UNIVERSITY OF PADOVA

Department of General Psychology

Master's degree in Cognitive Neuroscience and Clinical Neuropsychology

Final dissertation

Neural Noise as a Marker of Schizotypal Traits: EEG Patterns from Visual Noise Processing

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Academic Year 2025/26

Abstract

Perceptual processing occurs under conditions of both external noise and internally generated neural noise, understood here as neural noise within cortical systems. Within the psychosis continuum framework, schizotypal traits provide a useful model for examining whether individual differences in neural noise are related to perceptual performance in non-clinical populations. The present study investigates whether resting-state neural noise, indexed by the aperiodic (1/f-like) component of the EEG power spectrum, was associated with schizotypal traits and perceptual accuracy in a visual motion discrimination task. Twenty-eight healthy participants completed a two-interval forced-choice motion coherence task with systematically varied dot numerosity, alongside pre-task and post-task resting-state EEG recordings. Schizotypy was assessed using a multidimensional self-report questionnaire (O-LIFE), and neural noise was quantified using aperiodic exponent and offset parameters derived from resting-state EEG. Correlational analyses revealed no statistically significant associations between resting-state neural noise, schizotypy, and overall perceptual accuracy. However, mixed-effects modelling showed that the relationship between dot numerosity and perceptual accuracy was moderated by the aperiodic exponent, whereas the corresponding interaction with aperiodic offset was not statistically significant. In addition, both aperiodic parameters showed strong pre–post stability across the experimental session, indicating that they reflect relatively stable characteristics of resting-state cortical activity. These findings suggest that aperiodic neural activity may not function as a simple standalone marker of schizotypy or perceptual performance in non-clinical samples but may be relevant in a more context-dependent manner. Larger studies are needed to clarify its role in perception and psychosis-related vulnerability.

Keywords: neural noise, schizotypy, aperiodic activity, EEG, perceptual accuracy

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1. Introduction

1.1 Overview

Perception unfolds under conditions of variability. Sensory systems must continuously interpret information that is incomplete, ambiguous, and embedded in environmental noise, while the brain itself generates ongoing fluctuations that shape how incoming signals are processed. A central question in cognitive neuroscience is therefore how noise contributes to perception: when variability disrupts performance, when it reflects meaningful neural noise, and when it may become relevant to individual differences in cognition and vulnerability to psychopathology (Arieli et al., 1996; Faisal et al., 2008; McDonnell & Abbott, 2009; Snyder & Raichle, 2012). In this thesis, noise is not treated as a purely negative by-product of neural processing, but as a feature of brain function that may constrain or, under some conditions, support perception (Battaglini et al., 2023; McDonnell & Ward, 2011; Moss, 2004).

Within this broader problem, it is important to distinguish between external noise and internal neural noise. External noise refers to variability in the stimulus environment, such as changes in luminance, motion density, or signal-to-noise ratio (Barlow, 1956; Reeves et al., 1998). Internal neural noise, by contrast, refers to variability generated within cortical systems themselves (Faisal et al., 2008; Shadlen & Newsome, 1998). In the present study, this construct is defined specifically as intrinsic variability within distributed neural networks (Findling & Wyart, 2021; Guo et al., 2018). External noise can be manipulated experimentally, whereas internal neural noise must be inferred indirectly from physiological measures (Faisal et al., 2008; He, 2014). This thesis investigates whether neural noise varies with schizotypal personality traits by examining changes in perceptual performance under different levels of external noise.

A promising candidate for operationalizing neural noise is the aperiodic (1/f-like) component of the EEG power spectrum. Unlike narrowband oscillatory rhythms, the aperiodic signal reflects the broadband structure of neural activity across frequencies and has been interpreted as indexing properties of large-scale cortical dynamics (Donoghue et al., 2020; He, 2014; Miller et al., 2009; Voytek et al., 2015). In particular, the aperiodic exponent and offset have been proposed as quantitative measures of background neural activity, with flatter exponents often interpreted as reflecting greater neural noise or reduced large-scale synchrony, and steeper exponents as reflecting more coordinated activity across neural populations (Dave et

al., 2018; Donoghue et al., 2020; Muthukumaraswamy & Liley, 2018; Voytek et al., 2015). This interpretation should be made cautiously: aperiodic parameters do not provide a direct readout of "noise" in a purely random or pathological sense, nor can they be reduced to a single mechanism such as excitation–inhibition balance (Donoghue, 2025; Gyurkovics et al., 2021; Kramer & Chu, 2024). Nevertheless, they provide a biologically grounded and increasingly used way of characterizing intrinsic neural noise in humans during resting-state EEG (Donoghue et al., 2020; He et al., 2010; Voytek et al., 2015).

This issue is especially relevant in the context of the psychosis continuum. Schizotypal traits are subclinical personality and cognitive characteristics that resemble attenuated aspects of psychosis and are distributed dimensionally across the general population (Barrantes-Vidal et al., 2020; DeRosse & Karlsgodt, 2015; Ettinger et al., 2014). Studying schizotypy offers an important advantage, it allows the investigation of psychosis-related variation without many of the confounds that characterize clinical groups, such as long-term medication use, illness chronicity, hospitalization, and broader health complications (Barrantes-Vidal et al., 2020; Ettinger et al., 2014). If resting-state increased neural noise is associated with higher schizotypal traits in healthy individuals, this would support the idea that neural noise may relate to vulnerability to the disorder rather than merely reflecting illness consequences (Barrantes-Vidal et al., 2020; Federmann et al., 2025).

The literature remains mixed. Prior work has suggested that neural noise may be relevant to cognition and perception, but much of this evidence has relied on indirect proxies, such as behavioral variability, age-related change, or task-level performance patterns (Cessa et al., 2025; Di Ponzio et al., 2024; Voytek et al., 2015). Research on aperiodic neural activity in clinical populations has also reported heterogeneous findings across disorders, recording contexts, and analytic approaches (Donoghue, 2025; Gyurkovics et al., 2021). This heterogeneity is particularly evident in psychosis-spectrum research, where some studies suggest that aperiodic activity may be potentially clinically informative (Abbasi et al., 2023; Peterson et al., 2023), whereas others report region-specific or context-dependent effects rather than simple global differences (Earl et al., 2024; Hasanaj et al., 2025; Spencer et al., 2023). At present, all the available literature on aperiodic neural activity in relation to psychosis-relevant traits comes from schizophrenia-spectrum or clinical samples rather than from non-clinical schizotypy (Donoghue, 2025; Earl et al., 2024; Peterson et al., 2023). As a result, it remains unresolved whether these findings generalize to schizotypal traits in healthy populations, and whether resting-state aperiodic activity is behaviorally meaningful in this context.

A second theoretical issue concerns the relationship between neural noise and external noise. In nonlinear systems, intermediate levels of noise can sometimes improve detection of weak signals, a phenomenon described as stochastic resonance (McDonnell & Abbott, 2009; McDonnell & Ward, 2011; Moss, 2004). This framework has often been used to argue that noise does not simply degrade performance but may interact with task context in a nonlinear way (Battaglini et al., 2023; Matthews et al., 2024; McDonnell & Abbott, 2009) . In the present thesis, stochastic resonance is treated as an important background framework for thinking about how internal and external noise might interact. At the same time, the empirical focus is deliberately more specific: the primary aim is to test whether individual differences in resting-state aperiodic exponent and offset are related to individual differences in schizotypal traits and perceptual accuracy, and secondarily whether these neural differences moderate the effect of externally manipulated visual noise on task performance. In this way, the study combines a trait-focused approach with a more specific test of internal–external noise interaction.

The present study addresses these questions by combining resting-state EEG, self-report measurement of schizotypal traits, and a visual motion discrimination task in which external noise is manipulated through dot numerosity. Participants completed pre-task and post-task eyes-closed resting-state EEG recordings, allowing estimation of aperiodic exponent and offset as indices of intrinsic neural noise (Donoghue et al., 2020; Voytek et al., 2015). They also completed a two-interval forced-choice motion coherence task using random-dot kinematograms, in which the density of moving dots varied systematically across trials. This manipulation served as the study's operationalization of external visual noise (Manning et al., 2019; Niedeggen & Wist, 1999; Wei et al., 2019). By integrating these components, the design allows examination of associations among neural noise indices, schizotypy, and behavior, and the possibility that resting-state neural noise alters how perceptual performance changes across levels of external noise.

Four hypotheses guided the investigation. H1 predicted that schizotypal traits would be negatively correlated with perceptual accuracy in the motion coherence task. H2 predicted that higher levels of neural noise, operationalized as flatter aperiodic slopes, would be associated with higher schizotypal trait scores. H3 predicted that higher neural noise would be associated with lower perceptual accuracy. H4 predicted that the effect of dot numerosity on perceptual accuracy would be moderated by resting-state aperiodic neural activity.

By directly quantifying neural noise using EEG rather than relying on behavioral proxies alone,

this thesis aims to provide a more mechanistically grounded account of neural noise in a schizotypy framework (Cessa et al., 2025; Donoghue et al., 2020; Voytek et al., 2015). More broadly, the present study asks whether higher schizotypal traits are associated with greater neural noise, indexed by resting-state aperiodic EEG activity, and whether variation in this neural activity influences how perceptual performance changes across levels of externally manipulated visual noise.

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2. Theoretical Background

2.1 Perception and Noise

Perception refers to the process by which sensory information is detected, organized, and interpreted to form a meaningful representation of the environment (Goldstein & Cacciamani, 2022). This process allows humans to make sense of the world despite constantly receiving information that is incomplete and noisy. When we observe a visual stimulus, conscious experience can fluctuate from moment to moment, even when the physical input remains similar. These fluctuations are thought to arise from two principal sources: external noise and internal noise. External noise refers to randomness in environmental signals, such as physical fluctuations in light or variations in stimulus characteristics (Barlow, 1956; Reeves et al., 1998). By contrast, internal noise, sometimes also referred to as neural noise, reflects variability generated within the nervous system itself. Neural noise can be present even when the external environment is stable, and it may arise from random fluctuations in neuronal activity (Faisal et al., 2008; Pinneo, 1966), trial-to-trial variability in neuronal discharge timing (Shadlen & Newsome, 1998), and spontaneous cortical activity in the absence of externally imposed stimulation (Arieli et al., 1996; Snyder & Raichle, 2012).

2.2 Defining Neural Noise

When discussing internal noise in the context of perception, it is important to clarify the level of the system under consideration. In the present study, neural noise is defined as intrinsic variability in cortical network activity that is generated within the brain itself, rather than by changes in the external stimulus, and is operationalized through the aperiodic component of the resting-state EEG signal. Even in the absence of external stimulation, neural systems exhibit ongoing fluctuations driven by stochastic ion-channel activity, probabilistic synaptic release,

membrane excitability dynamics, and recurrent network interactions (Faisal et al., 2008; Guo et al., 2018; Scarciglia, Bonanno, et al., 2025; Scarciglia, Magliaro, et al., 2025). These processes introduce variability directly into the system's dynamics and shape how information is processed over time. Importantly, neural noise is not inherently detrimental. Elevated baseline neural noise has been associated with poorer perceptual processing and age-related cognitive decline (Tran et al., 2020). However, under certain conditions, moderate levels of neural noise may enhance signal detection through stochastic resonance mechanisms and facilitate coordination across brain regions (Battaglini et al., 2023; Di Ponzio et al., 2024; Guo et al., 2018; Kraikivski, 2021; Lacquaniti et al., 2023; McDonnell & Ward, 2011; Pisarchik & Hramov, 2023).

Taken together, these findings suggest that neural noise reflects a fundamental property of brain dynamics that can either constrain or support information processing depending on its magnitude and context (Lombardi et al., 2017; Nandi et al., 2022; Ping et al., 2025). Because such variability operates at the level of distributed neural populations, it cannot be directly observed at the single-neuron level in human participants. Instead, it must be inferred from aggregate measures of large-scale cortical activity (He, 2014; Miller et al., 2009; Voytek et al., 2015). In EEG research, one promising candidate measure is the aperiodic (1/f-like) component of the power spectrum, which captures the broadband structure of neural population activity (Gyurkovics et al., 2021; He, 2014; Miller et al., 2009; Voytek et al., 2015). The aperiodic exponent and offset provide quantitative indices of this background activity and have been interpreted as reflecting large-scale neural noise and excitation–inhibition balance. For this reason, the present study treats parameterized aperiodic EEG activity as a biologically grounded proxy for cortical neural noise, while acknowledging that it captures statistical properties of network dynamics rather than noise in a purely random or pathological sense (He, 2014; He et al., 2010; Kramer & Chu, 2024).

