
</tr>
<tr>
<td>HDDM-TMS</td>
<td>9972.68</td>
<td>-250.6</td>
<td>-15.25</td>
</tr>
<tr>
<td>HDDM-C</td>
<td>9988.93</td>
<td>-234.35</td>
<td>0.0</td>
</tr>
<tr>
<td>Null-model</td>
<td>10223.28</td>
<td>0.0</td>
<td>234.35</td>
</tr>
<tr>
<td>HDDM-TMS-CAPS</td>
<td>11216.66</td>
<td>992.38</td>
<td>1227.73</td>
</tr>
<tr>
<td>HDDM-TMS-PDI</td>
<td>11221.46</td>
<td>992.18</td>
<td>1232.53</td>
</tr>
<tr>
<td>HDDM-TMS-C</td>
<td>11857.4</td>
<td>1634.12</td>
<td>1868.47</td>
</tr>
</tbody>
</table>
Fig 1. HDDM parameters for psychotic phenotype groups. Drift rate (A), decision threshold (B) and non-decision time (C) posterior probability distributions from HDDM-TMS-PDI-C (top) and HDDM-TMS-CAPS-C (bottom). Parameters are compared for different TMS conditions (Sham vs. TMS; unbroken line) and for low and high motion coherence, PDI groups and CAPS groups (dashed lines).

A. Low Coherence

Delusion-like Annotation
- Low PDI
- High PDI

Hallucination-like Annotation
- Low CAPS
- High CAPS

B. Low Coherence

Decision threshold

C. Low Coherence

Decision threshold

P<0.05

P>0.05

* P<0.05
Group comparison. In Fig 1, we show distributions of posterior probability estimates of DDM parameters compared across motion coherence conditions, TMS sessions and psychotic phenotype groups in HDDM-TMS-PDI-C and HDDM-TMS-CAPS-C.

The high-PDI group is the only group where drift rates were lower in TMS than in Sham, although the effect only lies on the threshold of significance (P=0.05) (see Fig 1-A top-right).

Decision threshold showed higher estimates in TMS compared to sham for low-PDI and low-CAPS groups in the low motion coherence condition (see Fig 1-B left). Decision threshold estimates for TMS were significantly different between low- and high-CAPS groups with low-CAPS showing higher decision thresholds (see Fig 1-B bottom). HDDM-TMS-PDI-C and HDDM-TMS-CAPS-C did not show any significant difference for non-decision time.

Post hoc regression analysis. We constructed two HDDM-regression models, namely LR-HDDM-PDI and LR-HDDM-CAPS to directly test the interaction between TMS and, respectively, PDI and CAPS. Nevertheless, we found the validity of these models to be questionable, as both the DIC of the
LR-HDDM-PDI (DIC=11136.73) and the LR-HDDM-CAPS (DIC=11661.12) were higher than the DIC of the Null-model (DIC=10223.28). This discrepancy in fit between the between-group models presented above and the regression models may be explained by the questionable performance from the predictive check and parameter recovery (see Chapter VIII).

**Simple Reaction Time Task (SRT)**

*Mixed effect model.* Our mixed effect model showed no evidence of TMS (M= 0.01; Q[0.025]= -0.05, Q[0.975]= 0.07; p=0.74), stimulus presentation (left or right) (M= -0.01; Q[0.025]= -0.05, Q[0.975]= 0.03; p=0.61) or their interaction (M= 0.02; Q[0.025]= -0.04, Q[0.975]= 0.08; p=0.47) on RTs in SRT.

**HDDM modelling.** We ran post hoc HDDMs, namely HDDM-SRT-Null and HDDM-SRT-TMS to further investigate TMS effects on DDM parameters. The DIC of HDDM-SRT-TMS (DIC= -2786.31) was not significantly higher than the DIC of the HDDM-SRT-Null (DIC= -2780.78), showing that TMS does not add explanatory value to HDDM modelling of SRT data.

**Beads Task (BT)**

From the general linear model analysis, we did not find any significant effect of TMS manipulation on DTD in the BT (M= -0.99; Q[0.025]= -2.05, Q[0.975]= 0.08; p=0.07). This non-significant result was confirmed by the hierarchical Bayesian Poisson regression (M= -0.04; Q[0.03]= -1.02, Q[0.97]= 0.25). From visual inspection of MCMC trace plots and built-in diagnostics, both the GLMM and the hierarchical Bayesian regression showed good convergence.
Between-group demographics and psychotic phenotype

Table 3. Demographics and psychotic phenotype compared between TMS sessions and psychotic phenotype groups.

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Age, mean (SD)</th>
<th>Gender, n (%) F</th>
<th>Gender, n (%) M</th>
<th>PDI, median [Q1, Q3]</th>
<th>CAPS, median [Q1, Q3]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>68</td>
<td>20.8 (5.5)</td>
<td>48 (70.6)</td>
<td>20 (29.4)</td>
<td>60.0 [23.2, 80.0]</td>
<td>53.0 [17.2, 84.2]</td>
</tr>
<tr>
<td>High-PDI</td>
<td>34</td>
<td>19.4 (2.1)</td>
<td>28 (82.4)</td>
<td>6 (17.6)</td>
<td>80.0 [71.2, 107.0]</td>
<td>83.5 [54.5, 128.5]</td>
</tr>
<tr>
<td>Low-PDI</td>
<td>34</td>
<td>22.2 (7.3)</td>
<td>20 (58.8)</td>
<td>14 (41.2)</td>
<td>22.5 [13.0, 37.8]</td>
<td>26.5 [8.2, 50.0]</td>
</tr>
<tr>
<td>p value</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>&lt;0.001*</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td>High-CAPS</td>
<td>35</td>
<td>20.0 (2.6)</td>
<td>25 (71.4)</td>
<td>10 (28.6)</td>
<td>75.0 [60.0, 99.2]</td>
<td>84.0 [64.5, 125.0]</td>
</tr>
<tr>
<td>Low-CAPS</td>
<td>33</td>
<td>23 (69.7)</td>
<td>10 (30.3)</td>
<td>14 (41.2)</td>
<td>24.0 [13.0, 53.0]</td>
<td>15.0 [8.0, 34.0]</td>
</tr>
<tr>
<td>p value</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>&lt;0.001*</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td>Sham</td>
<td>32</td>
<td>20.3 (5.5)</td>
<td>24 (75.0)</td>
<td>8 (25.0)</td>
<td>57.0 [20.8, 80.8]</td>
<td>51.0 [24.0, 79.2]</td>
</tr>
<tr>
<td>TMS</td>
<td>36</td>
<td>21.2 (5.6)</td>
<td>24 (66.7)</td>
<td>12 (33.3)</td>
<td>60.0 [25.5, 76.2]</td>
<td>53.0 [15.0, 93.2]</td>
</tr>
<tr>
<td>p value</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.508*</td>
<td>0.627†</td>
</tr>
</tbody>
</table>

Table 3 shows differences in demographics, PDI and CAPS scores between TMS conditions, PDI and CAPS median-split groups. There was no significant difference in age, gender, PDI or CAPS scores between sham and rTMS conditions. We found significantly higher PDI scores in the high-CAPS group compared to the low-CAPS group and, correspondingly, CAPS scores were higher in the high-PDI group compared to the low-PDI group. Finally, we found age was significantly higher in the low-PDI group compared to the high-PDI group.
6.4 Discussion

In this study, we applied offline inhibitory TMS over P4 (right PPC) and compared group-level estimates of DDM parameters against a control group that received a sham TMS session. We evaluated the effect of TMS across groups of participants obtained by scores median-split by subclinical delusional phenotype (high- vs. low-PDI) and hallucinatory phenotype (high- vs. low-CAPS).

The HDDM models that best fitted RDM data showed increased decision thresholds in the TMS session compared to sham in participants with low psychotic phenotypes (low-PDI and low-CAPS groups). Instead, participants with higher hallucinatory phenotypes showed stable values of this parameter across TMS sessions. Furthermore, we found that disruption of right PPC activity decreased the precision of sensory evidence (i.e., drift rate) only in participants with a high delusional phenotype. As expected, both delusional and hallucinatory phenotypes moderated the impact of TMS on evidence accumulation. Nonetheless, these findings are partially surprising. Contrary to our expectations, the hallucinatory phenotype did not moderate the effect of TMS on drift rate.

Importantly, the TMS manipulation did not affect the performance on a control decision task where no accumulation of ambiguous evidence was involved. Nor did we find any effect of TMS on DDM estimates of the non-decision time parameter which approximates the time in the RT taken by non-decisional processes (i.e., stimulus encoding and motor execution).

Disruption of right PPC in low psychotic phenotype decreases decision thresholds.

To give an account of why TMS over right PPC affected DDM parameters differently in low compared to high psychotic phenotype individuals, we need to discuss what mechanisms TMS may have disrupted in perceptual inference in one case and not in the other.

Evidence from neurophysiological studies shows that, although correlated with the tally of accumulated evidence, neuronal activity in IPS in humans and LIP in non-human primates does not seem to be causally involved
in the discrimination of coherent movement (i.e., RDM performance) (Hanks & Summerfield, 2017; Katz et al., 2016; O’Connell et al., 2018). In line with this literature, our TMS protocol did not affect the rate at which participants accumulated motion evidence (i.e., drift rate), at least not in individuals with low psychotic phenotypes. Our decision threshold results expand this understanding of PPC activity in perceptual inference by showing that the excitability of the cortical area around the right PPC (in the vicinity of IPS) is causally involved in the decision to stop evidence accumulation (i.e., decision threshold).

