**Stochastic resonance and internal noise in schizotypal traits: a random dot kinematograms paradigm**

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**Abstract**

Stochastic resonance (SR) is a phenomenon where an optimal level of noise enhances the detection of subthreshold signals in nonlinear systems, including the human brain. Psychophysical research suggests that SR in human perception arises from the interaction between external noise and inherent neural noise. This interaction is examined using behavioral paradigms that manipulate external noise to infer internal noise levels, which vary with factors such as attention, age, and psychiatric conditions like schizophrenia. While SR effects on perception have been studied in aging, this study investigates their role in schizotypy, a personality trait continuum related to schizophrenia, where preliminary evidence suggests disruptions in neural variability and excitatory-inhibitory balance, key factors thought to influence internal noise. Using a visual motion discrimination task, we examine how measures of schizotypy are related to performance under varying external noise conditions. Participants complete a random dot kinematogram (RDK) task, where motion detection performance is assessed as external noise increases logarithmically. Schizotypy is measured using the Oxford-Liverpool Inventory of Feelings and Experiences (O-LIFE) and anomalous experiences are further assessed with the Cardiff Anomalous Perceptions Scale (CAPS). We hypothesize that higher schizotypy individuals exhibit altered SR effects, with peak perceptual performance shifting due to internal noise differences. Through large-scale remote testing, this study explores how neural noise imbalances correlate with early perceptual markers of psychosis risk.

**Introduction**

Each time we perceive a visual scene, our conscious experience is subject to considerable variability, which arises from two primary sources: **external noise** and **internal noise**. External noise refers to randomness in environmental signals, such as physical fluctuations in light and stimulus characteristics (Barlow, 1956; Reeves et al., 1998) or atmospheric distortions that affect how light travels (Tatarskii, 1971). For simplicity, we will collectively refer to these factors as **external noise**. In contrast, **internal noise** stems from the inherent unpredictability of the nervous system. This internal variability can result from multiple factors, including random fluctuations in neuronal activity (Faisal et al., 2008; Pinneo, 1966), inconsistencies in the timing of neural oscillations (Shadlen & Newsome, 1998), or spontaneous activity in the cortex, even in the absence of external stimuli (Arieli et al., 1996). Here, we adopt the definition provided by Dave et al. (2018), referring to the aperiodic component of the EEG spectrum, also known as 1/f activity. The aperiodic slope of the EEG power spectrum refers to the gradual decrease in power across frequencies in neural activity, following a 1/f-like distribution in the EEG spectrum. Unlike oscillatory (rhythmic) activity, which appears as distinct peaks in specific frequency bands, the aperiodic component reflects background neural noise and is thought to index excitatory-inhibitory balance and neural variability (He et al., 2010; Podvalny et al., 2015). A steeper slope indicates lower neural noise, while a flatter slope suggests increased neural noise and excitability.

While external noise can be minimized or controlled in an experimental setting, internal noise is an unavoidable and fundamental source of variability, shaping perceptual experience. This distinction is crucial because, once external factors are held constant, it allows us to focus on the internal fluctuations of the nervous system as the primary driver of perceptual variability.

In this study, we aim to explore how internal neural variability interacts with external noise to influence visual perception, leveraging the relationship between schizotypy and neural noise. Schizotypy refers to a continuum of traits associated with, but less severe than, schizophrenia (Barrantes-Vidal et al., 2015; Ettinger et al., 2014, 2015). The study will examine how individuals with different levels of schizotypal traits perform in a motion discrimination task under varying levels of external noise. Specifically, we will assess interactions between schizotypy, measured through self-report questionnaires, and external image noise, which will be manipulated by altering on-screen stimulus properties.

Internal neural noise has been found to correlate with schizophrenia (Earl et al., 2024; Peterson et al., 2023; Spencer et al., 2023). Although no direct evidence is present for the same correlation in schizotypy, schizophrenia and schizotypy share disruptions in oscillatory EEG activity across multiple frequency bands. For instance, individuals with schizophrenia exhibit altered topography in the theta and alpha neural responses (Basar-Eroglu et al., 2008; Koshiyama et al., 2021), as well as altered gamma oscillations (for a review, see Sun et al., 2011), which are similarly observed, albeit to a lesser degree, in individuals with high schizotypal traits (Hu et al., 2020; Koychev et al., 2010; Trajkovic et al., 2021). These findings support the idea that schizophrenia and schizotypy lie on a continuum, sharing underlying neurophysiological processes.

While previous studies have primarily focused on oscillatory activity, recent work has highlighted the role of aperiodic activity as an important aspect of neural noise and excitability that may relate to perceptual and cognitive impairments (Donoghue et al., 2020). It is plausible that aperiodic activity may show parallel, albeit subtler, disruptions in schizotypy as it does in schizophrenia. There are some advantages in a behavioral procedure as opposed to an EEG study measuring internal noise. First, we can test a broad sample of participants remotely, allowing us to capture a wide range of schizotypal traits through online recruitment. Second, the link between schizotypy and internal noise can be put to an empirical test because we have an hypothesis about how schizotypy will relate to performance.

The study also aims to replicate earlier findings (Di Ponzio et al., 2024), examining whether internal neural noise interacts with external noise in a nonlinear manner, potentially leading to unexpected perceptual effects. Finally, it also investigates whether individuals with high schizotypy experience a shift in peak performance relative to the amount of external noise, compared to individuals with lower schizotypy, who are expected to perform best at intermediate levels of external noise, similar to young adults in Di Ponzio (2024).