2.3 Neural Noise and EEG (1/f Activity)

In EEG research, neural noise is commonly indexed using the aperiodic 1/f component of the power spectrum (Donoghue et al., 2020; Gyurkovics et al., 2021; He et al., 2010; Miller et al., 2009; Voytek et al., 2015). A flatter 1/f slope has been interpreted as reflecting greater background neural noise and reduced large-scale synchronization of brain activity (Dave et al., 2018; Lombardi et al., 2017; Muthukumaraswamy & Liley, 2018; Voytek et al., 2015), whereas a steeper slope is thought to indicate more coordinated activity across neural populations

(Donoghue et al., 2020; He et al., 2010; Miller et al., 2009). Unlike specific oscillatory rhythms such as alpha or beta activity, the 1/f component is considered to reflect broader aspects of brain network organization (Aggarwal & Ray, 2025; Dave et al., 2018; Voytek et al., 2015). Measures of neural noise have been linked to a range of physiological and cognitive processes, including aging, schizophrenia, and lifespan prediction (Dave et al., 2018; Earl et al., 2024; Lombardi et al., 2017; Muthukumaraswamy & Liley, 2018; Peterson et al., 2023; Spencer et al., 2023; Voytek et al., 2015).

Previous research in healthy populations suggests that the 1/f slope, also referred to as aperiodic activity, is not simply random background noise, but a meaningful and functional aspect of brain activity that supports how the brain integrates and samples sensory information over time (Deodato & Melcher, 2024). Studies have shown that individuals who are less efficient at processing sensory input tend to exhibit higher aperiodic activity, reflected in a flatter 1/f slope (Krystecka et al., 2024). In general healthy population, increased 1/f noise has been associated with poorer perceptual accuracy and lower overall cognitive performance (Tran et al., 2020). Similarly, research has shown that neural noise is related to how effectively healthy individuals predict incoming stimuli, suggesting that 1/f activity plays an important role in perceptual processing efficiency (Smyrnis et al., 2023). Earlier work also demonstrated that neural activity naturally follows a 1/f pattern, which may reflect an intrinsic brain dynamic that supports precise perception of the external world (Lin et al., 2016). In addition, research indicates that the 1/f slope becomes flatter with healthy aging, especially at lower frequencies, reflecting increased neural noise that is associated with cognitive decline, particularly in visual working memory (Aggarwal & Ray, 2025; Voytek et al., 2015). Together, these findings indicate a strong relationship between 1/f activity, perception, and cognition in healthy individuals across the lifespan.

2.4 Stochastic Resonance and the Functional Role of Noise

Traditionally, noise has been understood as a factor that obscures sensory signals and reduces perceptual reliability (Barlow, 1956). Modern neuroscience has shown that noise is not uniformly detrimental to perception. In nonlinear systems, an intermediate level of variability can enhance the detection of weak signals through a mechanism known as stochastic resonance (Battaglini et al., 2023; Matthews et al., 2024; McDonnell & Abbott, 2009; Moss, 2004). Originally described in physical systems and later extended to neural systems, SR demonstrates that the relationship between noise and perceptual accuracy is nonlinear: insufficient noise may

fail to amplify weak signals, moderate noise can optimize signal detection, and excessive noise can again degrade performance (Kitajo et al., 2003; McDonnell & Ward, 2011). Thus, as a nonlinear dynamical system, the brain may under some conditions benefit from variability. (Aggarwal & Ray, 2025; Voytek et al., 2015).

Empirical evidence supports this nonlinear account. Di Ponzio et al. (2024) showed that aging alters the relationship between external noise and perceptual performance in a motion detection task. Specifically, older adults reached peak performance at lower levels of externally added noise than younger adults, a pattern consistent with elevated baseline neural noise. This finding suggests that differences in internal neural noise may shift the point at which external noise becomes beneficial.

Similarly, altered sensitivity to noise has been reported in schizophrenia-spectrum populations, where disruptions in excitation–inhibition balance and increased neural noise may help explain why the effects of external noise on perception differ from typical patterns, although direct evidence for shifted stochastic resonance effects remains limited (Abbasi et al., 2023; Freche et al., 2020). More broadly, heterogeneous findings on aperiodic neural activity across clinical populations have been reviewed by Donoghue (2025).

Within this framework, perceptual accuracy is expected to vary nonlinearly as a function of external noise, and the shape of this function is expected to differ as a function of I neural noise. In the present study, external noise is operationalized as dot density in a motion coherence task whereas neural noise is indexed by resting-state aperiodic exponent and offset. Specifically, variation in resting-state aperiodic exponent and offset is expected to shift the perceptual-accuracy curve across levels of external noise. Rather than predicting a simple linear relationship between neural noise and perceptual accuracy, the stochastic resonance account suggests a nonlinear pattern in which internal neural noise modulates how external noise influences perceptual performance. In this way, stochastic resonance provides the mechanistic framework for the present investigation: perceptual accuracy is hypothesized to reflect a dynamic interaction between externally manipulated noise and neural noise associated to a higher level of schizotypy.

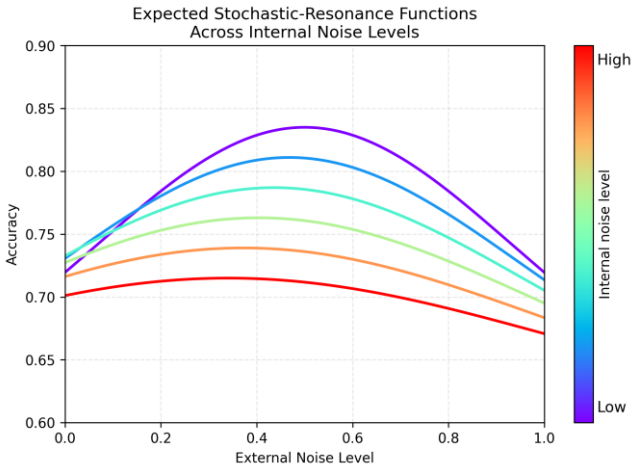

Figure 1. Conceptual illustration of the predicted stochastic-resonance relationship between external noise and perceptual accuracy across different levels of internal neural noise. The curves are schematic and are intended to illustrate the hypothesis that perceptual accuracy varies nonlinearly as a function of external noise, and that the shape and position of this function may differ depending on the level of internal neural noise.

Figure 1 provides a schematic illustration of the hypothesized stochastic-resonance relationship, in which perceptual accuracy varies nonlinearly with external noise and the shape of this function differs as a function of neural noise.

2.5 Neural Noise and Perceptual Accuracy

There are ongoing discussion and considerable complexity surrounding the relationship between neural noise and cognitive performance. One important question is whether the brain makes functional use of random variability in neuronal coding. Some research suggests that noise may have a beneficial and adaptive role in brain function (McDonnell & Abbott, 2009). Both theoretical and empirical work indicates that neural noise can carry meaningful information about sensory processing and cognitive state (Denfield et al., 2018; Dinstein et al., 2015). Rather than reflecting purely random disturbance, variability in neural activity may therefore contribute to flexible information processing and adaptive brain function (Nomi et al., 2017; Waschke et al., 2021).

At the same time, excessive neural noise has been associated with cognitive decline, particularly in domains such as attention and working memory (Dave et al., 2018; Kumral et al., 2020; Pathania et al., 2022; Tran et al., 2020). To address this apparent contradiction, it is useful to distinguish between variability and noise. A finding states that not all neural variability is necessarily detrimental or generated by the same mechanism; some variability may reflect deterministic properties of the system, whereas noise refers more specifically to

random disturbances that can interfere with information processing (Faisal et al., 2008), this distinction helps clarify why some forms of neural variability may support flexible processing, whereas excessive noise may impair cognitive function. Methodological differences may also contribute to these mixed findings. EEG, which is sensitive to rapid moment-to-moment fluctuations in neural activity, is often used in studies reporting detrimental effects of variability, whereas fMRI, which captures larger-scale and more slowly varying network-level activity, is more often used in studies suggesting beneficial effects (Brake et al., 2024; Kumral et al., 2020).

2.6 Random-Dot Kinematogram Tasks and the Motion-Related N2

Random dot kinematogram (RDK) tasks are widely used to study motion perception because they allow precise control over the sensory evidence available to the observer. In these paradigms, participants are required to detect or discriminate coherent motion embedded within randomly moving dots, making the task especially suitable for examining how the visual system integrates motion information under noisy conditions. By manipulating stimulus properties such as motion coherence or dot density, RDK tasks provide a controlled way to vary perceptual difficulty and external noise.

Electrophysiological research further shows that coherent motion in RDK paradigms is associated with reliable EEG markers. A posterior N2 component, typically observed over occipital or occipito-parietal electrodes approximately 200–300 ms after stimulus onset, has been linked to coherent motion processing and motion integration (Manning et al., 2019; Niedeggen & Wist, 1999; Wei et al., 2019). When coherent motion is introduced after an initial period of incoherent motion, this N2 is especially informative because it appears to reflect motion-specific processing rather than a general response to stimulus onset or luminance change (Manning et al., 2019; Niedeggen & Wist, 1999). Its amplitude has been reported to increase with motion coherence, with stronger posterior N2 responses observed for coherent motion than for low-coherence or incoherent motion, supporting the interpretation of the posterior motion-related N2 as an electrophysiological marker of coherent motion processing (Manning et al., 2019; Niedeggen & Wist, 1999). In the present study, this literature motivated the analysis of a posterior N2-like response over occipito-parietal electrodes within a predefined 160–260 ms time window as a task-related index of coherent motion processing. the motion-related N2 was analyzed not as a primary index of resting-state neural noise, but as a complementary task-evoked measure of coherent motion processing. This allowed an

exploratory assessment of whether individual differences in motion-sensitive neural responses were related to behavioral accuracy and schizotypal traits.

2.7 Neural Noise in Clinical Populations

Research in clinical populations further highlights the importance of the 1/f slope. Differences in 1/f slope have been observed in autism spectrum conditions, where altered power-law exponents suggest distinct patterns of neural organization that may influence communication-related behavior (McCleod et al., 2024). In addition, children with autism and lower IQ have been found to exhibit flatter 1/f slopes, which may reflect increased cortical excitation and could potentially serve as a non-invasive marker for monitoring treatment effects (Manyukhina et al., 2022). Aperiodic neural activity has also been shown to vary systematically with vigilance and alertness states, highlighting the importance of controlling for arousal when interpreting spectral parameters (Østergaard et al., 2024).

Schizophrenia-related EEG differences have in some cases been linked more strongly to the aperiodic component of the power spectrum than to conventional oscillatory band measures, suggesting that aperiodic activity may provide clinically useful information about schizophrenia-related brain dynamics (Peterson et al., 2023). At the same time, the broader literature is mixed. Donoghue's review notes that findings in schizophrenia are overall inconsistent, with reports of increased, decreased, and null differences in aperiodic exponent, as well as variation across task states and anatomical locations (Donoghue, 2025). More specifically, recent studies have reported no clear resting-state group difference in some samples (Earl et al., 2024), task-related decreases in others (Spencer et al., 2023), and stronger classification performance for aperiodic than oscillatory measures in a cognitive task (Peterson et al., 2023). Related work has also associated schizophrenia with increased neural noise and broader disruptions in brain signal variability (Abbasi et al., 2023; Freche et al., 2020). Together, these findings suggest that aperiodic neural activity may be relevant to schizophrenia-spectrum conditions, but not as a simple or uniformly reliable marker across all samples or contexts.

More broadly, alterations in the aperiodic (1/f-like) component of neural activity have been reported across a wide range of neurological and psychiatric conditions. A recent systematic review by (Donoghue, 2025), synthesizing 177 reports across 38 disorders, concluded that aperiodic parameters frequently show significant group differences in clinical research.

However, the review also emphasized substantial heterogeneity in effect direction, regional specificity, analytic approach, and recording context (rest vs. task), as well as the influence of medication and vigilance state. These considerations underscore both the promise and the complexity of interpreting aperiodic neural activity as a clinical marker.