By reducing cortical excitability, we can speculate that our TMS protocol induced PPC neurons to need more excitatory discharge from neurons sensitive to motion in MT in order to initiate the behavioural response. This interpretation would fit the prominent perspective supported by single-neuron and EEG recordings showing that PPC neurons accumulate sensory evidence until they reach a canonical threshold of firing rate for one option before decision (Gold & Shadlen, 2007; Hanks & Summerfield, 2017; O’Connell et al., 2018; Smith & Ratcliff, 2004). TMS may have reduced the baseline excitability of PPC, requiring more excitatory signalling (i.e., motion information accumulated from the motion-sensitive visual cortex) to reach the stereotypical firing rate, thus increasing decision thresholds. In this view, neurons in PPC are placed in the stream of information processing between stimulus encoding and action planning serving as evidence accumulators.

There is growing evidence that the accumulation of evidence from sensory cortical areas in PPC might be scaled by the oscillatory electrical activity arising in its neuronal population (Hanks & Summerfield, 2017; Spitzer et al., 2016; Wyart et al., 2012). This process has been described as the “parietal bottleneck”. The oscillatory activity would act as a filter increasing or decreasing the gain of evidence coming from sensory areas depending on whether it is accumulated during the peak of the wave cycle or not. On a neuronal population level, inhibitory TMS in our experiment might have disrupted oscillations in PPC reducing the evidence gained over time, consequently increasing the estimates of decision threshold. This would not implicate a reduction in the precision of sensory evidence which would be encoded by MT. Future studies devised to test the “parietal bottle-neck”
hypothesis might shed light on the effect of inhibitory TMS over MT or PPC on oscillatory activity and on variance in DDM parameters.

**No evidence of TMS on decision threshold in high psychotic phenotype.**

Given the account we discussed above, if TMS reduced decision thresholds by down-regulating baseline activity in people with low hallucinatory phenotype, the lack of this effect in the high-CAPS group might indicate a higher baseline level of PPC excitability in that group, allowing neurons to reach their canonical firing rate threshold despite the TMS. This account may find support in the evidence showing hyperactivity of sensory cortices in hallucinating patients (Horga & Abi-Dargham, 2019; Jardri et al., 2013) and in the population experiencing anomalous perceptions (Braithwaite et al., 2013). However, no evidence suggests that this is the case for associative areas like PPC. Our findings raise the question of whether the hallucinatory phenotype is also associated with increased cortical activity in areas involved in decision-making such as the PPC.

This finding acquires aetiological interest when considered with the evidence linking PPC activity and the emergence of perceptual conscious experiences. In fact, reaching a critical threshold of firing rate in PPC neurons might underlie the perceptual experience of a stimulus. Some compelling evidence for this comes from Pereira et al. (2020) who recorded single-neuron activity in the PPC of an epileptic patient performing a tactile signal detection task. Neurons in PCC showed the typical ramping activity for tactile stimulations that were detected while firing rates were lower for those stimuli that did not trigger a conscious experience. Supporting this correlational evidence, TMS pulses over the IPS induced perceptual fading of stimuli that were presented peripherally in the visual field (Kanai et al., 2008). A higher baseline level of PPC excitability might make individuals prone to experience percepts but with a lower amount of excitatory signal coming from sensory areas. Hence, this mechanism might contribute to the emergence of conscious percepts from neural activity non-induced by external stimuli, that is hallucinations.
TMS over right PPC reduces sensory precision in the delusional phenotype.

We showed that TMS over the right PPC decreased sensory precision (proxied by drift rate) only in individuals with a higher delusional phenotype. This result can be understood in light of PCA and dysconnectivity associated with psychosis and proneness to psychosis (Diez et al., 2017; Roiser et al., 2013; Stephan et al., 2009). When performing probabilistic decision tasks where the accumulation of evidence is required, patients with schizophrenia show abnormal recruitment of regions within the task-positive network (including PPC) and the default mode networks (Andreou, Steinmann, Leicht, et al., 2018; Krug et al., 2014; Rausch et al., 2014). The disruption of PPC neuronal activity by TMS in people with a higher delusional phenotype might have exacerbated aberrant connectivity patterns in the network that could be already present in people prone to delusion. The specificities of these dysconnectivity patterns are a matter for further investigation.

**PPC role in perceptual vs. cognitive inference.**

It is not clear whether the role of PPC in terminating evidence accumulation we found in RDM is the case for decisions involving higher cognitive functions. Nevertheless, some evidence from correlational studies associated IPS activity with the commitment to choice in probabilistic decision tasks (Andreou, Steinmann, Kolbeck, et al., 2018; Furl & Averbeck, 2011).

We did not find any significant effect of TMS on the quantity of collected evidence in BT, which, like RDM, involves evidence accumulation over sequential samples. It is plausible that a larger sample is needed for offline TMS on P4 to affect data-gathering in tasks requiring higher cognitive functions. Alternatively, this discrepancy might suggest that, although involving PPC recruitment, the neural mechanisms that terminate data-gathering in probabilistic reasoning are different from those in perceptual decisions. Further investigation will be needed to test these two competing ideas.

We did not find any interaction between TMS and the psychotic phenotype. Instead, the different impact between individuals with low and high psychotic phenotypes that PPC disruption showed on RDM in our study.
supports the idea that mechanisms of perceptual rather than cognitive inference might underlie key differences in neurocomputational mechanisms along the psychotic phenotype.

One key limitation of our study involves the method we used to target IPS. Although P4 in the 10-20 system can reliably target the cortical region around IPS (Okamoto et al., 2004), using neuronavigation through individual MRI scans can offer a more precise anatomical localisation of the area targeted by the TMS stimulation. A second matter to be aware of when considering our findings is that offline TMS did not disrupt cortical activity at precise time points but had an effect along the whole task execution. Inhibitory single pulses coupled with stimulus encoding might differently affect the performances of the tasks we employed. Finally, we explored the effects only of unilateral TMS on rIPS. Future studies using bilateral inhibition of IPSs could bring different results and expand our findings, for example answering the questions of whether bilateral IPS inhibition affects drift rates irrespective of delusional phenotype, decision threshold in participants with higher hallucinatory phenotype, or DTD in BT.

Altogether, our findings show that PPC plays a pivotal role in terminating evidence accumulation in perceptual decisions and that this area might be involved in decision-making and computational patterns associated with psychosis. Neural mechanisms localised in PPC or that involve this area on a network level might be of relevance for changes in inferential processes in the psychotic phenotype. Our results showed that the disruption of the right PPC affects delusional and hallucinatory phenotypes differently, suggesting that the mechanisms involving PPC might be different in nature for the two psychotic phenotypes.

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Supplementary materials

Distributions of psychotic phenotype measures

**A. PDI (delusion-like experiences)**

**B. CAPS (hallucination-like experiences)**

*Fig 1. Frequency distribution of psychotic phenotype measures.* Distribution in participant percentage of (A) Peters et al. Delusion Inventory (PDI), (B) Cardiff Anomalous Perceptions Scale (CAPS).
To provide a comprehensive representation of the data on the psychotic phenotype within our sample, we present the medians and frequency distribution as a percentage of the sample for both PDI and CAPS in Figure 1-A-B.
VII. Decoupling Evidence Accumulation and Confidence: the Role of Posterior Parietal Cortex

In this chapter, we investigated the role of the posterior parietal cortex (PPC) in metacognition of perceptual and probabilistic decisions. Using data collected in Study 2 (Chapter VI), we tested the hypothesis that inhibitory transcranial-magnetic stimulation over P4 would affect confidence ratings in the random dot motion task and the beads task.

Abstract

AIMS. In this chapter, we set out to investigate the role of the right posterior parietal cortex (PPC) in the encoding of decision confidence for both perceptual and probabilistic decisions. Specifically, we aimed to test the hypothesis that inhibitory transcranial magnetic stimulation (TMS) applied to the right PPC would lead to reduced confidence ratings in both the Random Dot Motion task (RDM) and the Beads task (BT). Additionally, we examined whether the influence of TMS on confidence in perceptual decisions varied based on individuals' levels of psychotic phenotypes, as observed in our previous study for first-order decisions. Furthermore, we explored the potential impact of psychotic phenotypes and delusion-like experiences on decision confidence.

METHODS. We tested 68 participants divided into two groups who underwent a 15-minute session of either 1Hz repetitive TMS or sham TMS over the right PPC. Participants performed the Random Dot Motion task (RDM) and the Beads task (BT). After each RDM trial and after choosing an urn in BT, participants reported how confident they were of their answers. We applied hierarchical regression models and assessed whether TMS, psychotic phenotypes (measured using the Peters Delusion Inventory (PDI) and Cardiff Anomalous Perceptions Scale (CAPS)) or their interactions predicted these confidence ratings.
RESULTS. Contrary to our initial hypothesis, we found that the inhibitory TMS protocol applied over the right PPC did not have a significant impact on confidence ratings in either the RDM or BT tasks. Additionally, we did not observe any interactions between TMS, psychotic phenotypes, and confidence ratings in perceptual decisions.

CONCLUSION. Our findings suggest that dampening the excitability of PPC neurons does not lead to lower confidence ratings, excluding PPC involvement in encoding decision confidence (second-order decisions) in both RDM and BT. Moreover, our results discard the idea that the psychotic phenotype affects confidence ratings in the general population.

7.1 Introduction

In the previous chapters, we described neural correlates of evidence accumulation and decision commitment that have been shown in monkeys to involve a build-up of neuronal activity in the lateral intraparietal cortex (LIP) (Hanks & Summerfield, 2017; Kira et al., 2015; Roitman & Shadlen, 2002; Shadlen & Newsome, 1996; Yang & Shadlen, 2007) and in humans, a positive centroparietal event-related potential, known as the centroparietal positivity (CPP) (Kelly & O’Connell, 2013; O’Connell et al., 2012), and increased BOLD activity in the posterior-parietal cortex (PPC) (Andreou et al., 2018; Furl & Averbeck, 2011).