This study builds on the methodology and partially replicates hypotheses from previous research, where aging, rather than schizotypy, was used as a proxy for neural noise (Di Ponzio, 2024). By adopting a similar experimental framework, we aim to explore how neural noise varies with schizotypy. By adopting a similar experimental framework, we aim to explore how neural noise varies with schizotypy. In this specific study, we operationalize external noise as the number of dots presented on the screen in the RDK task, which modulates visual clutter and task difficulty.

**Aperiodic neural activity**

Aperiodic (scale-free) neural activity refers to the continuous, non-rhythmic component of brain signals, following a 1/f power distribution in which spectral power decreases with increasing frequency (Pritchard, 1992). Unlike oscillatory activity, which appears as distinct peaks in specific frequency bands, the aperiodic component reflects background neural noise (He et al., 2010; Podvalny et al., 2015) and is thought to capture the balance between excitation and inhibition (Gao et al., 2017). The slope of this activity, known as the spectral exponent, serves as an index of neural variability: flatter slopes indicate higher internal noise and excitability, while steeper slopes suggest greater neural stability (Harris & Thiele, 2011; Waschke et al., 2021). These findings support the broader hypothesis that internal noise influences perceptual performance. Aperiodic activity is not just background noise, but it reflects meaningful aspects of brain state and cognitive function. It has been linked to age-related changes in excitability excitability (Voytek et al., 2015), cognitive decline (Finley et al., 2024) and perceptual decision-making (Donoghue et al., 2020). Alterations in slope and offset have also been reported in schizophrenia, suggesting disrupted excitation-inhibition balance (Earl et al., 2024; Peterson et al., 2023), As such, aperiodic activity is increasingly viewed as a useful index of neural noise across both typical and clinical populations.

**Stochastic Resonance and Nonlinear Effects**

Neural noise is not the only source of variability; external stimuli can also introduce noise, such as indistinct background chatter. This study hypothesizes that internal and external noise interact to influence visual performance. Surprisingly, this interaction can sometimes yield nonlinear effects, where slight increases in noise improve rather than impair performance (Sasaki et al., 2008). The interplay of these noise sources is particularly relevant for non-linear systems, like the brain. Stochastic resonance (SR) is a counterintuitive phenomenon where the right amount of external noise enhances the detection of weak signals, first demonstrated in visual processing by Riani & Simonotto, (1994). SR typically follows an inverted U-shaped curve, with optimal performance at intermediate noise levels (Kitajo et al., 2003; Usher & Feingold, 2000). Recent theories suggest internal noise plays a pivotal role in SR effects (Aihara et al., 2008; Ward, 2004).

**Neural Noise and Cognitive Performance**

The relationship between neural noise and cognitive performance is complex and a matter of ongoing debate. One key question is whether the brain incorporates random noise into neural coding. Some evidence suggests that noise may play a positive, adaptive role in brain function (McDonnell & Abbott, 2009). Variability in neuronal firing has been shown to convey task-related information in both animal (Denfield et al., 2018) and human studies (Burlingham et al., 2022; Dinstein et al., 2015), making neural variability adaptive by promoting flexibility (Nomi et al., 2017; Waschke et al., 2017).

However, excessive neural noise has been linked to cognitive decline, especially in working memory and attention (Dave et al., 2018; Pathania et al., 2022; Tran et al., 2020; Voytek et al., 2015). The distinction between beneficial variability at the network level and harmful asynchronous activity helps resolve this paradox (Faisal et al., 2008). Studies finding positive effects of variability often use fMRI, which captures large-scale, network-wide brain activity, while those finding negative effects often use EEG, which detects smaller, moment-to-moment fluctuations (Kumral et al., 2020).

BOLD signal fluctuations, as measured by fMRI, integrate long-term neural activity from large populations, indicating network-level variability tied to structural brain connectivity (Baracchini et al., 2021; Fallon et al., 2020). In contrast, EEG captures finer-scale oscillatory activity, shaped by aperiodic neural activity (Brake et al., 2024).

**Internal neural noise in the psychosis spectrum**

Previous work from our group (Di Ponzio et al., 2024) investigated the effects of stochastic resonance (SR) on motion detection across different age groups (18-82 years). We observed an age-related decline in SR effects: while younger adults (18-50 years) reached optimal performance with intermediate levels of external noise, older adults (50-82 years) required lower noise levels for optimal performance. This shift suggests increased internal neural noise with aging, leading to a diminished signal-to-noise ratio (SNR), consistent with the neural noise hypothesis of aging.

Contrary to the prediction by Li et al. (2006) that older adults would require higher external noise to optimize performance, our findings align with those of Battaglini et al. (2023), showing that aging increases internal noise, making it harder to filter irrelevant information (Layton, 1975).

Similarly, individuals with schizophrenia exhibit elevated levels of internal noise, which contribute to various perceptual and cognitive abnormalities. Early research by Thomas (1973) identified disruptive, supracritical levels of cognitive noise in schizophrenia, characterized by arbitrary mental activity that disrupts cognitive processes and reduces information processing precision. More recent work by Adámek et al. (2022) highlighted how increased internal noise in schizophrenia leads to biased perceptual models, resulting in instability when predicting reality and processing contextual information. This instability is thought to arise from noisy signals in peripheral visual fields that affect higher-order cortical areas.