2.7.1 Psychosis and Schizophrenia Spectrum Disorders

Schizophrenia-spectrum conditions have been among the most extensively studied in relation to neural noise. Some studies suggest that aperiodic neural activity may provide clinically useful information and, in some cases, may distinguish schizophrenia-spectrum groups from controls more effectively than conventional oscillatory band-power measures (Peterson et al., 2023). At the same time, findings on aperiodic alterations remain mixed. For example, Earl et al. (2024) reported regionally specific rather than global resting-state differences, and Spencer et al. (2023) found a more context-dependent pattern in which aperiodic slope contributed only partly to broader task-related abnormalities. Similarly, Hasanaj et al. (2025) reported increased aperiodic exponent and offset at the global scalp level in schizophrenia-spectrum disorders, but no significant aperiodic differences in frontoinsular source-localized regions; in the same study, periodic alterations, particularly increased theta power, were more strongly associated with cognitive impairment than aperiodic parameters (Hasanaj et al., 2025). Together, these findings suggest that aperiodic neural activity may be relevant to schizophrenia-spectrum conditions, but not as a simple or uniformly reliable marker across all recording contexts or anatomical levels.

In addition to spectral alterations, schizophrenia-spectrum populations have been associated with increased neural noise and disruptions in excitation–inhibition balance. These findings suggest elevated background neural noise and reduced synchrony across large-scale neural networks (Abbasi et al., 2023; Freche et al., 2020). Complementary evidence indicates that abnormalities in gamma bursting contribute to differences in spontaneous gamma activity in schizophrenia, further suggesting that oscillatory and aperiodic processes may jointly shape the spectral alterations observed in this population (Spencer et al., 2023).

Importantly, aperiodic measures are also influenced by state-related factors. Østergaard et al. (2024) demonstrated that the aperiodic exponent varies systematically with vigilance state, highlighting the importance of controlling for arousal when interpreting spectral parameters and group differences.

Taken together, findings from schizophrenia-spectrum research suggest frequent, but heterogeneous alterations in aperiodic slope and offset parameters. These alterations appear to be influenced by multiple factors, including regional specificity, illness stage, medication status, and cognitive context.

2.6.2 Neurodevelopmental Conditions

Altered aperiodic activity has also been observed in neurodevelopmental disorders. In autism spectrum disorder (ASD), (Manyukhina et al., 2022), using source-level MEG, reported flatter 1/f slopes in children with ASD and below-average IQ compared to both typically developing peers and children with ASD who had average IQ. The effect was interpreted as reflecting a global shift toward increased cortical excitation and showed relative stability across eyes-open and eyes-closed conditions, suggesting trait-like characteristics. Earlier work has likewise suggested altered neural organization in ASD associated with changes in power-law dynamics (McCleod et al., 2024).

In attention-deficit/hyperactivity disorder (ADHD), converging evidence points to flatter aperiodic exponents. Ostlund et al.(2021) reported reduced exponents in adolescents with ADHD during resting-state EEG, with slope values correlating with behavioral and cognitive variability. Arnett et al.(2022) further demonstrated that aperiodic slope varies with task demands and anticipatory state, suggesting both trait-like and state-dependent components. Chen et al. (2024) similarly found lower aperiodic exponents in children with ADHD and emphasized the importance of accounting for regional variation, lateralization, and demographic covariates when modelling spectral parameters. Collectively, findings in neurodevelopmental conditions suggest that flatter aperiodic slopes may index altered excitation–inhibition balance or increased cortical variability, although the magnitude and interpretation of these effects depend strongly on methodological context.

2.6.3 Affective and Developmental Contexts

Aperiodic alterations have also been documented in affective disorders. Rosenblum et al.(2023) reported flatter aperiodic slopes during sleep EEG in unmedicated individuals with major depressive disorder compared to controls, with additional flattening observed in medicated participants. These findings illustrate both state sensitivity and the pharmacological modulation of broadband neural activity. At early developmental stages, Wilkinson et al.(2025) demonstrated that longitudinal changes in aperiodic EEG parameters during the first year of

life in infants with a familial likelihood of autism were associated with later autism diagnosis and language outcomes. This work provides a developmental extension of aperiodic parameterization and highlights its potential sensitivity to emerging neurobiological risk markers.

Across psychosis-spectrum, neurodevelopmental, and affective conditions, aperiodic neural activity frequently shows alterations in slope and offset parameters. However, the direction of effects (flatter vs. steeper), spatial distribution (global vs. regional), and functional significance vary considerably across studies (Donoghue, 2025). Reported findings are also influenced by medication status, vigilance state, developmental stage, and analytic parameterization. Thus, while aperiodic EEG measures provide a promising index of large-scale neural noise and excitation–inhibition balance, their interpretation requires methodological rigor and theoretical caution.

2.8 Schizotypy and the Continuum Model

Schizotypy refers to a set of personality traits that resemble symptoms observed in schizophrenia and other psychotic disorders, but in a milder form. Research increasingly suggests that schizotypal traits exist along a continuum and vary in degree across the general population (Asai et al., 2011; Barrantes-Vidal et al., 2020; DeRosse & Karlsgodt, 2015; McCarthy, 2015). From this perspective, psychotic experiences are not viewed as all-or-nothing phenomena, but as part of a gradual spectrum ranging from typical experiences to severe clinical symptoms.

Schizotypy is usually divided into three dimensions: positive traits, such as unusual perceptual experiences; negative traits, such as social withdrawal and reduced emotional expressiveness; and disorganized traits, such as cognitive disorganization and odd speech patterns. Although individuals with elevated schizotypal traits may show a higher vulnerability to mental health difficulties, most do not develop a psychotic disorder (Barrantes-Vidal et al., 2020; Ettinger et al., 2014; Fonseca-Pedrero et al., 2025). This continuum model suggests that higher levels of schizotypal traits may be associated with psychotic-like experiences and may serve as indicators of latent psychosis risk, particularly in non-clinical populations. In addition, schizotypy shares certain neurobiological and genetic features with schizophrenia without constituting a disorder itself (Ettinger et al., 2014; Federmann et al., 2025), making it a useful framework for studying vulnerability to psychosis.

According to Barrantes-Vidal et al.(2020) and Ettinger et al.(2014) schizotypy can be understood as a spectrum of characteristics that resemble schizophrenia, but in attenuated form. Although direct evidence linking schizotypy to aperiodic neural activity remains limited, both schizophrenia and schizotypy have been associated with disturbances in oscillatory EEG activity across multiple frequency bands. Individuals with schizophrenia show altered topography in theta and alpha neural responses (Basar-Eroglu et al., 2008; Koshiyama et al., 2021), as well as changes in gamma oscillations (Sun et al., 2011). Similar, though less pronounced, alterations have also been reported in individuals with high schizotypal traits (Hu et al., 2020; Koychev et al., 2010; McCarthy, 2015). Together, these findings support the view that schizophrenia and schizotypy lie on a continuum and may share underlying neurophysiological mechanisms (Barrantes-Vidal et al., 2020; Ettinger et al., 2014). In this study, schizotypal traits were assessed using the Oxford-Liverpool Inventory of Feelings and Experiences (OLIFE) (Mason et al., 1995, 2005), a questionnaire which is widely used to measure schizotypy related personality traits in non-clinical population. For the Italian version of the questionnaire, administered to Italian-speaking participants, we relied on the translation from Cella et al. (2013).

2.9 Study Rationale

Internal noise is an unavoidable and fundamental source of variability that shapes perceptual experience, whereas external noise can be reduced or controlled in an experimental setting. This distinction is important because it allows the present study to focus on internal neural noise as a principal source of perceptual differences once external sources of noise are experimentally constrained.

Despite growing interest in the role of neural noise in perception and cognition, relatively few studies have directly examined its relationship within the schizophrenia spectrum, with no evidence on schizotypal traits. Most existing research relies on indirect proxies for internal noise, such as behavioral variability or age-related changes, rather than measuring neural noise more directly through EEG (Cessa et al., 2025; Di Ponzio et al., 2024). Consequently, there remains a substantial gap in understanding how internal neural noise interacts with schizotypy to influence perceptual processing.

Furthermore, behavioral work has proposed that schizotypal traits may influence motion-perception performance under different external-noise conditions, potentially by altering the

interaction between internal and external noise (Cessa et al., 2025), these findings are often based on indirect measures and do not account for the underlying neurophysiological mechanisms. Direct evidence combining EEG-derived indices of neural noise with behavioral assessment remains limited. Such studies are important for clarifying whether neural noise could serve as a reliable biomarker of schizophrenia, particularly if observed in non-clinical at-risk populations, where confounding factors associated with clinical samples, such as medication and illness duration, are minimized. Overall, the literature highlights the need for integrated EEG and behavioral research that directly links neural noise, schizotypal traits, and perceptual accuracy, thereby addressing both the mechanistic and functional aspects of this relationship.

2.10 Rationale for Studying Schizotypy

Studying schizotypal traits has several important advantages. Clinical samples are often affected by confounding factors such as long-term medication use, illness duration, hospitalization, and general health problems, all of which may influence brain activity and EEG measurements. By contrast, studying schizotypal traits in non-clinical populations allows brain and behavioral processes to be examined in a more controlled way, with reduced influence from these confounding factors. It also offers the possibility of identifying early markers of psychosis risk before the onset of clinical disorder, which may have important implications for prevention.

Investigating schizotypal traits in healthy individuals therefore provides a useful approach for identifying early neural characteristics associated with psychosis vulnerability. If specific changes in brain activity or EEG patterns are found to be related to schizotypy, this would suggest that such neural features may reflect vulnerability-related markers rather than simply the consequences of illness. In this way, studying non-clinical schizotypy offers a valuable framework for testing whether neural noise may serve as a marker of increased risk for psychosis.

2.11 Present Study

In the present study, we investigate how internal neural noise influences visual perception under experimentally manipulated external noise conditions. Specifically, we examine the relationship between neural noise, schizotypy, and perceptual accuracy using EEG. This work extends the preregistered behavioral protocol by Cessa et al. (2025), which proposed that

schizotypal traits may influence perceptual accuracy through neural noise acting as a mediator. Building on that framework, the present study systematically manipulates external noise in a random dot kinematogram task to examine individual differences in internal neural noise and to test whether these differences are associated with shifts in perceptual performance across levels of external noise. Whereas the original behavioral protocol relied on indirect proxies such as behavioral performance and stochastic resonance to estimate neural noise, the present study examines it more directly using EEG. Specifically, the study quantifies the aperiodic (1/f-like) component of the EEG signal, which provides a physiologically grounded index of large-scale neural activity. Although interpreting aperiodic activity as internal neural noise remains a working hypothesis rather than a direct measurement, this approach offers a more mechanistic assessment of neural variability than behavioral proxies alone. Combining these EEG-derived indices with behavioral measures therefore allows a more direct test of whether individual differences in aperiodic activity are related to perceptual performance under varying levels of external noise, while extending earlier behavioral paradigms.

The present study therefore aims to examine whether neural noise, as quantified by the aperiodic (1/f) component of the EEG signal, is associated with schizotypal traits and how it relates to perceptual accuracy under controlled visual noise conditions.

2.12 Hypotheses

Based on the theoretical framework outlined above, the present study tests whether individual differences in resting-state aperiodic neural activity are related to schizotypal traits and perceptual performance. In addition, the study examines whether internal neural noise interacts with externally manipulated visual noise and if they both influence accuracy in the task. These hypotheses are designed to connect the behavioral and EEG components of the study within a common neural-noise framework.

- H1: Schizotypal traits will be associated with changes in perceptual accuracy.
- H2: Higher levels of neural noise, reflected in a flatter 1/f slope, will be associated with higher schizotypal trait scores.
- H3: Higher neural noise will be associated with reduced perceptual accuracy
- H4: The effect of dot density on perceptual accuracy will be moderated by resting-state aperiodic neural activity.

Together, these hypotheses examine whether behavioral performance and EEG-based measures of neural noise are related to schizotypal traits, and whether neural noise may contribute to perceptual differences relevant to psychosis vulnerability.

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3. Method

3.1 Participants

Forty-two participants were initially recruited through university mailing lists, campus advertisements, online student platforms, and colleagues' referrals as part of a broader data collection project. Following the application of predefined exclusion criteria and quality-control procedures, including the removal of datasets with incomplete behavioral responses, excessive EEG artefacts, or recording failure, 28 participants were retained for the main behavioral–EEG analyses. For the resting-state pre–post stability analysis, usable data were available from 34 participants. Sample sizes are therefore reported separately for each analysis throughout the thesis, in line with the structure of the Results section. All included participants reported normal or corrected-to-normal vision and no history of psychotic disorders. Exclusion criteria included self-reported visual impairment, and excessive EEG artefact contamination during preprocessing. The final behavioral–EEG sample ($N = 28$) had a mean age of 22.54 years ($SD = 2.64$, range = 19–31) and included 21 female and 7 male participants. The study was approved by the Ethics Committee of the Department of General Psychology at the University of Padua [protocol number: 1453-b] and was conducted in accordance with the Declaration of Helsinki. All participants provided online informed consent prior to participation.