In Chapter VI (Study 2), we tested the impact of reduced excitability of right PPC on first-order decisions by using off-line inhibitory transcranial magnetic stimulation (TMS). We investigated participants’ performance in perceptual and probabilistic decisions. For perceptual decisions, we tested performances in the random dot motion task (RDM), which involves discerning the coherent movement direction within a field of randomly moving dots. For probabilistic decisions, we used the beads task (BT) where participants draw coloured beads from a container to make probabilistic judgments based on the number of beads they decided to draw. For RDM, we showed that TMS over the right PPC affected evidence accumulation
differently in people reporting more or fewer delusion-like (measured by the Peter’s et al. Delusion Inventory; PDI) and hallucination-like (measured by the Cardiff Anomalous Perceptions Scale; CAPS) experiences. For cognitive decision-making (i.e., BT), we did not find any significant effect.

In addition to decision-making performance, PPC activity has been associated with the confidence rating of decisions. In the decision-making literature, confidence ratings are regarded as “second-order” decisions, meaning decisions individuals make about the accuracy of their first-order decisions, and for this reason, confidence ratings are considered an example of metacognitive judgements (Grimaldi et al., 2015; Yeung & Summerfield, 2012). The neural underpinnings of second-order decisions are still largely debated. One key issue that has been posed is whether the second-order decisions are encoded by the same neural processes and in the same brain regions as those involved in first-order decisions (Grimaldi et al., 2015; Yeung & Summerfield, 2012). Here, we specifically investigated the role of PPC in second-order perceptual and probabilistic decisions.

In perceptual decision-making, evidence from electroencephalography (EEG) (Gherman & Philiastides, 2015) and functional magnetic resonance imaging (fMRI) combined with EEG (Pereira, Faivre, et al., 2020) supports the idea that neural activity in frontal and parietal regions, involved in evidence accumulation, encodes decision confidence. In an fMRI experiment involving perceptual decisions, Yeon et al. (2020) tested to what extent the topography of BOLD signals overlaps between perceptual decisions and confidence ratings. The overlap they identified involved an extensive group of regions in the prefrontal cortex, the dorsal anterior cingulate cortex, the precuneus, the insula, and PPC. Single neuron recording in monkeys’ LIP (Kiani & Shadlen, 2009) and humans’ PPC (Pereira, Megevand, et al., 2020) showed that neurons in these areas, already associated with the encoding of evidence accumulation (Hanks & Summerfield, 2017; Kira et al., 2015; Roitman & Shadlen, 2002; Shadlen & Newsome, 1996; Yang & Shadlen, 2007), showed similar build-up of neural activity for confidence ratings where firing-rates were attenuated for low-confidence trials.

These studies prompt the hypothesis that in humans, dampening the excitability of PPC neurons during decision-making would result in lower
confidence ratings. In this chapter, we tested this hypothesis by using data from *Study 2* to investigate the role of the right PPC in encoding decision confidence (second-order decisions) in both RDM and BT. Additionally, we tested whether delusion-like and hallucination-like experiences affect decision confidence and interact with TMS modulation.

We hypothesised that participants undergoing inhibitory TMS over P4 (right PPC) would show lower single-trial confidence ratings in RDM and BT. Given results from *Chapter VI* where TMS impacted first-order perceptual decisions differently for low and high psychotic phenotype groups, we would expect, if mechanisms encoding first- and second-order decisions are the same, that TMS to PPC would also interact with PDI and CAPS in modulating perceptual decision confidence. Additionally, in *Chapter IV* and *Chapter V*, we showed confidence ratings after the last draw in BT to be positively associated respectively with psychotic phenotypes and DTD. Given these findings, we expected here psychotic phenotypes and DTD to predict higher post-decision confidence ratings.

### 7.2 Methods

In *Study 2*, 68 healthy participants underwent 15 minutes of either a session of 1Hz repetitive TMS or sham TMS. After the session, they performed the RDM and BT in randomised order. At the end of each trial of RDM and after the urn decision in BT, participants rated confidence in their decision on a continuous scale from zero to 10. For further details about the study, we refer the reader to the *Methods* section in *Chapter VI*.

**Statistical analyses**

We conducted Bayesian regression analyses using the *PyMC3* 3.11.2 package within the *Anaconda Python 3.8 environment* to investigate the factors influencing participants' trial-level confidence ratings in RDM and BT. Hierarchical models allow modelling the variability at multiple levels of the data, capturing individual-level variations as well as group/condition level patterns. This makes them well-suited for dealing with hierarchical data such as behavioural data where observations at the trial level are dependent on the
participant- and group/condition levels. Additionally, hierarchical Bayesian analysis improves parameter estimation when individual group sample sizes are small. By integrating information across data levels, hierarchical models yield more stable and robust estimates, reducing the impact of noise and enhancing the overall accuracy of the model (Wiecki et al., 2013). Furthermore, by evaluating the performance of the models against models that do not take into account the predictors of interest (“null” models), we are able to draw conclusions about null effects.

We tested the effect of TMS, motion coherence (in RDM) and psychotic phenotype by devising three regression models for each task as shown in Table 1. We assessed the model fit by examining the Widely Applicable Information Criterion (WAIC) computed for each model (Watanabe, 2013). The WAIC provides a measure of a model's goodness-of-fit by quantifying its ability to predict new data points while also penalising for model complexity. Lower WAIC values indicate a better fit. By following the rule of thumb used for the deviance information criterion, a difference (Δ) of 10 WAIC units was deemed significant (Spiegelhalter et al., 2002). The pWAIC is the WAIC complexity penalisation term that contributes to the building up of the value of WAIC. We used the pWAIC to evaluate the complexity added by the models in comparison to Null-model-RDM and Null-model-BT (see Table 1).

We defined hierarchical Bayesian models with priors for group-level parameters. The group-level parameters included the intercepts and β coefficients for the effects of the predictors shown in Table 1. For the intercept, we set a prior distribution centred on the median confidence rating, with a standard deviation of 5. For β coefficients, we considered relatively weak priors specifying a distribution centred on 0, with a standard deviation of 5. Each model allowed the intercept and β coefficients for each predictor to vary for each participant. We estimated the model parameters using Markov Chain Monte Carlo (MCMC) sampling with 10,000 iterations and 10,000 tuning steps.
Table 1. Specifications of Bayesian regression models. Bayesian regression models predicting confidence rating in RDM and BT.

<table>
<thead>
<tr>
<th>RDM Models</th>
<th>Predictor</th>
<th>BT Models</th>
<th>Predictor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null-model-RDM</td>
<td>Intercept model</td>
<td>Null-model-BT</td>
<td>Intercept model</td>
</tr>
<tr>
<td>LR-RDM-C</td>
<td>Motion Coherence</td>
<td>LR-BT-DTD</td>
<td>DTD</td>
</tr>
<tr>
<td>LR-RDM-TMS</td>
<td>TMS</td>
<td>LR-BT-TMS</td>
<td>TMS</td>
</tr>
<tr>
<td>LR-RDM-C-TMS</td>
<td>TMS</td>
<td>Motion Coherence</td>
<td>TMS</td>
</tr>
<tr>
<td>LR-RDM-C-TMS-PDI</td>
<td>TMS</td>
<td>Motion Coherence</td>
<td>TMS</td>
</tr>
<tr>
<td>LR-RDM-C-TMS-CAPS</td>
<td>TMS</td>
<td>Motion Coherence</td>
<td>TMS</td>
</tr>
</tbody>
</table>

7.3 Results

We fitted linear Bayesian regression models (specified in Table 1) to confidence ratings from RDM and BT. The convergence of each model was confirmed through visual inspection and assessment using the Gelman-Rubin diagnostic, with values ranging between 0.9 and 1.1.

Model selection

In Table 2 and Table 3, we report WAIC values for Bayesian hierarchical regression models fitted respectively to RDM and BT confidence data. No models including predictors for either RDM or BT showed WAICs significantly lower (better) than the intercept models’ WAICs (Null-model-RDM and Null-model-BT). These results indicate that the models without additional predictor variables provided a better fit to the data than models with predictors, supporting the validity of the null hypothesis.
### Table 2. WAIC for RDM regression models.
Bayesian regression models predicting confidence rating in RDM, sorted by WAIC (from best to worst model fit).

WAIC = Widely Applicable Information Criterion  \(p\text{WAIC} = \) complexity penalisation

<table>
<thead>
<tr>
<th>Model</th>
<th>WAIC</th>
<th>(p\text{WAIC})</th>
<th>(\Delta \text{WAIC})</th>
</tr>
</thead>
<tbody>
<tr>
<td>LR-REDM-TMS</td>
<td>1250.44</td>
<td>68.74</td>
<td>-0.39</td>
</tr>
<tr>
<td>Null-model-REDM</td>
<td>1250.83</td>
<td>68.31</td>
<td>0.00</td>
</tr>
<tr>
<td>LR-REDM-C-TMS-CAPS</td>
<td>1405.06</td>
<td>104.84</td>
<td>154.23</td>
</tr>
<tr>
<td>LR-REDM-C</td>
<td>1405.59</td>
<td>102.02</td>
<td>154.76</td>
</tr>
<tr>
<td>LR-REDM-C-TMS</td>
<td>1405.67</td>
<td>103.35</td>
<td>154.84</td>
</tr>
<tr>
<td>LR-REDM-C-TMS-PDI</td>
<td>1408.31</td>
<td>102.73</td>
<td>157.48</td>
</tr>
</tbody>
</table>

### Table 3. WAIC for BT regression models.
Bayesian regression models predicting confidence rating in BT, sorted by WAIC (from best to worst model fit).