Studies on brain aging and schizophrenia reveal overlapping neurobiological features. Accelerated brain aging in schizophrenia is reflected by a larger "brain age gap" compared to other disorders (Ballester et al., 2022), suggesting more severe neurodegenerative changes. These effects may be linked to brain-derived neurotrophic factor (BDNF) dysfunction, which impairs neuronal plasticity and survival in cortical and hippocampal regions (Angelucci et al., 2005).

**Recent research using layer-specific fMRI has shown that high-confidence false percepts can arise from spontaneous, stimulus-like activity in the input layers of the early visual cortex, independent of top-down expectations (Haarsma et al., 2023), highlighting a feedforward mechanism by which internal noise can directly alter perception.**

Winterer et al. (2000) observed increased cortical noise, particularly in auditory perception, among schizotypal individuals. This increase, tied to neurochemical system changes, mirrors the effects observed in aging, suggesting that increased internal noise could disrupt normal perceptual processing in both populations.

Recent computational evidence also suggest that hallucination-proneness is associated with reduced sensory precision and greater reliance on prior beliefs, which can lead to perceptual distortions (Benrimoh et al., 2024). This supports the hypothesis that internal noise may play a key role in anomalous perceptual experiences, even in the general population.

While studies on aging consistently show a flattening of the aperiodic 1/f exponent, indicative of increased asynchronous neural activity in the cortex (Cesnaite et al., 2023; Clark et al., 2024; Dave et al., 2018; Finley et al., 2024; Merkin et al., 2023; Pathania et al., 2022; Tran et al., 2020; Voytek et al., 2015; Waschke et al., 2017), findings on SZ are more variable. Some studies report that the aperiodic slope differs significantly between SZ and healthy controls (HC). For instance, Peterson et al. (2023) found that a steeper slope was more predictive of SZ than oscillatory power across frequency bands during a target detection task. Similarly, Molina et al. (2020) reported steeper slopes during an auditory task, suggesting an altered excitation-inhibition (E/I) balance in SZ.

Other studies, however, found no significant slope differences. Earl et al. (2024) and Jacob et al. (2023) both reported null effects on slope, although they observed alterations in the aperiodic offset and oscillatory activity. Spencer et al. (2023) found that the aperiodic slope was less negative in SZ than in HC during auditory stimulation, though slope changes contributed less to increased gamma activity than gamma burst power. Jacob et al. (2023) also noted reduced coupling between gamma EEG signals and the BOLD response in SZ, suggesting impaired sensory gating despite no slope change. Sponheim et al. (2024) reported a general slowing of neural oscillations in SZ, while Earl et al. (2024) studying first-episode schizophrenia spectrum psychosis (FESSP), found no global slope difference but reduced aperiodic offset in central, temporal, and parietal regions, consistent with widespread slowing.

In our study we aim to investigate the relationship between schizotypal traits and perceptual processing, focusing on how internal and external noise influence visual perception. Participants will first complete the Oxford-Liverpool Inventory of Feelings and Experiences (O-LIFE) questionnaire (Mason et al., 1995), which assesses schizotypal traits across four different dimensions. Among these, we are particularly interested in the Unusual Experiences (UE) subscale, as it is most closely aligned with the perceptual phenomena examined in this study. This subscale captures perceptual anomalies, hallucination-like experiences, and magical thinking (Mason et al., 1995). Such experiences have been associated with atypical sensory processing and may reflect elevated levels of internal noise in the visual system (Adámek et al., 2022). One proposed mechanism is impaired filtering of early sensory input, which may allow irrelevant excitatory signals to reach higher processing stages, an idea consistent with thalamic gating models of hallucinations (Behrendt & Young, 2004). This interpretation is also consistent with predictive coding accounts of psychosis, which propose that perceptual anomalies arise from disruptions in the integration of sensory input with prior expectations, leading to misinterpretations of environmental stimuli (Fletcher & Frith, 2009).

To better assess the association between anomalous perceptual experiences and internal noise, participants will also complete the Cardiff Anomalous Perceptions Scale (CAPS), a psychometric tool designed to measure anomalous perceptual experiences, such as hallucinations, in both clinical and non-clinical populations (Bell et al., 2006). The CAPS is widely used in schizophrenia research due to the strong association observed between perceptual anomalies and hallucinations (Teufel et al., 2015). Additionally, significant correlations have been reported between CAPS scores and the three O-LIFE subscales included in this study, with the strongest correlation observed for the Unusual Experiences subscale (Aynsworth et al., 2017; Bell et al., 2006). This makes the CAPS questionnaire well-suited to investigate the hypothesis of an association between unusual perceptual experiences and altered neural noise. Given the specificity of CAPS in capturing perceptual anomalies, we will analyze it separately from schizotypal traits measured by O-LIFE to clarify the distinct contribution of anomalous perceptual experiences to perceptual accuracy and sensitivity to external noise.

Following the questionnaires, participants will complete a random dot kinematogram (RDK) task to assess motion detection under varying levels of external noise. This design allows us to examine how stochastic resonance (SR) effects differ across schizotypy levels by estimating internal noise through performance changes. Prior studies using RDK tasks have shown that low-to-medium external noise impairs motion perception in schizophrenia more than in controls, though this impairment diminishes at higher noise levels (Chen et al., 2014; Faivre et al., 2021). Marsicano et al. (2022) demonstrated that web-based tasks are effective for measuring schizotypal traits and cognitive function in the general population. Based on previous work (Laycock et al., 2019; O’Donnell et al., 2006), we do not expect schizotypal traits to impact basic motion detection under low-noise conditions, but differences may emerge as noise increases. These simple, scalable methods may ultimately support early identification of schizophrenia risk.