3.2 Measures

3.2.1 Schizotypy Questionnaire

Schizotypal characteristics were assessed using the Oxford–Liverpool Inventory of Feelings and Experiences (O-LIFE; Mason et al., 1995), a 104-item self-report instrument grounded in a dimensional model of schizotypy. In line with empirical support for a three-factor structure (Fonseca-Pedrero et al., 2015), the analyses focused on three subscales: Unusual Experiences (positive schizotypy), Cognitive Disorganization, and Introvertive Anhedonia (negative schizotypy). The Impulsive Nonconformity subscale was excluded because of its more limited

predictive validity in non-clinical samples (Chapman et al., 1994; Polner et al., 2021). All questionnaires were administered online prior to the EEG session.

3.2.2 EEG Recording

Electroencephalography (EEG) was recorded using a BioSemi ActiveThree system with 64 active scalp electrodes arranged according to the extended international 10–20 system. Signals were digitized at a sampling rate of 1024 Hz using the CMS/DRL reference configuration and were subsequently downsampled to 256 Hz prior to preprocessing. The data were stored for offline analysis and following preprocessing the EEG signals were re-referenced to the common average across all scalp electrodes.

3.3 Task and Procedure

Participants performed a two-interval forced-choice (2IFC) motion coherence task using random-dot kinematograms (RDKs) implemented in PsychoPy. The task was presented on a monitor with a 1920 × 1080-pixel resolution and a 60 Hz refresh rate. Participants were seated at a viewing distance of approximately 57 cm from the screen in a dimly lit room. The stimuli consisted of white dots presented on a black background within a circular aperture subtending approximately 10° of visual angles. The task was designed to assess perceptual sensitivity to coherent motion while systematically varying stimulus density and minimizing response bias.

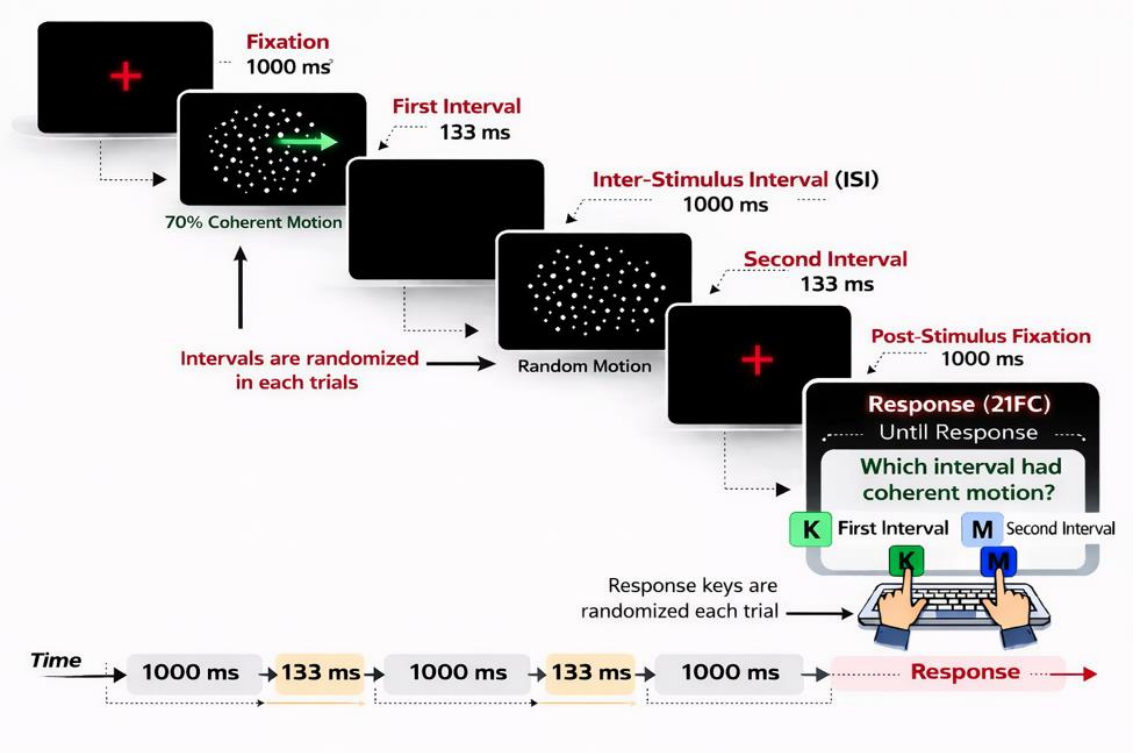

Figure 2. Schematic illustration of the two-interval forced-choice random-dot kinematogram task. Each trial began with a 1000 ms fixation, followed by two 133 ms stimulus intervals separated by a 1000 ms inter-stimulus interval, and a final 1000 ms fixation before the response screen. One interval contained coherent motion (70% coherence) and the other random motion (0% coherence). Interval order and response mapping were randomized on each trial.

Participants first completed the O-LIFE questionnaire online prior to the laboratory session. Upon arrival at the laboratory, they were welcomed, provided consent, and their demographic information and eligibility criteria were confirmed. EEG electrodes were then applied using a 64-channel BioSemi ActiveThree system, and electrode offsets were checked and maintained within the manufacturer-recommended range throughout preparation. The experimental session began with a three-minute eyes-closed resting-state EEG recording. Participants were instructed to relax, remain still, and keep their eyes closed.

Following the resting-state recording, participants completed a 10-trial practice block of the motion coherence task to familiarize themselves with the procedure. Each trial began with a 1000 ms fixation cross, followed by two sequential RDK intervals (133 ms each) separated by a 1000 ms inter-stimulus interval. A final 1000 ms fixation period preceded the response phase. Each trial contained one coherent-motion interval (70% coherence) and one random-motion interval (0% coherence), presented in randomized order. Coherent motion was always rightward. Dot numerosity varied across trials to familiarize participants with the full range of stimulus densities used in the main experiment. Responses were made using the keyboard, with the K and M keys assigned to the first and second interval in randomized order on each trial to reduce motor preparation and response bias. Immediate feedback (“Correct” or “Wrong”) was provided during practice only. Practice data was not included in the analysis.

The main task followed the same temporal structure. Stimuli were presented within a circular aperture of approximately 10° of visual angle. Dot speed (approximately 2°/s) and dot lifetime were held constant across trials. Dot numerosity varied systematically across 14 levels (20, 29, 41, 58, 83, 118, 168, 239, 340, 485, 691, 999, 1403, and 2000 dots), with 10 repetitions per condition. The full task comprised 280 trials in total. Participants completed the task while continuous EEG was recorded. The task was divided into four equal blocks to minimize fatigue, and short self-paced breaks were allowed after each block. No accuracy feedback was given during the main task to minimize learning effects and strategy adjustments across trials. Event triggers were sent at the onset of each stimulus interval, with distinct codes indexing interval position and stimulus type.

After completion of the task, a second three-minute eyes-closed resting-state EEG recording was obtained using the same instructions as in the pre-task session. This post-task recording allowed the assessment of within-session stability in aperiodic neural measures. At the end of the session, EEG electrodes were removed, participants were debriefed, and any questions were addressed.

3.4 Design

The study employed a within-session experimental design combining resting-state EEG, behavioral assessment, and self-report measurement of schizotypal traits. Participants first completed a schizotypy questionnaire, the O-LIFE, available in the English version (Mason et al., 2005) or the Italian version (Cella et al., 2013) followed by a laboratory session including pre-task resting-state EEG, a motion coherence discrimination task, and post-task resting-state EEG. External noise was manipulated through dot numerosity in the visual task, while internal neural noise was indexed using resting-state aperiodic EEG activity.

3.4.1 Variables

The primary experimentally manipulated variable was dot numerosity, defined as the total number of moving dots presented on each trial of the motion coherence task. Dot numerosity varied parametrically across trials and served as the study's manipulation of external visual noise. Increasing the number of dots increased stimulus density and correspondence ambiguity within the fixed circular aperture, thereby making coherent motion more difficult to isolate perceptually. For this reason, dot numerosity was treated as the experimental manipulation of externally introduced noise. For this reason, dot numerosity was treated as the experimental manipulation of externally introduced noise.

Neural noise was measured as the aperiodic exponent (1/f slope) derived from parameterization of the resting-state EEG power spectrum. Flatter slopes were interpreted as reflecting higher levels of intrinsic neural noise. Where relevant, the aperiodic offset was also examined as a complementary broadband spectral measure.

Schizotypal traits were measured using scores from a multidimensional schizotypy questionnaire administered prior to the laboratory session. Both total schizotypy scores and subscale scores reflecting positive, negative, and disorganized dimensions were included in the analyses to assess dimension-specific associations with neural noise and behavioral

performance. In separate analyses, schizotypy scores were additionally examined as outcome variables to test whether neural noise was associated with individual differences in schizotypal traits.

The primary dependent variable was perceptual accuracy in the motion coherence discrimination task. At the trial level, accuracy was coded as a binary outcome indicating whether the participant correctly identified the interval containing coherent motion.

3.5 EEG Preprocessing and Feature Extraction

EEG preprocessing was performed in MATLAB(R2025b) using EEGLAB (v2026.0) within a fully scripted pipeline to ensure reproducibility. Because task-related ERP analyses and resting-state spectral analyses have different preprocessing requirements, task EEG and resting-state EEG were processed using closely matched pipelines that differed only where necessary, primarily in the high-pass filter settings and segmentation strategy. In both pipelines, channel locations were assigned using a standardized BioSemi-64 coordinate file and 50 Hz line noise, together with its harmonic at 100 Hz, was attenuated using the CleanLine plugin (bandwidth = 2 Hz) applied to all channels.

For the task EEG recorded during the RDK task, continuous data were band-pass filtered between 0.1 and 40 Hz using zero-phase FIR filtering. To reduce transient high-amplitude artefacts and identify noisy channels, Artifact Subspace Reconstruction (ASR) was then applied. This procedure was used to detect channels with poor signal quality and to suppress large non-stationary artefacts while preserving as much usable data as possible. Segments with strong high-amplitude bursts were corrected rather than discarded outright, and channels identified as noisy were later restored using spherical spline interpolation to the original montage. Ocular and myogenic artefacts were subsequently addressed using independent component analysis (ICA). To improve the stability of the ICA decomposition, the PICARD algorithm was computed on a temporary copy of the data high-pass filtered at 1 Hz, and the resulting ICA weights were then transferred back to the main analysis dataset filtered at 0.1–40 Hz. Independent components were automatically classified using ICLabel, and components with a high probability of reflecting eye activity, muscle artefacts, cardiac activity, line noise, or channel noise were removed using conservative rejection thresholds. After component removal, the data were interpolated back to the full electrode montage and re-referenced to the common average reference.

Task EEG was then segmented into epochs time-locked to stimulus events using a window from −500 to 1000 ms relative to stimulus onset, and baseline correction was applied using the −200 to 0 ms interval. Only trials with correct behavioral responses were retained. Automated epoch rejection combined three criteria: amplitude thresholding (±120 μV), linear trend detection (maximum slope = 75 μV/epoch; minimum $R^2 = 0.50$), and kurtosis-based rejection (±7 SD). This combination provided a consistent approach for removing residual artefacts while maintaining comparability across participants. For ERP analyses, cleaned epochs were averaged separately for coherent-motion and random-motion conditions. Motion-related ERP effects were quantified within a predefined posterior region of interest (O1, O2, Oz, PO3, PO4, PO7, PO8) and a predefined N2 time window of 160–260 ms, based on the expected posterior negativity associated with motion discrimination. In addition to condition-specific averages, coherent-minus-random difference waves were computed to characterize motion-sensitive ERP responses during the task.

Resting-state EEG recorded before and after the task (PRE and POST) was processed using the same general approach, but with settings optimized for spectral estimation. Continuous resting-state data were band-pass filtered between 1 and 40 Hz to reduce slow drift and improve the stability of power spectral density estimates. CleanLine and ASR were then applied using the same parameter settings as in the task pipeline. ICA was again computed using PICARD on a 1 Hz high-pass filtered copy of the data, with ICA weights transferred to the analysis dataset, and ICLabel-based component rejection was applied using the same probability thresholds. After interpolation to the original montage and average re-referencing, the continuous resting recordings were segmented into non-overlapping pseudo-epochs of 2 seconds by inserting regularly spaced markers across the recording. These pseudo-epochs were subjected to the same automated artefact rejection criteria (±120 μV amplitude; 75 μV/epoch trend slope with $R^2 \geq 0.50$; kurtosis ±7 SD), yielding a cleaned set of short segments suitable for spectral analysis.