WAIC = Widely Applicable Information Criterion  \(p\text{WAIC} = \) complexity penalisation

<table>
<thead>
<tr>
<th>Model</th>
<th>WAIC</th>
<th>(p\text{WAIC})</th>
<th>(\Delta \text{WAIC})</th>
</tr>
</thead>
<tbody>
<tr>
<td>LR-BT-TMS</td>
<td>741.72</td>
<td>66.45</td>
<td>-0.2</td>
</tr>
<tr>
<td>Null-model-BT</td>
<td>741.92</td>
<td>66.2</td>
<td>0.0</td>
</tr>
<tr>
<td>LR-BT-DTD-TMS-PDI</td>
<td>858.2</td>
<td>125.43</td>
<td>116.28</td>
</tr>
<tr>
<td>LR-BT-DTD-TMS</td>
<td>858.33</td>
<td>123.27</td>
<td>116.41</td>
</tr>
<tr>
<td>LR-BT-DTD</td>
<td>858.92</td>
<td>125.32</td>
<td>117.0</td>
</tr>
<tr>
<td>LR-BT-C-TMS-CAPS</td>
<td>860.05</td>
<td>123.35</td>
<td>118.13</td>
</tr>
</tbody>
</table>

Similar to other Bayesian information criteria, the WAIC is a trade-off of model evidence and complexity (effective number of parameters quantified by \(p\text{WAIC}\)). Hence, the models that did not show a significantly lower WAIC compared to the relative null model might have introduced complexity that is not justified by any improvement in fit.
Regarding the models with TMS as the only predictor (LR-TMS-RDM and LR-TMS-BT), they showed WAICs and pWAICs very close to the null models' ones. These results suggest that these models performed as well as the null models in fitting the data without adding unnecessary complexity.

In both tables, we can see that, except for LR-TMS-RDM and LR-TMS-BT, all the other models showed a higher pWAIC (WAIC complexity penalisation term) compared to the null model. This evidence suggests that these models have unnecessary complexity when fitting the data. Fitting models that are unnecessarily complex can eventually lead to data overfitting. Overfitted models risk eventually capturing random variance in the data as meaningful variance, and show false positives.

For these reasons, our main interpretation of the results from these models is that none of the variables considered was a good predictor of decision confidence in either RDM or BT.

### 7.4 Discussion

In Study 2, we asked participants to rate confidence in their decisions after each trial of RDM and BT. We used these data to explore how the right PPC contributes to decision confidence encoding. We tested the hypothesis that inhibitory TMS over this region leads to lower confidence ratings in both RDM and BT. Additionally, we hypothesised that TMS effects on confidence in perceptual decisions might vary depending on the levels of psychotic phenotypes, as observed for first-order decisions in Chapter VI. Furthermore, based on findings presented in Chapter IV and Chapter V, we hypothesised that higher levels of psychotic phenotypes and DTD would predict increased confidence ratings.

From our model selection, none of the variables we considered proved to be a valid predictor of decision confidence. Our results showed that the inhibitory TMS protocol we applied over P4 did not affect confidence ratings in RDM or BT. Moreover, in Chapter VI, we found dissociable effects of TMS depending on psychotic phenotypes. If the mechanisms underlying evidence accumulation in PPC were also responsible for the encoding of decision
confidence, we would have expected here that the same disruption of the right PPC would impact confidence in a similar way. However, we did not find TMS affecting decision confidence in RDM. These results support the idea that, within the frontoparietal network associated with confidence encoding in previous studies (Gherman & Philiastides, 2015; Pereira, Faivre, et al., 2020; Yeon et al., 2020), the area around the right IPS does not play a causal role in the encoding of decision confidence.

Despite these discrepancies, our results better align with those of Martin et al. (2022), who found no effect of bilateral PPC disruption on second-order perceptual decisions. Martin et al. (2022) employed bilateral continuous theta-burst TMS to disrupt the dorsolateral prefrontal cortex (DLPFC) and PPC in perceptual decision-making. In Martin et al.’s protocol, participants were required to identify the position of objects in the visual periphery and to rate how clearly they saw the objects. Disruption of DLPFC reduced participant’s metacognitive efficiency but did not affect performance; while bilateral disruption of PPC showed no effect on metacognitive efficiency or performance. Hence, both our study and the study of Martin et al. showed no effect of PPC disruption on second-order decisions but, unlike them, we found an effect of PPC inhibition on perceptual decision-making performance (first-order decisions). Advocating for the view of PPC as involved in evidence accumulation (see Discussion in Chapter 6), we could argue that the absence of an effect of PPC on first-order decisions in Martin et al. (2022) is due to the fact that, compared to our paradigm, the task used by these authors does not require sequential sampling of evidence.

Overall, our findings and those of Martin et al. support the idea that reduced excitability of PPC does not impact second-order decisions. These findings also suggest that although prefrontal and parietal areas correlated with first- and second-order decisions (Yeon et al., 2020), PPC and DLPFC might have different causal roles. It is possible that PPC is involved in evidence accumulation but not in confidence rating, where DLPFC might play a pivotal role (Martin et al., 2022).

The correlation of PPC activity with second-order decisions found in previous studies contradicts the hypothesis we just outlined (Gherman & Philiastides, 2015; Kiani & Shadlen, 2009; Pereira, Faivre, et al., 2020;
Pereira, Megevand, et al., 2020). The association of PPC activity and metacognition in these studies could hide a mediating factor that contributes to the observed activity in PPC associated with second-order decisions. For example, in the paradigms used to test metacognition in non-human primates in Kiani and Shadlen (2009), the monkeys could give an answer (through eye gaze) about the direction of coherent motion and receive a reward if correct, or choose to receive a poorer but guaranteed reward. The idea is that monkeys would choose a guaranteed reward when less confident about their first-order decisions. This assumption was validated by associating trial motion coherence and choosing the guaranteed reward option. Primates were hence presented with a forced choice (answering or going for a guaranteed reward) that might have triggered some type of accumulation of information about the expected reward. Compared to confidence rating in our tasks, this process would have required the activation of LIP neurons without reflecting the processing of metacognitive information.

Nevertheless, given the paradigm in Kiani and Shadlen (2009), it is also possible that firing-rates of LIP neurons reflected the accumulation of metacognitive information. If the computational contribution of PPC in second-order decisions was to accumulate metacognitive evidence, we could expect that perturbations of PPC activity would affect decision thresholds of second-order decisions. In fact, based on the findings we presented in Chapter VI where inhibition of PPC affected first-order decision thresholds, we could speculate that the effects of disruption of PPC might be detectable in terms of the threshold of the second-order decision and not in changes in confidence ratings. Analysing second-order decision response times in paradigms made suitable for drift-diffusion modelling could further test any possible effect of PPC disruption on decision threshold in metacognitive decisions.

One important factor to consider when interpreting our results is that we applied TMS unilaterally on the right PPC. We cannot exclude that our inhibitory protocol applied bilaterally might impact confidence ratings. In fact, Simons et al. (2010) showed that patients with bilateral lesions of PPC presented impaired metacognition. It would be interesting for future studies to investigate whether bilateral repetitive 1-Hz TMS over PPC shows a behavioural outcome mimicking the results in Simons et al. (2010).
Psychotic phenotypes did not correlate with confidence rating. For BT confidence rating, we do not replicate in this study results shown in Chapter IV where psychotic phenotypes predicted higher confidence ratings after the final draw in BT. Equally, we did not replicate the positive association between DTD and confidence that we found in Chapter V. These replication failures might be due to the smaller sample size of Study 2 (N=68) compared to Study 1 (N=191).

In conclusion, the evidence presented in this chapter showed that reduced excitability in the right IPS does not influence confidence ratings in RDM. Our results align with the hypothesis that PPC may be primarily associated with evidence accumulation, while confidence rating appears to be more reliant on frontal regions, as suggested by Martin et al. (2022). Future research could test this hypothesis and incorporate inhibitory TMS targeting PPC and DLPFC with DDM modelling to further investigate the involvement of these areas in evidence accumulation and metacognitive judgements.

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This chapter provides a comprehensive overview of the performance of the hierarchical drift-diffusion models (HDDMs) fitted to the data from the Random Dot Motion task (RDM) in the main empirical sections of this thesis: Chapter IV (Study 1) and Chapter VI (Study 2). Following good practice guidance in computational modelling of behaviour (Vandekerckhove & Tuerlinckx, 2007; Wiecki et al., 2013; Wilson & Collins, 2019), we assessed the validity of our models through two main steps: simulation of data and recovery of parameters. Although HDDMs have recently become very popular, most studies do not report comprehensive model validations (Davies et al., 2018; O’Callaghan et al., 2017). By evaluating the performance of our models, we also evaluated the relative merits of different modelling techniques, including median split versus regression techniques with a view to developing modelling guidance for future studies.

Here, we present a qualitative comparison between observed and simulated data, followed by the recovery of the estimated parameters. In Section 1, we present the methodology we used, in Sections 2 and 3 the results of data simulation and parameter recovery respectively for Study 1 and Study 2; and finally, in the Discussion Section, we comment and draw conclusions from Sections 2 and 3.

The outcomes of our data simulations and parameter recovery guided the inclusion of results in Chapter IV (Study 1) and Chapter VI (Study 2) such that the results from the most robust and well-supported analyses were reported. These include the increased drift rates observed in both high-PDI and high-CAPS groups, in Study 1; and in Study 2, the positive influence of TMS on decision thresholds within the low-PDI and low-CAPS groups, along with the adverse impact of TMS on drift rates specifically within the high-PDI group. Finally, our examination of the HDDMs elicited insights about approaches to modelling information processing within the psychotic phenotype, suggesting that median-split grouping might result in more successful model performances compared to linear regression.
8.1 Methodology

Data simulation

We simulated the data using the hddm.generate.gen_rand_data(...) function of the HDM 0.8.0 package (Wiecki et al., 2013). This function simulates reaction times (RTs) and responses given the mean and standard deviation of DDM parameters. The function allows specification of the values of parameters for different discrete levels (e.g., conditions or groups), and reproduces the size and structure of the data in terms of the number of trials and participants per level. For between-group HDDMs (see Chapter IV and Chapter VI methods and results sections), we inputted the mean and standard deviation of the fitted parameters for each condition/group level and obtained RTs and responses for each group/condition.