**Procedure**

The study has been approved by the General Psychology Ethics Committee of the University of Padua under protocol number 691-b. Each participant will first complete the O-LIFE questionnaire, an instrument based on the fully dimensional approach to schizotypy and schizophrenia. This approach conceptualizes these traits as existing on a continuum with typical psychological functioning, rather than as distinct or separate categories (Claridge & Beech, 1995). The questionnaire consists of 104 items divided into four subscales: Unusual Experiences (30 items), Cognitive Disorganization (24 items), Introvertive Anhedonia (27 items) and Impulsive Nonconformity (23 items). We chose to only include the first three subscales, as there is evidence that Impulsive Nonconformity has limited predictive validity (Chapman et al., 1994; Polner et al., 2021) and that a three-factor model best fits the O-LIFE data (Fonseca-Pedrero et al., 2015).

Participants will then complete the CAPS questionnaire (Bell et al., 2006), a self-assessment tool for anomalous perceptual experiences across both clinical and non-clinical populations. It comprises 32 items that assess the distress, intrusiveness, and frequency of these experiences using neutral language to ensure high content validity. CAPS scores are significantly associated with psychosis-like experiences in non-clinical populations, suggesting that anomalous perceptions are part of a broader psychosis spectrum that extends beyond clinically diagnosed psychosis (Humpston et al., 2016).

The motion detection task will employ a 2-interval forced-choice paradigm (Figure 1). Participants will be asked to decide which of two sequentially presented RDKs contains coherent motion in a rightward direction. Each trial will begin with a 1000 ms fixation cross, followed by two RDK intervals, each lasting 133 ms, separated by a 1000 ms post-stimulus gap. After the second interval, participants will be prompted to respond by indicating which interval contained the coherent motion. During the practice block, visual feedback will be provided following each response, while in the experimental block, a red circle will replace feedback, indicating when participants should respond.

The experiment will consist of two main blocks: a thresholding block and a constant stimuli block. Each block will be preceded by a 10-trial practice session.

* **Thresholding Block**: In this block, the total number of dots will be **400** in each interval and will remain constant. The proportion of coherently moving dots will vary using a one-up, two-down staircase procedure (Levitt, 1971). The coherence level will begin at 70% (i.e., 70% of the dots moving coherently in the same direction), with the step size decreasing after each reversal until the staircase concludes after 12 reversals. The percentage of coherently moving dots will increase or decrease based on the participant's responses:
  + After two consecutive corrects responses, the coherence level will decrease (making the task more difficult).
  + After one incorrect response, the coherence level will increase (making the task easier).

The coherence threshold will be calculated as the average coherence level across the final 8 reversals, indicating the minimum level of coherence required for participants to detect motion 70.7% of the time.

* **Constant Stimuli Block**: This block will present a fixed ratio of coherent-to-random dots based on the individual threshold calculated in the first block. The number of dots will vary across 14 levels, ranging from 20 to 2000 dots, spaced along a quasi-logarithmic scale (20, 29, 41, 58, 83, 118, 168, 239, 340, 485, 691, 999, 1403, and 2000 dots), but it will always be the same for each pair of intervals. By increasing the number of dots, the external noise in the visual field will be manipulated:
  + Low numerosity (e.g., 20 dots) will introduce less noise, making the coherent motion signal easier to detect.
  + High numerosity (e.g., 2000 dots) will introduce more visual clutter (external noise), making the coherent motion harder to perceive.

In each trial, participants will be presented with two intervals and will be required to detect which interval contains coherent motion. Each level will include 20 trials for a total of 280 pseudorandomized trials, and participants’ accuracy will be measured as the proportion of correct responses at each noise level.

The Random Dot Kinematogram (RDK) task is widely used in motion studies both in lab-based and online environments (Rajananda et al., 2018). The stimuli will consist of white dots moving on a black background. A percentage of these dots will move coherently in one direction (rightward), while the remaining dots will move randomly in various directions. The aperture through which the dots will be viewed is a square window of 10 degrees, centrally displayed on the screen. Each dot will have a diameter of 0.075 degrees, and the displacement per frame will be 0.05 degrees, resulting in a speed of 3 degrees per second. The dot lifespan, representing the time before a dot disappears and reappears at another location within the aperture, will exceed the duration of each stimulus. If a dot reaches the edge of the aperture, it will be relocated to the opposite side. The stimuli will be generated using the jsPsych RDK plugin (Rajananda et al., 2018).

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Descrizione generata automaticamente

**Figure 1**. The trial structure of the perceptual experiment involves an initial 133 ms interval displaying either coherently or randomly moving dots. This is followed by a 1000 ms post-stimulus black screen. Then, a second 133 ms interval is shown, featuring either randomly or coherently moving dots. After another 1000 ms black screen, participants are prompted to indicate whether the dots moving to the right appeared in the first or second interval. During the practice block, participants receive visual feedback after their response, along with trial-by-trial instructions. In the experimental trials, a red circle replaces the instructions, indicating when participants should respond.

**Sampling plan**

Participants will be recruited combining the online data collection platform Prolific (Palan & Schitter, 2018), knowledge of the experimenters and advertisement through flyers in the University of Padova. Participants recruited through Prolific will receive a £4.50 compensation after completing the experiment.