Preprocessing quality-control outcomes were logged automatically for each participant. For the PRE-resting-state recordings, an average of 1.91 channels were interpolated following ASR-based channel rejection ($SD = 1.95$, range = 0–8). Independent component analysis led to the removal of 5.80 components on average ($SD = 3.98$, range = 1–20). Artefact rejection at the pseudo-epoch level removed 2.14 epochs on average ($SD = 1.70$, range = 0–7), leaving 89.91 retained epochs per participant ($SD = 6.61$, range = 65–116) for spectral estimation.

Power spectral density was computed from the cleaned resting-state pseudo-epochs using Welch's method with a 2-second Hann window, 50% overlap, and an FFT length set to the larger of the window length or the next power of two. Spectra were computed separately for each channel and parameterized over the 2–40 Hz range. The aperiodic component of each spectrum was then estimated in Python using the FOOOF/specparam algorithm (Donoghue et al., 2020), with the aperiodic mode set to fixed. Peak detection was performed relative to the fitted aperiodic background using predefined constraints on peak width, maximum number of peaks, minimum peak height, and detection threshold. Aperiodic offset and exponent values were obtained for each channel, and mean values were then calculated across a predefined posterior region of interest (O1, O2, Oz, PO3, PO4, PO7, PO8) to derive participant-level estimates of resting-state aperiodic activity. These measures were used as indices of intrinsic neural noise in subsequent analyses.

3.6 Data Analysis

3.6.1 Behavioral Data Analysis

For descriptive and correlational analyses, behavioral performance in the motion coherence task was quantified as perceptual accuracy, operationalized as the proportion of correct responses across the 280 trials. Descriptive statistics were computed for perceptual accuracy and the other main study variables, including mean, standard deviation, minimum, and maximum values. In addition, variable distributions were inspected visually using histograms with overlaid density curves to provide a descriptive overview of the sample prior to hypothesis-driven analyses. To characterize behavioral performance, participant-level perceptual accuracy was summarized across the full task and examined descriptively in relation to the range of observed scores. These descriptive analyses were intended to assess overall task performance and the degree of variability across participants.

To test H1, which predicted an association between schizotypal traits and perceptual accuracy, Pearson correlation analyses were conducted between participant-level perceptual accuracy and schizotypy scores. These analyses included both global schizotypy scores and the three schizotypy subscales (Unusual Experiences, Cognitive Disorganization, and Introvertive Anhedonia) to assess dimension-specific relationships.

3.6.2 EEG Data Analysis

To test H2, which predicted that higher levels of neural noise would be associated with higher schizotypal trait scores, Pearson correlation analyses were conducted between resting-state aperiodic EEG parameters and schizotypy measures. To test H3, which predicted an association between neural noise and perceptual accuracy, Pearson correlations were also conducted between resting-state aperiodic parameters and participant-level behavioral accuracy. These analyses included both global schizotypy scores and schizotypy subscale scores to evaluate dimension-specific associations.

To test H4, which predicted that the effect of dot numerosity on perceptual accuracy would be moderated by resting-state aperiodic neural activity, trial-level generalized linear mixed-effects models with a binomial link function were fitted in R using the glmer function from the lme4 package (Bates et al., 2015). In these models, trial accuracy was coded as a binary outcome indicating whether the participant correctly identified the interval containing coherent motion. Dot numerosity was log-transformed and entered as the predictor external noise, and separate models were fitted for the aperiodic exponent and aperiodic offset as moderators. Both neural-noise predictors were standardized prior to analysis, and each model included a random intercept for participant to account for repeated observations within individuals. Because the effect of dot numerosity on perceptual performance was expected to be potentially nonlinear, polynomial models of increasing degree were compared, and the best-fitting model was selected using AICc from the AICcmodavg package (Mazerolle, 2009). Fixed effects were evaluated using Type III Wald χ^2 tests implemented in the car package (Fox & Weisberg, 2019). These models tested the main effects of dot numerosity and aperiodic neural activity, as well as their interaction, to examine whether internal neural noise altered the relationship between external noise and perceptual accuracy.

For resting-state EEG, power spectral density estimates were obtained from the cleaned pseudo-epochs and parameterized using the FOOOF/specparam approach described above. This procedure yielded participant-level estimates of the aperiodic exponent and aperiodic offset, which were interpreted as markers of intrinsic neural noise. Analyses were conducted separately for pre-task and post-task resting-state recordings to examine within-session stability of aperiodic neural activity.

In addition, pre–post correlations were computed for the aperiodic exponent and offset to assess

the stability of these neural measures across the experimental session. Because Pearson correlations can be sensitive to outliers in relatively small samples, Spearman rank correlations were additionally calculated as a robustness check. For the exploratory analyses involving multiple schizotypy subscales, false discovery rate (FDR) correction using the Benjamini–Hochberg procedure was applied to control for Type I error.

For task-related EEG, event-related potentials (ERPs) were computed by averaging cleaned epochs time-locked to stimulus onset separately for coherent-motion and random-motion trials. A motion-related N2-like component was quantified within a predefined 160–260 ms time window over a posterior region of interest (O1, O2, Oz, PO3, PO4, PO7, PO8). Mean amplitudes were calculated separately for coherent and random stimulus conditions, and a difference wave was computed as coherent minus random to characterize motion-sensitive neural activity. Group-level ERP time courses, 95% confidence intervals, and scalp topographies at peak latency were computed to visualize the temporal and spatial characteristics of motion processing. To examine whether this task-related ERP measure was behaviorally relevant, additional Pearson correlations were computed between the posterior coherent-minus-random N2 mean amplitude and perceptual accuracy. Associations with global schizotypy were examined as exploratory analyses.

All statistical analyses were conducted in R (RStudio 2026.01.1+403; R version 4.4.1) and MATLAB(R2025b) using EEGLAB (v2026.0).

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4. Results

4.1 Descriptive Statistics

Variables	Mean	SD	Min	Max
Neural Offset	0.93	0.27	0.5	1.68
Neural Exponent	1.17	0.25	0.68	1.83
Schizotypy	10.82	6.12	2	24
Perceptual accuracy (Proportion Correct)	0.81	0.15	0.46	0.96

Table 1. Descriptive statistics for neural noise parameters, schizotypy scores, and Perceptual accuracy.

As shown in Table 1, neural offset values had a mean of 0.93 (SD=0.27), with scores ranging from 0.50 to 1.68. The neural exponent had a mean of 1.17 (SD=0.25), with values ranging from 0.68 to 1.83. Global schizotypy scores had a mean of 10.82 (SD=6.12), with observed values ranging from 2 to 24. Perceptual accuracy in the motion coherence task had a mean of 0.81 (SD=0.15). This indicates that participants correctly identified the interval containing coherent motion on approximately 81% of trials. Overall, the variables showed sufficient variability across participants to support the subsequent correlational and model-based analyses.

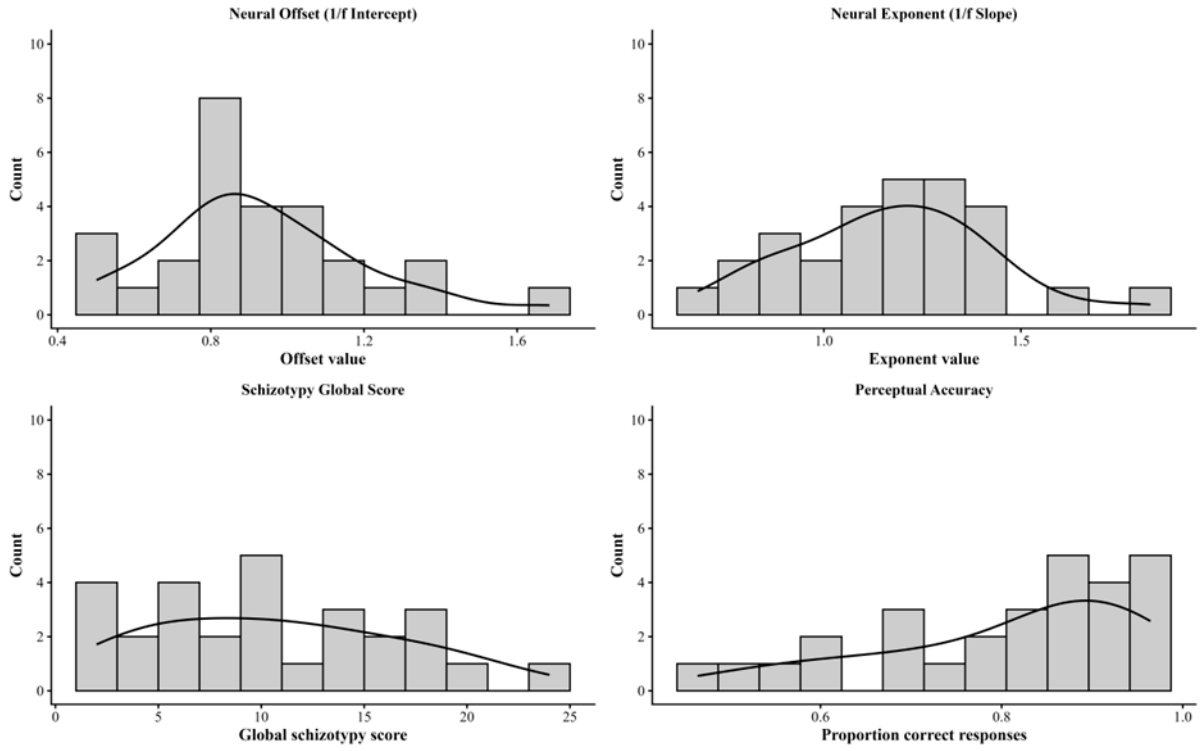

Figure 3. Distribution of neural noise measures, perceptual accuracy, and schizotypy scores. Histograms with overlaid density curves illustrate the distributions of neural exponent (1/f slope), neural offset (1/f intercept), perceptual accuracy, and global schizotypy scores.

As shown in Figure 3, the distributions of the main study variables were inspected visually using histograms with overlaid density curves. Neural exponent values were concentrated primarily between approximately 1.0 and 1.5, with some spread toward lower and higher values. Neural offset values were similarly concentrated in the lower-to-mid range of the observed distribution, with most values falling between approximately 0.7 and 1.2, although a small number of higher values were also present. Perceptual accuracy, defined as the proportion

of correct responses in the motion coherence task, was concentrated toward the higher end of the scale, with most participants achieving values above 0.75, indicating generally high task performance across the sample. In contrast, global schizotypy scores were more broadly distributed across the observed range. Overall, the figure suggests that perceptual accuracy was skewed toward higher values, whereas neural exponent, neural offset, and schizotypy scores showed broader dispersion across participants. These distributions provide a descriptive, visual overview of the sample prior to the hypothesis-driven analyses.

4.2 Behavioral Data Analysis

4.2.1 H1: Schizotypy and Perceptual Accuracy

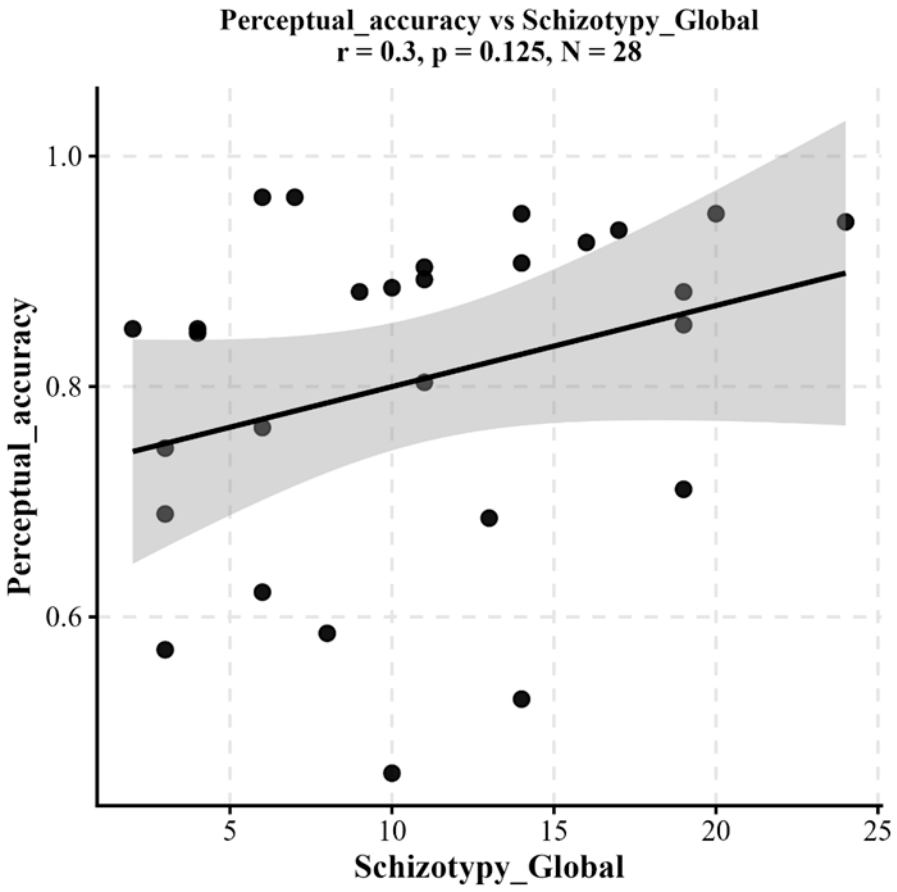

Figure 4. Relationship between global schizotypy and perceptual accuracy. The figure illustrates the

association between global schizotypy scores and perceptual accuracy in the motion coherence task. Each point represents an individual participant, and the regression line indicates the least-squares linear fit with a 95% confidence interval.