For regression HDDMs, more steps than for the between-group HDDMs were needed to simulate data sets that reproduce the structure of the observed ones. In fact, in the regression HDDMs, we had a two-level dummy coded variable (motion coherence or TMS session) and a continuous variable (PDI, CAPS or ASI) predicting each parameter of interest (drift rate or decision threshold). One obstacle in the data simulation was to inform the simulation function of the effect of the continuous variable on the parameters. In fact, hddm.generate.gen_rand_data(...) simulates data given discrete parameter values. We approached this problem by computing a mean predicted value of parameters for each level of the dummy coded variable including the regression coefficients of the continuous variable in each level as shown below in Equation 1 and Equation 2.

\[ \begin{align*}
(1) \quad c &= (0, 1), Y = a + b_1(c) + b_2(X)
\end{align*} \]

In Equation 1, \( Y \) denotes the array of predicted values (e.g., drift rate, decision threshold or non-decision time) for the level of the dummy coded variable \( c \) \((c=0 \lor c=1)\), \( X \) the continuous variable predictor (e.g., PDI, CAPS or ASI) and \( a \) the intercept. We computed \( Y \) for both \( c=0 \) and \( c=1 \) and obtained two arrays, one for each level of the dummy coded variable, of the predicted parameters \( Y_0 \) and \( Y_1 \). We then averaged the values for each array.
and obtained the average $Y_0$ for level 0 and average $Y_1$ for level 1, which are the mean predicted parameters to be inputted to `hddm.generate.gen_rand_data(...)`. To simulate the models, we needed to include in the simulated dataset a value of the continuous variable (PDI, CAPS and ASI) per simulated participant. Since the data were simulated employing a stochastic approximation of the effect of the continuous variable on the parameters (i.e., the mean predicted value), we took a similarly stochastic approach and pooled randomly from our empirical data values of PDI, CAPS and ASI and assigned them to the simulated participants.

To capture the average performance of the model, we simulated 100 datasets for each model and averaged the 10th, 30th, 50th, 70th and 90th quantiles of the simulated RT distributions for correct and error responses. We then plotted in a linearity plot (or QQ plot, shown in Figure 2 and Figure 6) the observed RT quantiles on the x-axis and the simulated quantiles on the y-axis to obtain a line that we contrasted with an “optimal simulation line” drawn by plotting observed quantiles on both axes. To quantify the distance between the simulated and the observed quantiles, we took as metrics the root-mean-squared error (RMSE) and the Standardised Mean Difference (SMD; also known as Cohen’s D). RMSE is a measure of the average difference between predicted and observed values and it is expressed in the units of the variable value. The SMD is the ratio of the difference between the means and the sum of the standard deviations of the two distributions. Unlike the RMSE, the SMD is a standardised metric suitable for comparing the prediction performance across different magnitudes of RTs (e.g. between correct and error responses, the latter usually slower).

**Parameter recovery**

We performed the parameter recovery for between-group and regression HDDMs that included PDI, CAPS and ASI from *Chapter IV* and *Chapter VI*. We refer here to these models as empirical models, because their parameters were estimated from fits to empirical rather than simulated data. For each empirical model, we simulated one dataset (following the procedures described in the preceding paragraph) and fitted an equivalent simulation
model. We evaluated the distance between the distributions of the simulated and empirical parameters using RMSE and SMD. For between-group HDDMs, we computed RMSE and SMD between the estimated and simulated distributions of DDM parameters per group (e.g. low-PDI) or condition (e.g. high motion coherence). For regression HDDMs, we computed the RMSE and SMD between the empirical and simulated \( \beta \) coefficients. Lower RMSE and SMD between estimated and simulated parameters indicate a better recovery and a more precise estimation of the true parameters for groups, conditions or predicted variables. Additionally, we considered whether the simulation models could reproduce the effects that were shown in the empirical models. If the simulated parameters adequately recover the effects observed, it suggests that the model is accurately capturing the processes underlying the observed behaviour.

Overall, the recovery of parameters is an essential step in validating computational models of behaviour as it helps to establish the reliability, validity, and generalizability of the model's results, and increases confidence in the model's ability to accurately describe and explain data from different samples of the same population (Vandekerckhove & Tuerlinckx, 2007; Wiecki et al., 2013; Wilson & Collins, 2019).

### 8.2 Study 1 - Data simulation and parameter recovery Study

Here, we report the data simulation and parameter recovery for between-group and regression HDDMs from Study 1 (see Chapter IV). In the between-group HDDMs, drift rate and decision threshold were allowed to vary for motion coherence (high vs. low) and median-split groups for PDI (HDDM-PDI-C), CAPS (HDDM-CAPS-C), and ASI (HDDM-ASI-C).
In the regression models, drift rate and decision threshold were free to vary as the response variable of a linear regression model with motion coherence and PDI (HDDM-LR-PDI-C), CAPS (HDDM-LR-CAPS-C) or ASI (HDDM-LR-ASI-C) scores as predictors. In Figure 1, we show the distribution of RTs inputted to these models.

**Between-group HDDMS**

In Figure 2, we show the quantiles of simulated RT distribution over the observed RT quantiles for between-group models. The first three quantiles of predicted RTs for correct responses align almost completely with the observed quantiles, while for the fourth and the last quantiles, RTs have been underestimated with a mean RMSE of 0.123 s. Predicted RT quintiles for error responses showed a general underestimation with a mean RMSE of 0.654 s for error responses.
Fig. 2 RT predictions of between-group HDDMs Study 1. Linearity plots of observed reaction time (RT) quantiles (x-axis) and simulated RT quantiles (y-axis) for correct and error responses of between-group models in Study 1. SMD = Standardised mean difference; RMSE = Root mean squared error.
From Figure-3, -4 and -5, it can be noticed that simulated parameters tend to be higher than the estimated parameters. This overestimation did not prevent the recovery of the significant differences in drift rate between median-split groups shown by the empirical models in Study 1 (see: Figure 3 top-right; Figure 4 top-left and bottom-right; Figure 5 top-left). The effect of PDI-grouping on the drift rate in low precision of motion coherence was the only one not recovered in the simulation model, although the simulated pattern shows a trend in the same direction as the empirical result; see Figure-5 top-right). Another divergence between empirical and simulation models is evident in decision threshold estimates for the high-PDI group in high precision (SMD=−5.57, RMSE=0.226); see Figure-5 bottom-right), where the simulation model shows a significant difference between low- and high-PDI groups that is not present in the estimates of the empirical model.

![Figure 3 Parameter recovery HDDM-PDI-C.](image)

Recovery of drift rates and decision thresholds for HDDM-PDI-C (motion coherence - PDI groups). SMD = Standardised mean difference; RMSE = Root mean squared error.
Fig. 4 Parameter recovery HDDM-CAPS-C. Recovery of drift rates and decision thresholds for HDDM-CAPS-C (motion coherence - CAPS groups).
SMD = Standardised mean difference; RMSE = Root mean squared error.

Fig. 5 Parameter recovery HDDM-ASI-C. Recovery of drift rates and decision threshold for HDDM-ASI-C (motion coherence - ASI groups). SMD = Standardised mean difference; RMSE = Root mean squared error.
Regression HDDMs

For regression HDDMs, the mean RMSE is 0.192 s for correct responses and 0.625 s for error responses (see Figure 6).

When predicting drift rate, regression models show a general underestimation of $\beta$ coefficients for PDI, CAPS and ASI (Figure-7 top). This underestimation affected the recovery of the effect of PDI and CAPS and produced in the simulation model a significant negative effect of ASI where there was no detectable effect in the empirical model. The recovery of the $\beta$ coefficient was more precise when predicting decision thresholds, at least for CAPS and ASI (Figure 6-bottom).

The simulated estimate for CAPS produced a pattern not reaching significance but compatible with the negative effect of CAPS on decision threshold present in the empirical model (Figure 8 bottom-centre). For the effect of motion coherence, we see a general overestimation of $\beta$s but both the effects on drift rate and decision threshold were well recovered in all models. Overall, the effects of psychotic phenotypes (PDI, CAPS, ASI) on DDM parameters were better recovered in the between-group models than in the regressions.
Fig. 6 RT predictions of regression HDDMs Study 1. Linearity plots of observed reaction time (RT) quantiles (x-axis) and simulated RT quantiles (y-axis) for correct and error responses of regression models in Study 1. SMD = Standardised mean difference; RMSE = Root mean squared error.
Fig. 7. Parameter recovery for psychotic phenotype HDM-LR-PDI-C, HDM-LR-CAPS-C, HDM-LR-ASI-C.
Recovery of $\beta$ for Schizotypy in HDM-LR-PDI-C (motion coherence - PDI groups), HDM-LR-CAPS-C (motion coherence - CAPS groups), HDM-LR-ASI-C (motion coherence - ASI groups). SMD = Standardised Mean Difference; RMSE = Root mean squared error.

Fig. 8. Parameter recovery for motion coherence HDM-LR-PDI-C, HDM-LR-CAPS-C, HDM-LR-ASI-C.
Recovery of $\beta$ for Motion Coherence in HDM-LR-PDI-C (motion coherence - PDI groups), HDM-LR-CAPS-C (motion coherence - CAPS groups), HDM-LR-ASI-C (motion coherence - ASI groups). SMD = Standardised Mean Difference; RMSE = Root mean squared error.
8.3 Study 2 - Data simulation and parameter recovery

Here, we report the data simulation and parameter recovery for between-group and regression models reported in Study 2. In HDDM-TMS-PDI and HDDM-TMS-CAPS, drift rate, decision threshold and non-decision time were allowed to vary for TMS sessions (sham vs. TMS) and also for PDI and CAPS groups. HDDM-LR-TMS-PDI and HDDM-LR-TMS-CAPS are regression HDDMs where drift rate, decision threshold and non-decision time were varied as response variables of dummy coded TMS sessions and respectively of PDI and CAPS (treated as continuous covariates, instead of as median-split groups). In Figure 9, we show the distribution of RTs inputted to these models.

![Figure 9](image)

*Fig. 9 RT distribution Study1.* Distribution of reaction times (in seconds) for correct and error responses as inputted to HDDMs in Study 2; fast outliers cut-off: 0.2 s; no slow outliers cut-off.
**Between-group HDDMS**

The between-group models show a mean RMSE of 0.283 s for correct responses. The predictions of the same models were less accurate for error responses with a mean RMSE of 2.621 s (see Figure 10, blue versus red lines).