The study will build upon a previous experiment from our research group (Di Ponzio et al., 2024). An age limit of 49 will be set, given that results on age showed no substantial differences in performance among individuals up to 49 years old, while the most pronounced differences emerged when comparing those under 50 with those 50 and older (Di Ponzio et al., 2024).

Participants will perform the task remotely on their personal computers via the internet. At the beginning of the experiment, they will be instructed to sit in a quiet, semi-dark room, ensuring no direct light illuminates the screen. Additionally, participants will be instructed to maintain a viewing distance of 57 cm from the screen, ensuring the monitor remains perpendicular to their line of sight throughout the experiment.

The task is implemented using HTML (HyperText Markup Language), CSS (Cascading Style Sheets), and jsPsych—an open-source JavaScript library designed specifically for web-based psychological experiments (de Leeuw, 2015). The experiment is hosted on a server located at the Department of General Psychology at the University of Padova and is made accessible online through a JATOS instance (Lange et al., 2015).

Each participant will receive a link to participate via email, along with a copy of the informed consent form. A computer with a screen size of at least 10 inches will be required for participation, while individuals using touchscreen devices (e.g., smartphones or tablets) will be excluded. The first screen will display the informed consent form, which participants must agree to before proceeding. On the following screen, participants will be asked to provide demographic information, including age, gender, handedness, educational level, country of origin, country of residence, diagnosed visual and/or psychiatric conditions, presence of developmental disorders, use of corrective eyewear, general physical health, and religious affiliation. They will then be prompted to enter the physical size of their monitor in centimeters. Using this input and the monitor resolution, the individual pixel density per degree of visual angle will be calculated. All visual elements in the experiment will be adjusted according to these calculations to maintain consistent stimulus sizes across participants.

**Sample size and power analysis**

We plan to recruit 130 participants to achieve our target sample, with an additional 20 to account for potential dropouts and exclusions (total of 150).

Power was calculated using the *simr* package in R (Green & MacLeod, 2016), extending a best-fitting generalized linear mixed model (GLMM) from Di Ponzio et al. (2024), which previously found an interaction between age and external noise (log-transformed number of dots, LogDots) in predicting perceptual accuracy. For the current study, we adapted this model to test the interaction between schizotypy and LogDots, assuming a smaller effect size than age. Specifically:

* **Base model**: A GLMM was fit using the binomial family to model correct vs. incorrect responses as the outcome, with predictors including polynomial terms of external noise, schizotypy, and their interactions. A random intercept for each participant was included to account for within-subject variability.
* **Model extension**: Using the extend() function in the *simr* package, we simulated data up to 300 participants to assess how power varies with sample size. Because we expect schizotypy to have a smaller effect than age, we halved the original *LogDots* × age interaction coefficients for a more conservative estimate in our new study. The effect size and variability for schizotypy were calculated starting from the effects found for age in Di Ponzio et al. (2024).
* **Effect size calculation**: Power was computed based on the omnibus Type III Wald test for the schizotypy × *LogDots* interaction, using the Anova() function from the car package. The interaction’s simplified η² was estimated at 0.0054, derived by halving the effect size of the Age × LogDots interaction in the original study (η² = 0.021).
* **Custom power simulation**: We built a custom test function in *simr* to isolate the *LogDots × age* interaction (used here as a proxy for the schizotypy effect) within Type III ANOVA outputs from the car package. Using this test function, we performed 500 simulations per sample size, varying the number of participants from 84 to 104 in steps of four. We used the *powerCurve()* function to generate a power curve and extract 95% confidence intervals for each sample size. Random intercepts were included to account for within-subject variability, while random slopes were omitted due to persistent convergence issues. Interaction coefficients were manually reduced by 50% compared to the original model (based on Di Ponzio et al., 2024), to simulate a more conservative effect size for schizotypy.
* **Model assumptions and checks**: Diagnostic checks were conducted using the DHARMa package (Hartig & Lohse, 2022). Although omitting random slopes may slightly inflate effect sizes, the simplified model ensured stable convergence. We will consider alternatives (e.g., rank-based methods or Bayesian models) if fit issues arise during actual analysis.

The simulation demonstrated that a sample of 100 valid participants yields power close to 90%, exceeding the conventional 80% threshold. To further improve power and account for exclusions, we plan to collect a minimum of 130 complete and usable datasets, ensuring robust detection of the predicted non-linear interaction between schizotypy and external noise.

**Planned statistical analyses**

We will use R (R Core Team, 2021) for all statistical analyses and figure generation. The analysis pipeline will follow Di Ponzio (2024), with the key difference being that Schizotypy scores from the O-LIFE questionnaire will replace age as the primary predictor. Our key hypothesis is that schizotypy modulates the interaction between internal and external noise, affecting motion perception performance in the random dot kinematogram (RDK) task. To test this, we will conduct two main analyses:

*Thresholding Block*

**Hypothesis tested:** Schizotypy influences the minimum level of motion coherence required for accurate perception (i.e., internal noise differences affect perceptual sensitivity).

* To examine the effect of schizotypy on coherence thresholds, we will employ a linear model with the natural logarithm (ln) of the coherence level thresholds as the dependent variable. Coherence thresholds represent the percentage of dots moving coherently, ranging from 0% to 100%.
* The significance of the effects of schizotypy on coherence thresholds will be assessed using Type III Wald chi-square tests with the Anova() function from the CAR package (Fox & Weisberg, 2019)

*Constant Stimuli Block*

**Hypothesis tested:** Schizotypy influences how external noise (dot numerosity) affects perceptual accuracy, leading to potential shifts in the stochastic resonance (SR) curve.