To test H1, Pearson correlation analyses were conducted to examine the association between schizotypy and perceptual accuracy in the motion coherence task. The primary analysis focused on global schizotypy scores, and participant-level perceptual accuracy Exploratory analyses additionally examined associations between schizotypy subscales and perceptual accuracy. The analysis revealed a positive, but non-significant, correlation between global schizotypy and perceptual accuracy, $r = .30$, 95% CI $[-.09, .60]$, $p = .125$, $N = 28$. As shown in Figure 4, participants with higher global schizotypy scores tended to show slightly higher perceptual accuracy; however, the confidence interval included zero, indicating that this association was not statistically reliable. As a robustness check, a Spearman rank correlation was also computed. This analysis yielded a similar non-significant result ($\rho \approx .30, p > .05$), suggesting that the observed pattern was not driven by outliers or strong violations of linearity. Overall, these findings do not provide evidence for a statistically significant association between global schizotypy and perceptual accuracy in the present sample. Hypothesis 1 was therefore not supported.

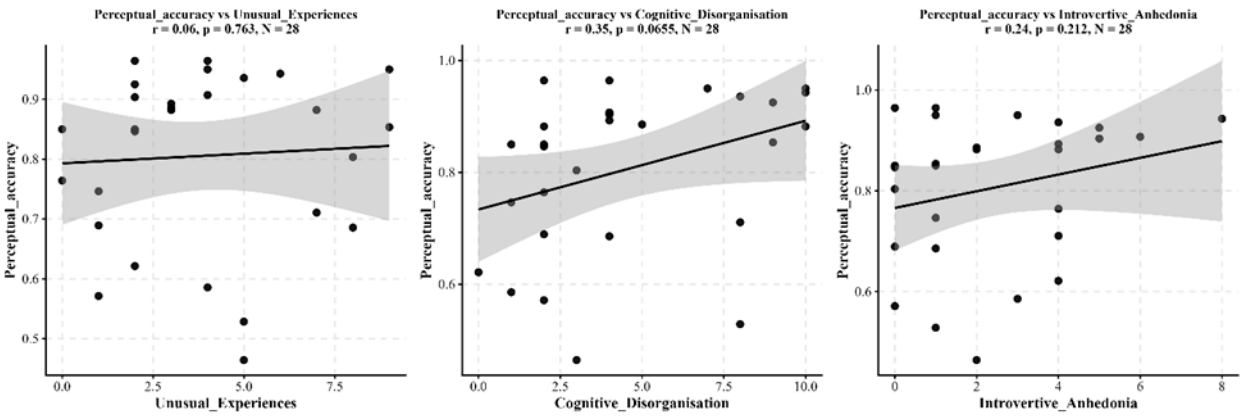

Figure 5. Relationships between schizotypy subscales and perceptual accuracy. The figure illustrates the associations between perceptual accuracy and the three schizotypy subscales: Unusual Experiences, Cognitive Disorganization, and Introvertive Anhedonia. Scatterplots display individual participant data with least-squares regression lines and 95% confidence intervals.

Exploratory Pearson correlation analyses were conducted to examine associations between schizotypy subscales and perceptual accuracy. Because these analyses involved multiple comparisons across the three subscales, false discovery rate (FDR) correction using the Benjamini–Hochberg procedure was applied. The correlation between Unusual Experiences

and perceptual accuracy was small and not statistically significant, $r = .06$, 95% CI $[-.32, .42]$, $p = .763$. Similarly, the association between Introvertive Anhedonia and perceptual accuracy was positive but non-significant, $r = .24$, 95% CI $[-.14, .57]$, $p = .212$. For Cognitive Disorganization, the correlation with perceptual accuracy was positive but did not reach statistical significance, $r = .35$, 95% CI $[-.02, .64]$, $p = .066$. After FDR correction for multiple comparisons, this association remained non-significant ($p_{\text{FDR}} = .196$). Spearman rank correlations were additionally conducted as a robustness check. These analyses showed similar patterns of association and did not materially alter the conclusions. Overall, none of the schizotypy subscales showed statistically significant associations with perceptual accuracy after correction for multiple comparisons. These findings therefore do not provide evidence that individual dimensions of schizotypal traits are associated with perceptual accuracy in the present sample.

4.3 EEG Data Analysis

4.3.1 Stability of Neural Measures (PRE–POST)

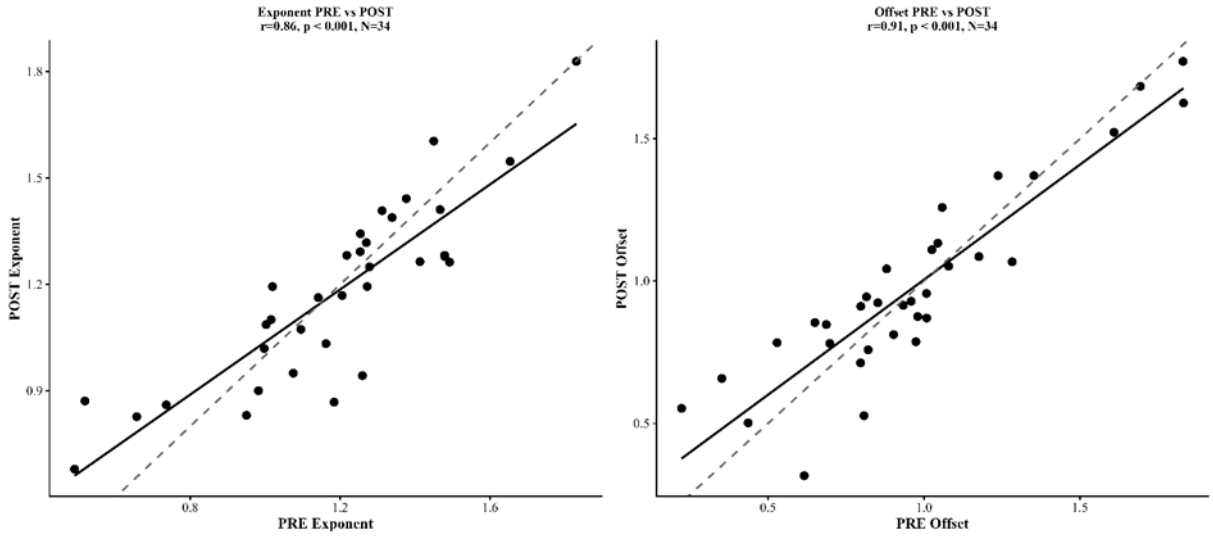

Figure 6. Relationship between pre-task and post-task neural noise measures. The figure illustrates the associations between neural noise parameters measured before (PRE) and after (POST) the task, including the aperiodic exponent (1/f slope) and aperiodic offset (1/f intercept). Scatterplots are shown for each parameter across participants.

To assess the within-session stability of resting-state neural noise measures, Pearson correlations were computed between pre-task and post-task estimates of the aperiodic exponent and offset. As shown in Figure 4, the aperiodic exponent showed a strong positive correlation

between PRE and POST measurements, $r = .86$, $p < .001$, $N = 34$. Participants with higher exponent values before the task generally showed similarly higher values after the task, indicating a high degree of consistency across recording periods. A similarly strong positive association was observed for the aperiodic offset, $r = .91$, $p < .001$, $N = 34$. Higher offset values in the pre-task recording were associated with higher offset values in the post-task recording. The close clustering of observations around the regression lines in both panels further supports the stability of these measures across time. Overall, both aperiodic parameters demonstrated strong and statistically significant pre–post correlations, indicating substantial within-session stability of resting-state neural noise measures.

4.3.2 H2: Schizotypy and Neural Noise

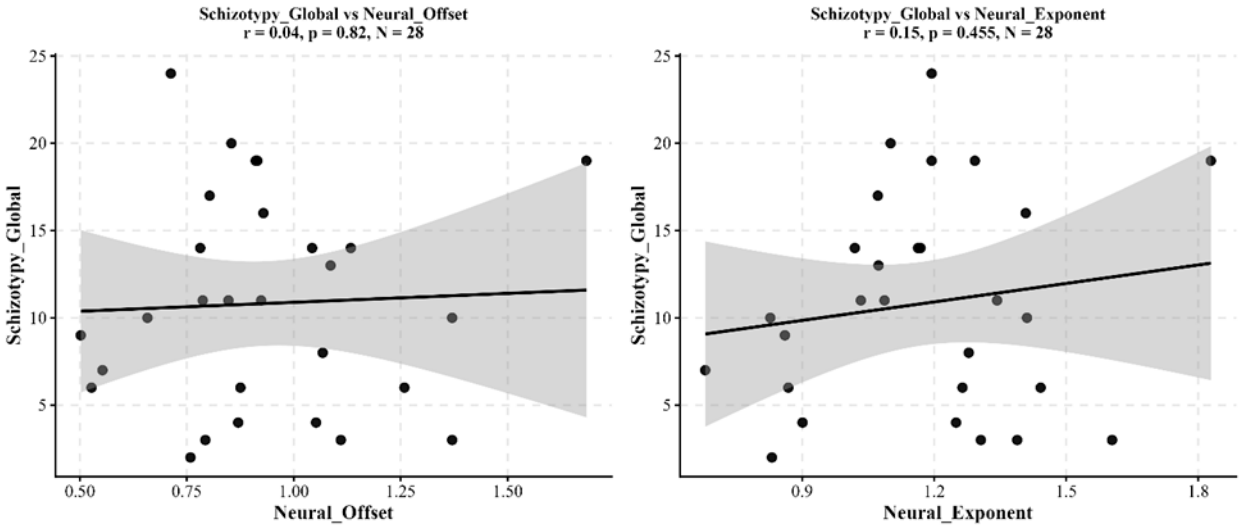

Figure 7. Associations between global schizotypy and neural noise measures. The figure illustrates the relationship between global schizotypy scores, and the resting-state neural noise parameters derived from EEG, including the aperiodic offset and exponent. Scatterplots display individual participant observations with least-squares regression lines and 95% confidence intervals.

To test H2, Pearson correlations were conducted between resting-state aperiodic EEG parameters and schizotypy measures. As shown in Figure 7, the correlation between global schizotypy and neural offset was small and not statistically significant, $r = .04$, 95% CI $[-.33, .41]$, $p = .820$. Similarly, the association between global schizotypy and neural exponent was also small and non-significant, $r = .15$, 95% CI $[-.24, .49]$, $p = .455$. Spearman rank correlations were additionally computed as a robustness check and yielded comparable results (offset: $\rho = .02$, $p = .932$; exponent: $\rho = .04$, $p = .831$), indicating that the findings were not driven by outliers. Overall, these results indicate that global schizotypy

scores were not significantly associated with resting-state neural noise measures in the present sample. Hypothesis 2 was therefore not supported.