The between-group models in Study 2 (see Figure 11 and Figure 12) showed a similar bias to that of the between-group models in Study 1 (see Figure 3, Figure 4 and Figure 5): recovered drift rates were slightly overestimated compared to the empirical models’ estimations. The SMDs between estimated and simulated drift rate values are in fact all negative and the SMD absolute values for drift rate were higher compared to the other parameters. Nevertheless, this overestimation generally did not affect the recovery of the differences between the sham and TMS groups: the difference in drift rate present on the threshold of significance in the empirical model was recovered in the high-PDI group (significant in the simulation model; see Figure 12, top-right). The simulation models reproduced the effect of TMS on decision thresholds in low-PDI and low-CAPS groups in the low motion coherence (see respectively Figure 11 and Figure 12 Low Coherence centre-left). Non-decision times were generally well recovered.
Fig. 10 RT predictions of between-group HDDMs Study 2. Linearity plots of observed reaction time (RT) quantiles (x-axis) and simulated RT quantiles (y-axis) for correct and error responses of between-group models in Study 2. SMD= Standardised mean difference; RMSE= Root mean squared error
Fig. 11 Parameter recovery HDDM-TMS-PDI-C. Recovery of drift rates, decision thresholds and non-decision times for HDDM-TMS-PDI-C (TMS session - PDI groups - Motion Coherence) divided by Low Coherence (A) and High Coherence (B) estimates. SMD = Standardised mean difference; RMSE = Root mean squared error.

A.
**Fig. 12 Parameter recovery HDDM-TMS-CAPS.** Recovery of drift rates, decision thresholds and non-decision times for HDDM-TMS-CAPS-C (TMS session - CAPS groups - Motion Coherence) divided by Low Coherence (A) and High Coherence (B) estimates. SMD = Standardised mean difference; RMSE = Root mean squared error.

A.
Regression HDDMs

HDDM regression models showed highly imprecise predictions of quantiles for both correct and error responses (all RMSEs over 2 s; see Figure 14). In Figure 14, we focus on the recovery of $\beta$ coefficients for the interaction terms between the psychotic phenotypes and TMS session which tested one of our main hypotheses for regression HDDMs in Study 2. The positive effect of the TMS-CAPS interaction was well-recovered, while the same effect for PDI was not reproduced by the simulation model. For non-decision times, the negative interactions of TMS with respectively PDI and CAPS were not reproduced by any simulation model. The empirical $\beta$ coefficients were well-recovered for the decision threshold by both simulation models.

Fig. 13 RT predictions of regression HDDMs Study 2. Linearity plots of observed reaction time (RT) quantiles (x-axis) and simulated RT quantiles (y-axis) for correct and error responses of regression models in Study 2. SMD = Standardised mean difference; RMSE = Root mean squared error.
Fig. 14 Parameter recovery for TMS interaction with psychotic phenotypes HDDM-LR -TMS-PDI and HDDM-LR-TMS-CAPS. Recovery of $\beta$ for TMS x Schizotypy in HDDM-LR -TMS-PDI (TMS session - PDI - interaction TMSxPDI), HDDM-LR-TMS-CAPS (TMS session - CAPS - interaction TMSxCAPS). SMD= Standardised mean difference; RMSE= Rooted mean squared error.
8.4 Discussion

We performed data simulation and parameter recovery of the HDDMs employed in Study 1 (Chapter IV) and Study 2 (Chapter VI) and evaluated to what extent our models were able to capture the hidden causes that produced our data. We specifically looked at whether our models were able to simulate the empirical data and recover within the simulated sample the effects identified in the empirical models. We recognised five common patterns across Study 1 and Study 2 that we will comment on before going into the specifics of the models for each study.

(1) From the comparison between simulated and empirical RT quantiles, we notice a systematic difference in models’ predictions for correct and error responses. In fact, in simple perceptual decision-making tasks (as the RDM), correct responses outnumber to a great extent error responses, as exemplified by the RT distributions from Study 1 and Study 2 in Figure-1 and Figure-9. With more data available, the models were hence better at predicting RT for correct responses than for error responses. In future experiments, the collection of larger samples might improve predictions of error responses.

(2) Generally, the models (except regression models in Study 2) underestimated RTs. This prediction error is mainly driven by an underestimation of slow RTs and increases for slower RTs (see Figure 10).

(3) Between-group models in both studies overestimated drift rates. This overestimation seems to be a systematic bias of the models that affected median-split and TMS groups uniformly and did not prevent the good recovery of the effects of grouping on the parameter. This overestimation might have produced in the simulated data the aforementioned underestimation of RTs, as RTs are inversely related to the drift rate.

(4) In a few cases, the simulation models produced what we can call “synthetic false positives”, meaning significant effects that were not present in the empirical models. Some of them (see Figure 5 bottom-right, Figure 11 top-left, Figure 12 top-left, centre-right and bottom-right) seem to have been produced by an “amplification” of differences in the empirical estimates of parameters. These synthetic false positives could potentially indicate a lack of
reliability in the null effects found in the empirical models, but it is uncertain if they can represent the possibility of actual false negatives in the empirical results.

(5) In both Study 1 and Study 2, between-group HDDMs seem to fit the data better than regression HDDMs. This might be due to the procedure we used to simulate data from regression HDDMs or might underlie specific specifics of DDM variability within the psychotic-like experiences in the general population (for more details, see the following subsections on Study 1 and Study 2).

**Study 1.** For Study 1, the simulation between-group models successfully recovered the effects of PDI, CAPS and ASI on drift rate. Although drift rates have been generally overestimated by the models, the simulations reproduced the differences between the median-split groups. Simulated estimates of decision threshold were also generally higher than the empirical estimates. This overestimation did not prevent the recovery of the negative effect of CAPS.

Regression HDDMs were as good as between-group HDDMs at predicting empirical RTs (see Figure 2 and Figure 6) and recovered quite precisely all the effects of motion coherence on DDM parameters. Nevertheless, regression HDDMs showed a less accurate recovery of the effects of psychotic phenotypes. In fact, only the negative effect of CAPS on the decision threshold has been fully recovered. The failed recovery of the psychotic phenotype effect on drift rates in regression HDDM presents us with a scenario where we see two types of models, the between-(median-split)-group and regression HDDMs, where the same positive effects of PDI and CAPS on drift rate were in one case well recovered (between-group HDDMs) but not in the other (regression HDDMs). This suggests that a positive association between drift rate and psychotic phenotype is present in the data but is better captured by models that make the parameter vary between median-split groups rather than linearly. This model comparison may open an interesting question about information processing alterations within the psychosis continuum. It is, in fact, possible that the precision of sensory evidence (proxied here by drift rate) in perceptual inference does not
increase linearly with psychotic phenotypes in the general population, but only after a threshold (in our studies the median of PDI and CAPS).

**Study 2.** The parameter recovery in *Study 2* showed an overall good fit of between-group models. In fact, simulation models reproduced the effects we found in empirical models, namely the TMS effect on decision threshold in low-PDI and low-CAPS groups (see *Figure 11, 12*, low coherence, centre-left) and the TMS effect on drift rate in high-PDI group (see *Figure 11*, high coherence, top-right). The drift rate for between-group models in *Study 2* showed the same overestimation pattern found in *Study 1* and likewise, this bias did not impact the recovery of significant effects.

The data simulation and parameter recovery of regression HDDMs in *Study 2* raise concerns about the validity of the models. In fact, the models' predictions showed a large error driven by an overestimation of RT throughout the entire distribution (see *Figure 13*). This clear failure in predicting empirical data led us to discard regression HDDMs. The poor fit of regression HDDMs in *Study 2* may further support the idea that variability in perceptual information processing within the psychotic phenotype is better captured by median-split grouping than linear regression models.

Overall, the data simulation and parameter recovery validate the most critical findings identified by our empirical models: increased drift rates in high-PDI and high-CAPS groups found in *Study 1*; and for *Study 2*, the positive effect of TMS on decision threshold in the low-PDI and low-CAPS groups and the negative effect of TMS on drift rate in the high-PDI group. Furthermore, the examination of the models we employed provided valuable insights into modelling information processing within the context of perceptual inference within the psychotic phenotype, hinting that employing a median-split grouping approach could represent a more successful modelling approach.
References


IX. General Discussion

In this final chapter, we will discuss our findings in a broader frame. For more detailed discussions within the context of each study, we redirect the reader to the Discussion sections of the empirical chapters. Here, we will draw more general conclusions, propose future directions and elicit some final reflections. Firstly, we offer the reader a summary of the core findings from our studies. Later, we discuss whether our findings reflect adaptive mechanisms that could promote the emergence of psychotic-like experiences; and finally, we explore the idea that psychotic-like phenomenology could represent an adaptive phenomenon in its own right.

9.1 Summary of Findings

The exploration of data-gathering in the context of psychosis has predominantly centred on the Beads-Task (BT) paradigm. While this paradigm seems to reveal characterisations of data-gathering and information processing among individuals on the schizophrenia spectrum, its use in the study of the psychotic phenotype within the general population has shown mixed results (see Chapter II). Our empirical works confirmed that the BT paradigm does not capture variability in data-gathering and decision-making associated with the psychotic phenotype. Instead, our findings suggest that focusing on perceptual inference, specifically on the Random Dot Motion Task (RDM), could offer more fertile ground for studying data-gathering mechanisms related to both delusion- and hallucination-like experiences.