In the constant stimuli block, accuracy (correct vs. incorrect responses) will be modeled as a binomial dependent variable using GLMM, with the glmer() function from the lme4 package (Bates et al., 2015).

* Number of dots (external noise) and schizotypy scores (as continuous predictors derived from the O-LIFE subscales) will be the primary predictors.
* Random intercepts will be included for each participant to account for repeated measures, capturing individual variation in performance across different dot numerosities and schizotypy scores.
* Given the hypothesized nonlinear relationship between accuracy, schizotypy, and dot numerosity, the number of dots will be modeled using polynomials up to the fourth degree, calculated using the poly() function in R.

Model assumptions will be assessed using the DHARMa package (Hartig & Lohse, 2022), which provides simulation-based methods for checking residuals in linear and generalized linear mixed models. Kolmogorov-Smirnov tests will be used to detect deviations from expected residual distributions. Additionally, we will check for heteroscedasticity and over/under dispersion to ensure the model assumptions are met. If no significant violations are found, we will proceed with analysis.

Model selection will be based on the Akaike Information Criterion corrected for small sample sizes (AICc), using the aictab() function from the AICcmodavg package (Mazerolle, 2009). This approach will allow us to determine whether a nonmonotonic (inverted U-shaped) model fits the data better than a linear model. Once the best-fitting model is identified, omnibus tests will be conducted using Type III Wald chi-square tests (via the Anova() function in the CAR package) to assess the overall significance of predictors, including interactions between schizotypy and external noise levels.

**Exploratory Analyses**

Additional exploratory analyses may be conducted by treating Schizotypy scores from the O-LIFE questionnaire as continuous predictors. Each of the three subscales—Unusual Experiences, Cognitive Disorganization, and Introvertive Anhedonia—will be analyzed separately. Alternatively, a median split of schizotypy scores could be used to create two subgroups (high vs. low schizotypy) for comparison.

We will also investigate whether certain O-LIFE subscales correlate more strongly with CAPS scores, providing further insight into how general schizotypy dimensions align with specific anomalous perceptual experiences. These exploratory correlations will help contextualize our main results. Given that CAPS specifically assesses perceptual anomalies distinct from general schizotypal traits (O-LIFE), analyses involving CAPS will be conducted separately to examine its unique contribution to perceptual processing under stochastic resonance conditions.

**Transformations**

A logarithmic transformation will be applied to dot numerosity to account for the compressive nonlinearity observed in numerosity and motion perception (Zanker, 1995).

**Inference Criteria**

For model selection, the model with the largest cumulative model weight and the lowest AICc score will be selected (ΔAICc > 1 will indicate a significant difference between models).

For the omnibus Type III Wald chi-square tests, an α level of < 0.05 will be considered statistically significant.

**Data exclusion**

To be eligible for the study, participants must be between 18 and 49 years old. This age range was selected based on findings from Di Ponzio et al. (2024) which showed no significant differences in stochastic resonance (SR) within this age group. Participants must be fluent in English, have normal or corrected to normal vision and not have a diagnosis of any DSM-V Axis 1 disorder. All criteria will be addressed in the demographics section at the beginning of the study, where participants will provide self-reported information. Those who do not meet the specified criteria will be excluded based on their responses.

Regarding exclusion after the data collection, we will check for the same criteria from Di Ponzio et al. (2024): (1) excluding participants with a coherent motion threshold below 75% in the initial block staircase, (2) ensuring a minimum of 6 reversals in the last 40 trials of the first block to prevent uncorrected threshold estimation, and (3) excluding participants with an average percentage of correct responses below 90% in the second block.

Each part of the experiment (questionnaire, adaptive block, and fixed block) must be completed sequentially, as participants are unable to proceed without finishing the previous section. Therefore, if a participant interrupts the study before completing it, their data will be excluded.

**Hypotheses**

We propose that the interaction between schizotypal traits and external noise will modulate perceptual performance, and we anticipate three possible outcomes, each supporting a different model of internal noise variation in the schizophrenia spectrum:

**Hypothesis 1a.** Improved performance under lower external noise: we expect individuals with high schizotypy to perform better under lower external noise conditions, showing a reduced and left-shifted SR curve. Elevated internal noise in these individuals may optimally interact with lower external noise to enhance weak sensory signals. This aligns with findings by Spencer et al. (2023), who observed increased aperiodic noise (flatter 1/f slope) at higher frequencies, and with studies on aging (Di Ponzio, 2024). This is the model we consider most likely, and it forms the basis for our study predictions.

Immagine che contiene linea, Diagramma, diagramma, pendio

Descrizione generata automaticamente

**Hypothesis 1b.** Better performance under higher external noise: if high schizotypy individuals perform better with higher external noise, it would suggest they have reduced internal noise at higher frequencies, enabling better filtering of irrelevant activity and resulting in a right-shifted SR curve. This is consistent with steeper 1/f slopes reported by Peterson et al. (2023), as well as reduced periodic activity observed by Sponheim et al. (2024) and Earl et al. (2024).

Immagine che contiene linea, Diagramma, diagramma, pendio

Descrizione generata automaticamente

**Hypothesis 1c.** No correlation between schizotypy and performance peak: As Jacob et al. (2023) propose, there may be no correlation between schizotypy and SR performance, with both high- and low-schizotypy individuals showing similar SR patterns across varying external noise levels. This would suggest that internal noise does not systematically vary with schizotypal traits.