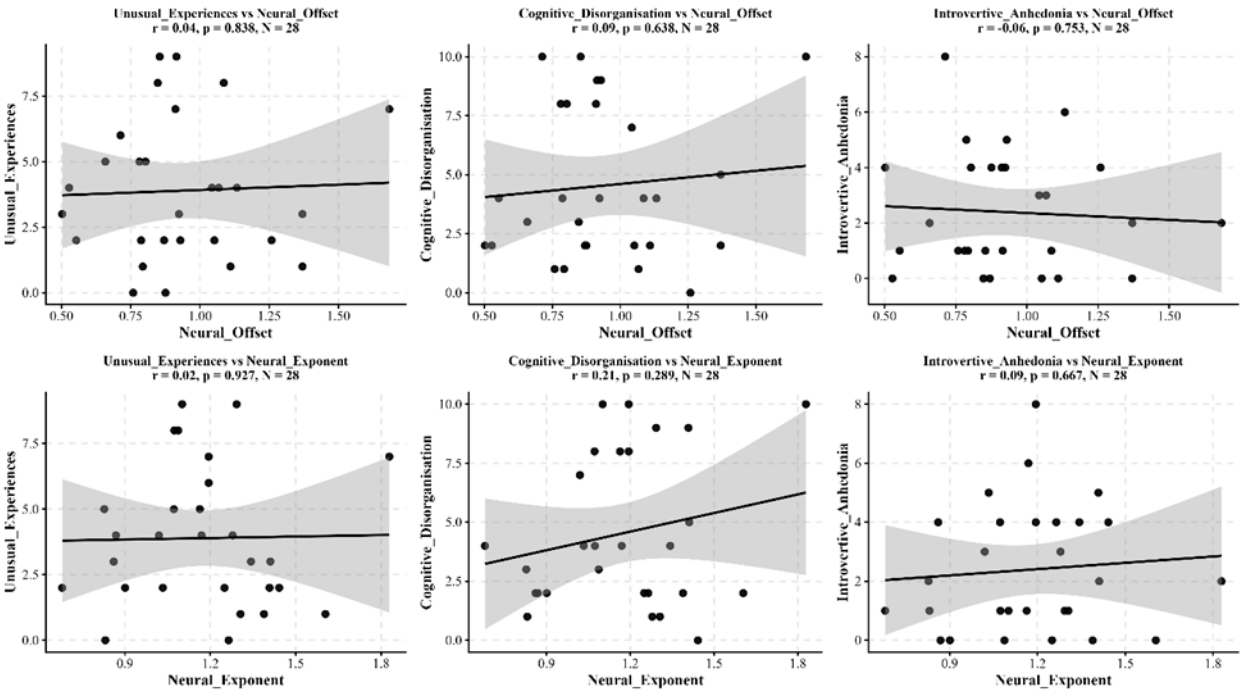

Figure 8. Associations between schizotypy subscales and neural noise measures. The figure illustrates the relationships between the three schizotypy subscales, Unusual Experiences, Cognitive Disorganization, and Introvertive Anhedonia, and the neural noise parameters derived from resting-state EEG (aperiodic offset and exponent). Scatterplots display individual participant observations with regression lines and 95% confidence intervals.

Exploratory Pearson correlation analyses were conducted to examine whether specific schizotypal dimensions were associated with neural noise parameters. For neural offset, correlations with the schizotypy subscales were small and not statistically significant. The association between Unusual Experiences and neural offset was $r = .04$, 95% CI $[-.34, .41]$, $p = .838$. The correlation between Cognitive Disorganization and neural offset was $r = .09$, 95% CI $[-.29, .45]$, $p = .638$. Introvertive Anhedonia also showed a small and non-significant relationship with neural offset, $r = -.06$, 95% CI $[-.43, .32]$, $p = .753$. For neural exponent, similar small and non-significant correlations were observed. The association between Unusual Experiences and neural exponent was $r = .02$, 95% CI $[-.36, .39]$, $p = .927$. Cognitive Disorganization showed a positive but non-significant correlation with neural exponent, $r = .21$, 95% CI $[-.18, .54]$, $p = .289$. Introvertive Anhedonia was also not significantly related

to neural exponent, $r = .09$, 95% CI $[-.30, .44]$, $p = .667$. After FDR correction, none of the correlations remained statistically significant ($p_{\text{FDR}} \geq .927$). Spearman rank correlations yielded comparable patterns of association and did not materially alter the interpretation of the results. Overall, these analyses indicate that none of the schizotypy subscales were significantly associated with resting-state neural noise parameters in the present sample.

4.3.3 H3: Neural Noise and Perceptual Accuracy

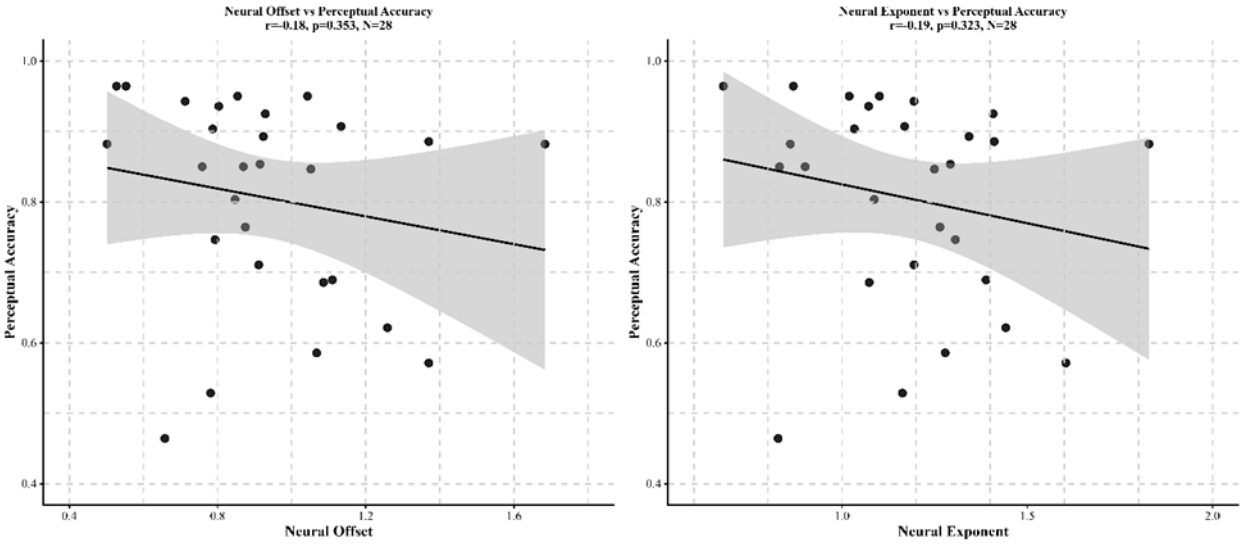

Figure 9. Associations between neural noise measures and perceptual accuracy. The figure illustrates the relationships between resting-state neural noise parameters, specifically the aperiodic offset and exponent, and perceptual accuracy in the motion coherence task. Scatterplots display individual participant observations, with solid lines representing least-squares regression fits and shaded areas indicating 95% confidence intervals.

To test H3, Pearson correlations were conducted between resting-state neural noise parameters and perceptual accuracy. The correlation between neural offset and perceptual accuracy was small and not statistically significant, $r = -.18$, 95% CI $[-.52, .20]$, $p = .353$, $N = 28$. Similarly, the correlation between neural exponent and perceptual accuracy was negative and non-significant, $r = -.19$, 95% CI $[-.53, .19]$, $p = .323$. Spearman rank correlations were additionally computed as a robustness check to evaluate the potential influence of outliers. These analyses yielded comparable results (offset: $\rho = -.25$; exponent: $\rho = -.27$), indicating that the observed associations were not dependent on the choice of correlation metric. Overall, these findings indicate that resting-state neural noise parameters were not significantly associated with perceptual accuracy in the present sample. Hypothesis 3 was therefore not supported.

4.3.4 H4: Aperiodic Neural Noise Moderates the Effect of Dot Numerosity on Perceptual Accuracy

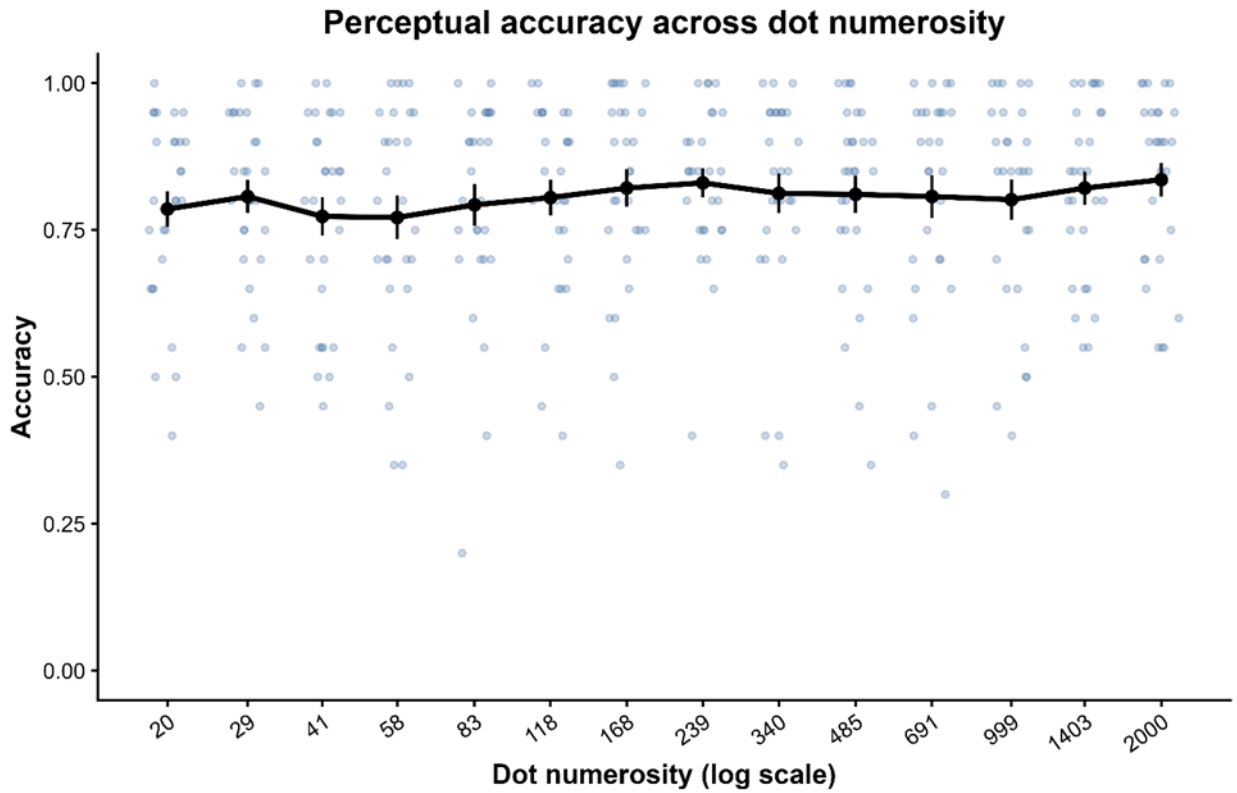

Figure 10. Perceptual accuracy across dot numerosity levels. Individual trial responses are shown as jittered points, while the black line represents mean accuracy at each numerosity level with standard error bars. The x-axis is displayed on a logarithmic scale.

Perceptual accuracy across dot numerosity levels is shown in Figure 10. Individual trial responses are displayed as jittered points, and the black line represents mean accuracy at each numerosity level with standard error bars. Overall, participants showed relatively stable performance across numerosity levels, with mean accuracy ranging from approximately 0.77 to 0.83. Although accuracy varied slightly across levels, participants maintained generally high performance across the full range of dot numerosity levels.

Effects	df	p
Dot numerosity	4	0.00457
Aperiodic offset	1	0.167
Dot numerosity × aperiodic offset	4	0.0948

Table 2. Inferential statistics from the mixed-effects logistic regression model testing whether aperiodic offset moderates the relationship between dot numerosity and perceptual accuracy.

To examine whether resting-state aperiodic offset moderated the relationship between dot numerosity and perceptual accuracy, a trial-level generalized linear mixed-effects model with a random intercept for participant was fitted. Model comparison based on AICc indicated that a quartic polynomial provided the best fit for the relationship between dot numerosity and accuracy. As shown in Table 2, dot numerosity had a significant effect on perceptual accuracy, indicating that performance varied systematically across numerosity levels. By contrast, the main effect of aperiodic offset was not statistically significant, suggesting that resting state offset alone did not directly predict perceptual accuracy. The interaction between dot numerosity and aperiodic offset also did not reach statistical significance, indicating that the relationship between externally introduced visual noise and perceptual accuracy did not differ reliably as a function of resting-state aperiodic offset. Predicted accuracy curves for the offset model are presented in Figure 11.