In general terms, the BT compared to the RDM presents some aspects that raise questions about its reliability as a measure of data-gathering. Previous literature has highlighted a primary concern regarding the number of trials typically used in the BT (Dudley et al., 2016; McLean et al., 2018; Ross et al., 2015). Notably, studies involving the BT often include one single trial (Dudley et al., 2016; McLean et al., 2018; Ross et al., 2015). This is because the jumping to conclusions bias appears to decay after a few trials and between-group differences might be detectable only in one-trial BTs (McLean et al., 2018). For the same reason, BT designs often do not make use of
practice trials (Dudley et al., 2016; McLean et al., 2018; Ross et al., 2015) and, when multiple trials are included, it is common to use the same sequence of beads repeatedly (Dudley et al., 2016; McLean et al., 2018; Ross et al., 2015). All these aspects of the BT paradigm can impact the quality of the data: 1) a limited number of trials per subject makes measurements more susceptible to random variance in performance; 2) the absence of practice trials increases the chance of participants misunderstanding the task; 3) the repeated use of the same bead sequence may lead participants to quickly learn how to respond to the task. In Study 2, we addressed these concerns in the design of the BT: we increased the number of trials to 20 per subject, implemented a fully random generator for the bead sequence in each trial, and included practice trials. With this more robust version of the BT, we did not find any data-gathering bias associated with the psychotic phenotype.

On the other hand, the RDM does not present the problematic aspects that characterise BT. In fact, the RDM performance can be evaluated over several trials per subject, offering a higher test-retest reliability (Clark et al., 2022). In RDM, evidence is presented as a continuous feature (the movement of the dots), rather than in discrete pieces (e.g., coloured beads in a sequence), meaning that the problem of establishing a random sequence of samples does not apply to RDM. For these reasons and in light of the results presented in this work, RDM might represent a more suitable paradigm than BT for testing data-gathering in relation to psychosis.

Study 1 (Chapter IV and Chapter V) showed a correspondence in data-gathering approaches between perceptual and cognitive inferences where cautious participants in cognitive inference (beads task) tended to accumulate higher quantities of evidence in the perceptual domain (random dot motion task). Even though participants' evidence accumulation strategies on the two tasks may appear to be influenced by some common factor, they are nevertheless dissociable too. Other findings from Study 1 have shown that psychotic phenotype did not impact the quantity of collected evidence in BT, while in RDM, delusional and hallucinatory phenotypes predicted higher mean reaction times (RTs) in the easiest RDM condition. By fitting drift-diffusion models (DDMs) to RDM data, we were able to break down the information processing component that contributed to producing this effect. We found
higher drift rates associated with both delusional and hallucinatory phenotypes. The drift rate parameter quantifies the gain of sensory evidence through time and represents the RT-accuracy trade-off, showing that participants with higher psychotic phenotypes actually performed better. The hallucinatory phenotype was shown to be also associated with lower decision thresholds. As discussed in Chapter II, DDM and Bayesian predictive coding can be considered compatible modelling approaches (Bitzer et al., 2014; Fard et al., 2017; FitzGerald et al., 2015; Hesselmann et al., 2010). The drift rate can serve as a proxy for the precision of sensory evidence and the decision threshold can be thought of as a boundary on posterior beliefs that when reached action is triggered. Thus, Study 1 showed that although decision strategies can be similar across perceptual and cognitive inferences (see Results section in Chapter V), psychotic phenotype shows information processing patterns specific to perceptual inference.

In Study 2 (Chapter VI and Chapter VII), the use of Transcranial Magnetic Stimulation (TMS) allowed us to further establish a connection between specific variations in DDM parameters associated with the psychotic phenotype and the modulation of excitability in the Posterior Parietal Cortex (PPC). TMS over PPC increased the quantity of accumulated evidence (decision threshold) in individuals with low psychotic phenotypes. Instead, groups with higher hallucinatory or delusional phenotypes did not show any impact of TMS on decision thresholds. Specifically for the hallucinatory phenotype, estimates for decision threshold in TMS were lower for people reporting more hallucination-like experiences compared to people reporting less. This suggests that the hallucinatory phenotype may be associated with higher resistance to the TMS inhibitory effect over PPC. One hypothesis that might explain this resistance is heightened baseline PPC excitability in the hallucinatory phenotype (see Discussion section in Chapter VI). This hypothesis could also explain the negative association between hallucination-like experiences and the decision threshold we found in Study 1. In fact, in line with the idea of PPC neurons as evidence accumulators, heightened baseline cortical excitability in PPC might underlie the decreased decision threshold we found in participants reporting more hallucination-like experiences. In the delusional phenotype, PPC excitability modulated the
encoding of sensory precision (as proxied by drift rate), possibly implicating PPC neural mechanisms in the variability of this neurocomputational pattern we found along the delusional phenotype.

We found mixed evidence on the impact of psychotic phenotype on confidence. In Study 1, we found that psychotic phenotype was positively associated with decision confidence in BT. In the smaller sample that was used in Study 2, psychotic phenotype did not show this effect nor an effect on RDM decision confidence. We also showed that our modulation of PPC did not impact confidence decisions in BT or RDM, suggesting that our TMS modulation affected evidence accumulation mechanisms in RDM while not inducing metacognitive changes.

Overall, our studies showed that delusional and hallucinatory phenotypes are both characterised by increased precision of sensory evidence in perceptual inference. Participants with a higher hallucinatory phenotype required lower quantities of evidence for making perceptual decisions. The reduction of PPC excitability affected perceptual inference differently depending on individuals’ psychotic phenotype, suggesting that evidence accumulation mechanisms in PPC are implicated in psychotic-like experiences. We did not find psychotic phenotype or inhibition of PPC to impact cognitive inference. Neither did these variables affect decision confidence in both perceptual and cognitive domains.

9.2 Beyond aberrant mechanisms: Experiences of Reality in the General Population

The hypotheses tested in this project were largely based on the predictive coding account of psychosis (PCA) (Adams et al., 2013; Sterzer et al., 2018). Anomalous precision encoding is at the core of the PCA. Predictive coding predicts that imbalances in precision encoding of prior or sensory evidence/prediction error (PE) bias posterior inferences toward the source of information (prior or PE) coded as more precise. The resulting biased inferences would prompt representations of reality that deviate from veridical inference. The PCA couples these computational mechanisms with neurobiological mechanisms associated with psychotic symptoms. The
precision of neural signals can be thought to be implemented by synaptic gain, meaning that synaptic alterations can be seen as alterations of precision encoding. This approach allows PCA to link biological, cognitive and phenomenological evidence, potentially explaining the emergence of psychosis in psychiatric and neurological conditions associated with aberrant synaptic functioning: in schizophrenia (Adams et al., 2013; Stephan et al., 2009; Sterzer et al., 2018), in Parkinson’s disease (O’Callaghan et al., 2017) or anti-NMDAR encephalitis (Stein et al., 2020).

The PCA primarily addresses psychosis within pathological contexts where alterations of inference are rooted in aberrant mechanisms. However, experiences resembling psychosis, involving a departure from the community's shared interpretations of reality, also occur in non-clinical settings (van Os, 2000; van Os et al., 2009). In these cases, when individuals do not develop psychiatric disorders, we lack clear evidence of maladaptation. This makes it challenging to argue that the emergence of psychotic-like experiences is driven by aberrant mechanisms.

Stemming from PCA integrated with attractor network theory, the review paper in Chapter I proposed reality inference, a reworking of classical reality testing, as a valuable construct for approaching the variability in the experience of reality beyond maladaptive contexts. Reality inference can be thought of as a fundamental function of the animal nervous system to represent reality in conscious experiences. As from predictive coding under the free-energy principle, representations of reality would reflect inferential mechanisms aiming at the minimisation of uncertainty. From Fletcher and Frith's (2009) explanatory levels of investigation for psychosis, we proposed that an account of reality inference variability should encompass (1) first-person experience, (2) physical mechanisms, and (3) natural computations. In accordance with PCA and attractor network literature (Adams, 2019; Adams et al., 2013; Rolls et al., 2008; Sterzer et al., 2018), we highlighted two main neurocomputational mechanisms possibly linked to the variability of reality inference in the general population. At the cellular level, the modulation of neural signal precision (implemented by synaptic gain) and at the brain dynamics level, the stability of attractor networks would be two main mechanisms critical for explaining variability in reality inference. These
neurocomputational mechanisms could vary in the general population, producing variability in individuals’ experiences of reality that can be adaptive or maladaptive.

9.3 Adaptive perceptual inference in the psychotic phenotype?

Our findings associate general population psychotic-like experiences in the general population with increased precision of sensory evidence proxied by the drift rate parameter. In our DDMs, the drift rate reflects the gain of evidence favouring the correct response (accuracy) through time. The drift rate can hence be considered a trade-off between RT and accuracy, signifying better performance. In other words, participants with higher psychotic phenotypes were better at capturing a signal (the left or right coherent motion) in the noise (the random dots) than people who showed a lower degree of psychotic phenotype. Similarly, Teufel et al. (2015) and Davies et al. (2017) (see Discussion section in Chapter IV for a comparison with our findings) found that participants with higher psychotic phenotypes are better at recognising figures in ambiguous images. Our and these latter studies support the idea of advantageous perceptual inference associated with psychotic-like experiences. Although it is hard to evaluate the adaptiveness of behaviour outside ecological contexts, we can argue that the enhanced capacity to recognise a signal in the noise (specifically for our studies, a motion pattern) shown by people who reported more psychotic-like experiences could potentially confer adaptive advantages. It is possible that the same mechanisms enhancing signal detection may contribute to psychotic-like phenomenology.