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Descrizione generata automaticamente

**Hypothesis 2.** Variability linked to Unusual Perceptual Experiences: individuals with high schizotypy, especially those scoring high on the Unusual Perceptual Experiences subscale, are expected to show greater performance variability. This would result in more pronounced shifts in their SR curves due to heightened perceptual instability and internal noise, leading to unpredictable interactions with external noise.

**Hypothesis 3**. No significant interaction is expected between schizotypal traits and basic coherent motion detection abilities. Both high and low schizotypy individuals should perform similarly in detecting motion coherence, particularly when external noise is low or absent, suggesting that schizotypal traits do not significantly influence performance in this type of task. This is coherent with what has been previously observed in schizophrenia by Laycock et al. (2019) and O’Donnell et al. (2006), supporting the idea that differences between higher and lower schizotypy in motion detection do not depend on basic task performance ability. Instead, the variation likely arises from the interaction between external and internal noise levels, rather than inherent differences in detecting motion coherence.

**Hypothesis 4.** Participants scoring higher on the CAPS are expected to display a similar behavior to those scoring high in the O-LIFE, in particular in the Unusual Experiences scale.

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| **Question** | **Hypotheses** | **Analysis Plan** | **Interpretation given different outcomes** | **Theory that could be shown wrong by the outcomes** | **Sampling plan** | **Rationale for deciding the sensitivity of the test for confirming or disconfirming the hypothesis** |
| How do different schizotypal traits influence performance in a motion perception task under varying levels of external noise? | **H1** Individuals with high schizotypy will show improved performance at lower external noise levels, indicating elevated internal noise and a left-shifted stochastic resonance (SR) curve. | We will consider schizotypy scores from the O-LIFE questionnaire as the primary predictor. In the constant stimuli block, we will employ a generalized linear mixed model (GLMM) to assess accuracy (correct vs. incorrect responses) as the dependent variable. The number of dots (representing external noise) and schizotypy scores will be the primary predictors. Random intercepts will account for individual variability, and polynomials up to the fourth degree will model the hypothesized nonlinear relationship between accuracy and external noise. The focus will be on determining how different schizotypal traits influence the peak of performance under varying external noise levels, using Type III Wald chi-square tests to assess significance. Model assumptions will be evaluated using the DHARMa package, and model selection will be guided by the Akaike Information Criterion (AIC).  The same analyses will be repeated for scores in the CAPS questionnaire. | **O1** If individuals with high schizotypy exhibit improved performance at lower external noise levels and a left-shifted SR curve, we could conclude that elevated internal noise in high schizotypy individuals optimally interacts with lower external noise, enhancing their ability to detect subthreshold sensory signals. | If individuals with high schizotypy show improved performance at lower external noise levels, indicating elevated internal noise and a left-shifted stochastic resonance (SR) curve, this would challenge the theory that schizotypy is characterized by more efficient filtering of irrelevant activity.  These findings would be inconsistent with studies that report steeper 1/f slopes (Peterson et al., 2023) and reduced periodic activity (Sponheim et al., 2024; Earl et al., 2024) in schizophrenia.  It could also contradict the prediction made by Li et al. (2006) that individuals with heightened internal noise, such as older adults, would require higher external noise to optimize performance. If the findings show better performance at lower noise levels, it would contradict the idea that increased internal noise necessitates more external noise to improve perceptual accuracy. | The study aims to recruit 100 participants, with a target of 120 participants to account for potential dropouts or exclusions. Participants will be recruited using a combination of methods, including the online platform Prolific, flyers, and the researchers' professional network at the University of Padova. Participants recruited through Prolific will be compensated £4.50 upon completing the experiment. To be eligible to take part in the study, participants must be between 18 and 49 years old, have normal or corrected-to-normal vision, and must not have any diagnosed DSM-V Axis 1 disorders. Proficiency in English is required, as both the O-LIFE questionnaire and the instructions for the perceptual experiment will be administered in English.  Exclusions will be determined based on participants' self-reported demographic information and details regarding their health conditions. Post-data collection exclusions include those with a coherence motion threshold below 75%, participants who do not complete the study, or those with incorrect responses below 90% in the second block of the experiment. | The target sample size has been assessed at 100 participants, with an additional 20 to account for potential dropouts. A power analysis was conducted using the *simr* package in R, which allows simulation of power for mixed models. The analysis extended the best-fitting model from a previous study (Di Ponzio et al., 2024), replacing age with schizotypy as a predictor, focusing on detecting interactions between schizotypy and external noise (operationalized by the log-transformed number of dots). The base model used a GLMM with correct vs. incorrect responses as the outcome, incorporating polynomial terms for external noise and schizotypy, with random intercepts for participants. The effect size was conservatively reduced by 30% to account for potentially weaker effects of schizotypy compared to age-related changes.  The power simulation involved generating 1000 datasets with varying sample sizes to evaluate the power to detect interaction effects between schizotypy and external noise. With a sample size of 100 participants, the study achieved 80% power to detect medium-sized effects, particularly the hypothesized nonlinear (inverted U-shaped) relationship between dot numerosity and perceptual accuracy. |