Notably, the Error-Management Theory suggests that evolution may favour decision-making strategies with a certain margin of error if these strategies result in outcomes that hold significant value for the specific environment in which the agents operate (Johnson et al., 2013). In the context of psychotic phenotype in light of our findings, we can speculate that, in some environments, human evolution might have favoured a perceptual system that is highly sensible to fluctuations in sensory data (i.e. with highly precise encoding of sensory evidence), maximising the detection of a signal when
present (true positive) over recognising a “false alarm” when no signal is present (true negative). This scenario can be described as a maximisation of sensitivity \( \frac{\text{true positives}}{\text{false negatives}} \) over specificity \( \frac{\text{true negatives}}{\text{false positives}} \) (see Figure 1 for a graphical illustration of this idea). Such an agent would excel at detecting signals in noisy environments when a signal is actually present (e.g., the detection of a poisoning snake in the grass). However, when confronted with noise in the absence of a signal, the heightened sensitivity to data variability might also lead to the detection of false positives.

\[ \frac{\text{true positives}}{\text{false negatives}} > \frac{\text{true negatives}}{\text{false positives}} \]

**Fig. 1 Maximisation of sensitivity over specificity.** The psychotic phenotype could have evolved for prioritising sensitivity (the ratio of true positives to false negatives) over specificity (the ratio of true negatives to false positives). This adaptation would excel in discerning signals within noisy environments, akin to the identification of a potentially dangerous entity, such as a venomous snake hidden in the tall grass. However, this system with heightened sensitivity could be predisposed to occasionally lead to the recognition of false positives when confronted with noise in the absence of a genuine signal.

This idea that heightened sensitivity in the psychotic phenotype can lead to false positives could be supported by evidence showing that auditory
hallucinations in healthy voice-hearers are associated with higher rates of false positives in auditory signal detection tasks (Barkus et al., 2007; Powers et al., 2017). Delusion-like and hallucination-like experiences have also been associated with higher rates of false positives in the recognition of words over non-words in fast-moving animations (Tsakanikos & Reed, 2005).

One way to examine whether the psychotic phenotype maximises sensitivity over specificity in motion detection would be to include in a future replication of Study 1 a version of RDM designed to measure false positive rates (e.g., including 0% motion coherence conditions and adapting response options accordingly: left, right or no coherent motion) and test the hypothesis that psychotic-like experiences are positively associated with drift rates in classic RDM and false positives in the version of RDM testing specificity. Based on our findings, we could also think that variability in PPC excitability might play a role in the hypothetical maximisation of sensitivity in psychotic-like perceptual inference. As shown by Study 2, perturbations of PPC excitability elicit different outcomes of evidence accumulation depending on the psychotic phenotype. However, further investigations into the mechanisms implicated by our findings are needed to attempt more structured speculations and hypotheses.

From an evolutionary perspective, we can think that in certain scenarios, the maximisation of sensitivity at the expense of specificity results in a better fitness of the individual, although leading to an acceptable occurrence of false inferences (i.e., false positives). The suggestion that evolution might favour non-veridical perceptual strategies is advocated by the interface theory of perception (ITP). Supported by evolutionary game simulations, the ITP proposes that natural selection may shape perceptual systems so that they maximise the fitness of the agent to the environment rather than veridical representations (Hoffman et al., 2015; Prakash et al., 2021). Depending on the goal of the agent and environmental conditions, a perceptual system based on fit rather than accuracy of representations could result in more adaptive strategies. When those conditions change rapidly those adaptations of the perceptual system can become so-called “evolutionary traps” (Robertson et al., 2013). For example, male giant jewel beetles (Julodimorpha bakewelli) often try to mate with brown beer bottles because
the bottles reproduce the right light and colour perceptive cues given by the same-species females (Hoffman et al., 2015; Robertson et al., 2013). From the ITP perspective, we could hypothesise that increased precision of sensory evidence could lead to advantageous maximisation of sensitivity and promote the agent’s fitness while bringing with it psychotic-like phenomenology as a by-product of adaptive reality inference. On the other hand, in certain environmental conditions and/or combinations of genetic polymorphisms, the same mechanism could create an evolutionary trap and promote the development of maladaptive reality inference as in schizophrenia-spectrum disorders.

Concluding this section, based on findings presented in this project, we proposed here the idea that increased precision of sensory evidence might maximise sensitivity over specificity in the psychotic phenotype. This mechanism could result in adaptive inference strategies that could promote the agent’s fitness to the environment. At the same time, in certain conditions, this same mechanism could represent an evolutionary trap and promote the emergence of psychotic symptoms. Alternatively, we cannot exclude that psychotic-like phenomenology may possess the potential to be adaptive in its own right. The next section will delve into this possibility.

9.4 Big questions: Is psychotic-like phenomenology adaptive? And are we brains floating in space?

Could altered experiences of reality play a beneficial role in human adaptation? The account we explored in the previous section, described psychotic-like experiences as incidental outcomes of mechanisms that under specific circumstances, may enhance an individual's fitness but become maladaptive in others. However, it is possible that psychotic-like phenomenology is not just a by-product of potentially adaptive mechanisms, but an adaptive phenomenon itself. This question opens up a very vast and mostly unexplored field of philosophical and experimental research that we will not be able to comprehensively cover here. Nevertheless, we would like to share some reflections exploring the possible adaptiveness of psychotic-like phenomenology.
The idea that the same mechanisms prompting psychotic-like experiences could lead to adaptive or maladaptive outcomes is also present in the pivotal mental state model proposed by Brouwer & Carhart-Harris (2021). These authors reviewed the evidence on serotoninergic stress-response mechanisms that are linked to psychosis, anomalous or mystical experiences and spiritual growth. They hypothesise that these stress-response mechanisms can promote the emergence of pivotal mental states, defined by the authors as: “transient, intense hyper-plastic mind and brain states, with exceptional potential for mediating psychological transformation.” (Brouer & Carhart-Harris, 2021; p.320). Alterations of serotoninergic signalling would enhance neuroplasticity during pivotal mental states and yield psychological changes that promote, depending on environmental conditions, successful stress coping or the development of psychiatric disorders. Importantly, the pivotal mental state proposal argues that the quality of the experience, that is its phenomenological content, is fundamental in determining the adaptive or maladaptive outcome of the stress-response mechanisms. In fact, the adaptive function of pivotal mental states would lie in their ability to induce radical changes in beliefs and behaviour mediated by altered experiences of reality. Experiences such as ego-dissolution, a sense of oneness or universal love could mediate a long-term psychological change that would allow the individual to cope with past and future intense stressors. The pivotal mental state model would thus imply that the psychotic-like phenomenology is not a by-product of potentially adaptive mechanisms but has a causal role in the adaptive outcome.

Other ideas about the adaptiveness of psychotic-like experiences have been explored regarding misbeliefs (McKay & Dennett, 2009). McKay and Dennett reviewed hypotheses about the adaptiveness of misbeliefs and found two types of beliefs particularly interesting to examine: placebo effect and supernatural agency. Intuitively, the placebo effect could represent a case of non-veridical reality inference where the phenomenological content of the belief determines possible adaptive outcomes. Placebo medications have proven effects on patients’ symptomatology in different clinical scenarios (Colagiuri et al., 2015; McKay & Dennett, 2009). Interestingly, dopaminergic, opioid, serotoninergic, and endocannabinoid genetic pathways have been
associated with placebo outcomes that include analgesic, antidepressant and anxiolytic effects (Colagiuri et al., 2015). McKay and Dennett argue against the relevance of placebos in human evolution, noting that placebo-controlled trials are a recent phenomenon in human history. Nonetheless, it is possible that the mechanisms contributing to the effectiveness of placebos were also triggered by traditional healing practices aimed at promoting mental well-being. It remains uncertain whether these mechanisms could overlap with those involved in experiences resembling psychosis. Surprisingly, as far as we know, no study has investigated whether individuals with higher psychotic phenotypes are also more inclined to respond to placebos.

Beliefs in supernatural agency, possibly reinforced by phenomenological evidence through hallucinatory experiences, might have significantly influenced the development of human societies. The primary rationale for the adaptive nature of such beliefs lies in their potential to foster the growth of large, enduring, and cooperative societies. This, in turn, could have favoured the survival and reproductive success of groups where these beliefs were more strongly held (McKay & Dennett, 2009; Norenzayan et al., 2016). Nevertheless, McKay and Dennett remark that it is arguable whether beliefs in supernatural agency are non-veridical representations of reality. In fact, although religious beliefs can be unlikely and resistant to contradictory evidence, they are distinguished from delusion in psychiatric diagnostic criteria (McKay & Ross, 2021). This distinction arises because religious beliefs are widely accepted and shared within a given culture. This cultural relativism in the definition of delusions introduces interesting paradoxes when examining historical and global perspectives. In some contexts, beliefs that might be deemed delusional could be entirely accepted in others. For example, McKay and Ross note that: “while adherents of popular religions may be exempt from delusion, the founders of those religions may not be.”

In a broader sense, assessing the accuracy of reality inference faces epistemological challenges. Determining whether a first-person experience is inaccurate in a manner that goes beyond species-specific, social, and cultural norms may often be outside the realm of scientific inquiry (Coltheart et al., 2011; Hoffman et al., 2015; McKay & Dennett, 2009; McKay & Ross, 2021). Indeed, it can often be quite challenging to find contradictory evidence for
psychotic and psychotic-like representations of reality that may result as unfalsifiable in the end (Coltheart et al., 2011). For example, let’s imagine meeting a sociable stranger at a party who claims not to be an actual human but a brain-like structure drifting through space. They doubt the reality we perceive, deny evolution and assert that we are transient sparks of self-awareness in a random universe. This belief might strike us as bizarre in the context of our communal understanding of reality but, in essence, it aligns with what cosmology recognises as a Boltzmann brain (Dasgupta et al., 2020; Linde, 2007). In fact, influential hypotheses about the universe's nature and origin would predict that in an eternally expanding universe, it is more likely that a subjective experience is produced by very rare quantum fluctuations, rather than by an organism shaped over billions of years of evolution (Dasgupta et al., 2020; Linde, 2007). Believing oneself to be a Boltzmann brain holds a peculiar status as a belief that is likely to be true given certain assumptions and observations but it is not widely shared by members of our society.

In conclusion, we have explored the idea that psychotic-like experiences might not merely be by-products of potentially advantageous mechanisms, but could themselves be adaptive phenomena. Epistemological limitations make it challenging to assess whether psychotic and psychotic-like representations of reality are actually deviating from reality, complicating the actual evaluation of the adaptiveness of psychotic-like experiences through time and space.

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