| **H2** High schizotypy individuals will perform better at higher external noise levels, suggesting reduced internal noise at higher frequencies and a right-shifted SR curve. | **O2** If high schizotypy individuals show better performance at higher external noise levels and exhibit a right-shifted SR curve, it would point towards the hypothesis that schizotypy is associated with reduced internal noise, allowing individuals to filter irrelevant noise more effectively and benefit from increased external noise. | If high schizotypy individuals perform better at higher external noise levels, showing a right-shifted SR curve, this would challenge the existing theory that links schizophrenia to increased internal noise.  This outcome would be inconsistent with a study as Spencer et al. (2023), who observed increased aperiodic noise (flatter 1/f slope) at higher frequencies, and studies on aging (Di Ponzio, 2024), supporting the idea of elevated internal noise in schizotypy.  This outcome could also contrast with findings by Battaglini et al. (2023) that associate increased internal noise with impaired filtering of irrelevant information, particularly in aging populations. Therefore, the results would imply that certain aspects of schizotypy may involve more efficient neural processing under conditions of higher external noise. |  |
| **H3** Schizotypy will have no significant impact on the SR curve, with both high- and low-schizotypy individuals showing similar performance across varying external noise levels. | **O3** If both high- and low-schizotypy individuals show no significant shift in the SR curve, this would suggest that schizotypy is not associated with different internal noise levels or that other variables, such as sensitivity of the task, compensatory mechanisms, or general measurement limitations may have obscured potential effects. | If schizotypy has no significant impact on the SR curve, with both high- and low-schizotypy individuals showing similar performance across varying external noise levels, this would disprove the theories suggesting that schizotypy is associated with increased or reduced internal noise. This result would offer little clarification on the actual role of internal noise in schizotypy or how it interacts with external noise to shape perceptual performance, leaving open questions about the mechanisms involved. |
| How do the different subscales of schizotypy addressed by the questionnaire (Unusual Experiences, Cognitive Disorganization, and Introvertive Anhedonia) individually influence performance in a motion perception task under varying levels of external noise? Is there a correlation with CAPS scores? | Individuals scoring high on the Unusual Experiences (UE) subscale will exhibit greater performance variability in the motion perception task. This variability will result in more pronounced and unpredictable shifts in their SR curves, reflecting heightened internal noise and perceptual instability when interacting with varying levels of external noise. As this part of the study is predominantly exploratory, we are not sure which schizotypal subscale will serve as the best predictor of internal noise. However, given that the task focuses on perceptual performance, we hypothesize that the UE subscale will more likely exhibit stronger effects.  We also expect similar performance in individuals scoring high on the CAPS questionnaire. | In the thresholding block, a linear model will assess the effect of schizotypy on coherence thresholds (log-transformed), with significance tested using Type III Wald chi-square tests.  In the constant stimuli block, a GLMM will analyze accuracy as the dependent variable. The number of dots and schizotypy scores, particularly from the Unusual Perceptual Experiences subscale, will be included as predictors. The number of dots will be modeled using polynomials up to the fourth degree to capture potential non-linear effects.  Model selection will then be based on the Akaike Information Criterion (AIC), and final significance will be evaluated using Type III Wald chi-square tests. | If individuals with higher scores on the UE subscale show the greatest variability in the SR curve, this would suggest that this subscale is the strongest predictor of heightened internal noise in schizotypy, paving the way for further exploration of this relationship. This would be further corroborated by observing similar results in individuals scoring higher in the CAPS as well. Alternatively, if there is no significant difference among the three subscales in predicting higher internal noise, it would imply that none of them is a better predictor and that elevated internal noise may be a general feature of schizotypal traits. Lastly, if other subscales, such as those related to cognition or negative symptoms, emerge as stronger predictors, it would indicate that aspects beyond perceptual experience play a more prominent role in driving internal noise disturbances in schizotypy. | Since this is a mainly exploratory question, there are no established theories specifically predicting how the different schizotypy subscales (Unusual Experiences, Cognitive Disorganization, and Introvertive Anhedonia) influence performance in a motion perception task under varying levels of external noise.  In the same way, there is no clear evidence that high scores on specific O-LIFE subscales or the CAPS are associated with the same alterations in visual perception or internal noise. This aspect of the study remains exploratory and is based primarily on previous findings showing general correlations between these scales. |
| Is there a significant difference in accuracy in the motion detection task across varying schizotypal traits? | There is not expected to be a significant interaction between schizotypal traits and basic motion coherence detection abilities. Both high and low schizotypy individuals are expected to perform similarly in detecting motion coherence, especially under low external noise conditions. | We will analyze the variation in accuracy (correct vs. incorrect responses) as a function of schizotypal traits, using the scores derived from the O-LIFE questionnaire.  We will use a GLMM to assess the effects of schizotypal traits on accuracy, and we will an F test to determine if there is a significant relationship between these traits and motion detection accuracy.  The same analysis can be repeated for CAPS scores. | If no difference is found in overall accuracy, it would suggest that schizotypal traits do not necessarily impact accuracy in this task, but rather influence the level of tolerated external noise, leading to different performance peaks. Conversely, if a significant difference is observed, it would indicate that this task may indeed reveal schizotypy-related differences, which would require further investigation of the underlying mechanisms. | If the outcomes reveal a significant interaction between schizotypy and performance in the motion detection task, this will disprove the theory, based on previous studies (e.g., Laycock et al., 2019; O’Donnell et al., 2006), that even schizophrenia does not significantly influence basic coherent motion detection abilities. Such findings would imply that schizotypal traits may impact perceptual processes beyond external noise tolerance. |

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