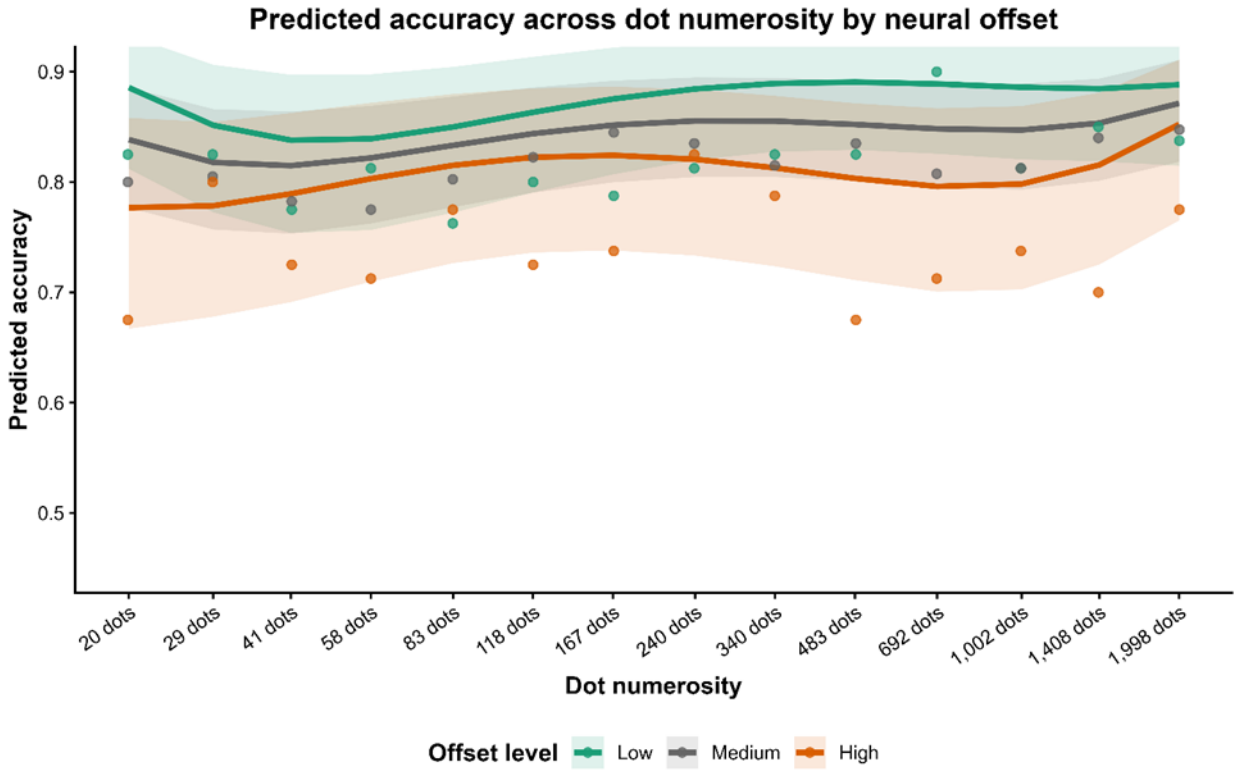

Figure 11. Predicted perceptual accuracy across dot numerosity levels for low, medium, and high neural offset values. Lines represent model-predicted accuracy, and shaded areas indicate confidence intervals.

Figure 11 displays the predicted relationship between dot numerosity and perceptual accuracy at low, medium, and high levels of neural offset. Predicted accuracy curves are shown for each offset level, with shaded areas representing confidence intervals. Across numerosity levels, the curves followed broadly similar patterns, with only modest separation between groups. Participants with lower offset values tended to show slightly higher predicted accuracy across several numerosity levels; however, these differences were small and inconsistent across the range of dot numerosity levels. Consistent with this visual pattern, the interaction between dot numerosity and neural offset did not reach statistical significance in the mixed-effects model, χ^2 (4) = 7.91, p = .095, indicating that neural offset did not significantly moderate the relationship between dot numerosity and perceptual accuracy.

Effect	df	p
Dot numerosity	4	0.00461
Aperiodic exponent	1	0.135
Dot numerosity × aperiodic exponent	4	0.00724

Table 3. Inferential statistics from the mixed-effects logistic regression model testing whether aperiodic exponent moderates the relationship between dot numerosity and perceptual accuracy.

To examine whether resting-state aperiodic exponent moderated the relationship between dot numerosity and perceptual accuracy, a trial-level generalized linear mixed-effects model with a random intercept for participant was fitted. Model comparison based on AICc indicated that a quartic polynomial provided the best fit for the relationship between dot numerosity and accuracy. As shown in Table 3, dot numerosity had a significant effect on perceptual accuracy, indicating that performance varied systematically across numerosity levels. By contrast, the main effect of aperiodic exponent was not statistically significant, suggesting that resting-state exponent alone did not directly predict perceptual accuracy. However, the interaction between dot numerosity and aperiodic exponent was significant, indicating that the relationship between externally introduced visual noise and perceptual accuracy varied as a function of resting-state aperiodic exponent. Predicted accuracy curves for the exponent model are presented in Figure

12.

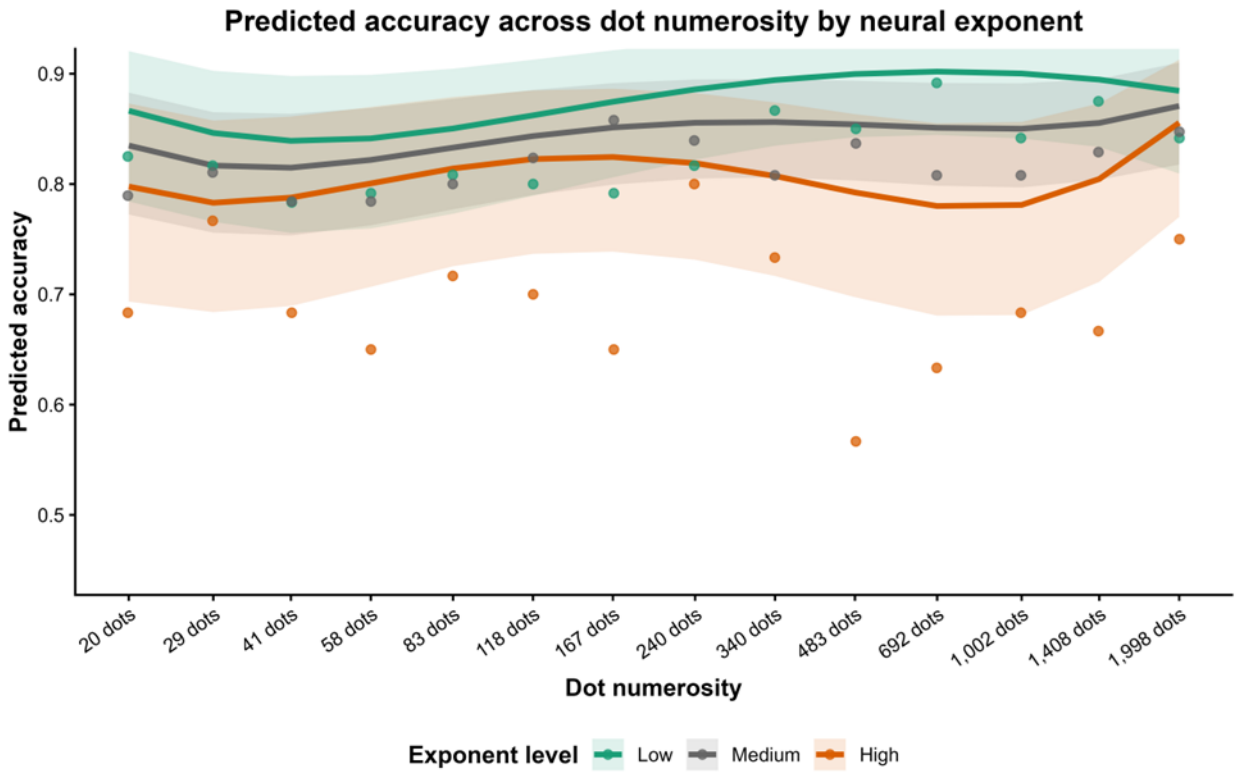

Figure 12. Predicted perceptual accuracy across dot numerosity levels for low, medium, and high neural exponent values. Lines represent model-predicted accuracy, and shaded areas indicate confidence intervals.

Figure 12 displays the predicted relationship between dot numerosity and perceptual accuracy at low, medium, and high levels of neural exponent. Predicted accuracy curves are shown for each exponent level, with shaded areas representing confidence intervals. Across numerosity levels, participants with lower neural exponent values showed higher predicted accuracy than those with higher exponent values. In contrast, participants with higher neural exponent values tended to show lower predicted accuracy across most numerosity levels. This visual pattern is consistent with the significant interaction between dot numerosity, and neural exponent observed in the mixed-effects model, χ^2 (4) = 14.02, p = .007, indicating that the effect of external noise on perceptual accuracy varied as a function of neural exponent.

4.4 Motion-Related ERP Responses During the RDK Task

In addition to the resting-state analyses, task-evoked ERP responses were examined to assess whether coherent motion elicited a reliable posterior N2-like effect during the RDK task and whether this measure was related to behavioral performance.

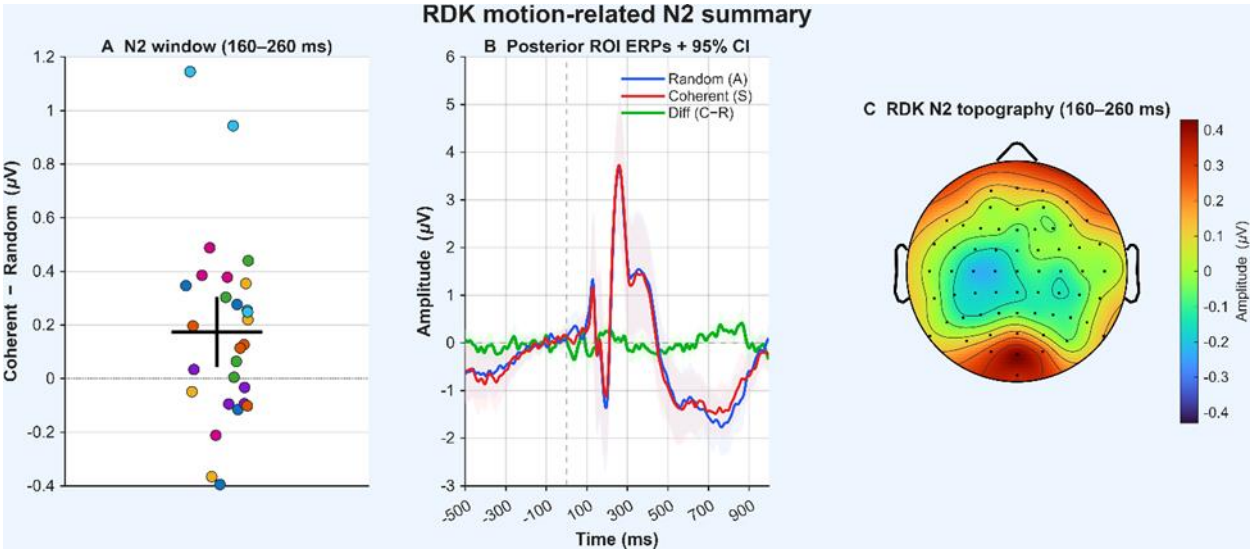

Figure 13. Motion-related ERP responses during the RDK task. **(A)** Individual participants' mean amplitudes for the coherent − random difference within the N2 time window (160–260 ms) over the posterior region of interest (O1, O2, Oz, PO3, PO4, PO7, PO8). Dots represent individual participants, and the black cross indicates the group mean and 95% confidence interval. **(B)** Grand-average ERP waveforms for the random (blue) and coherent (red) motion conditions, together with the difference waveform (coherent − random; green). Shaded areas represent 95% confidence intervals across participants. **(C)** Scalp topography of the coherent − random difference averaged across the N2 time window (160–260 ms), illustrating the spatial distribution of motion-related activity across the scalp.

Event-related potentials were analyzed to examine neural responses to coherent and random motion during the random-dot kinematogram (RDK) task. Analyses focused on a posterior region of interest (ROI; O1, O2, Oz, PO3, PO4, PO7, PO8) and a predefined 160–260 ms time window. This analytic choice was based on prior electrophysiological work showing that coherent motion in RDK paradigms is associated with a posterior N2 component over occipital and occipito-parietal electrodes, typically emerging approximately 200–300 ms after stimulus onset and linked to motion integration and coherent motion processing (Manning et al., 2019; Wei et al., 2019). As shown in Figure 13B, the grand-average ERP waveforms for coherent and random motion conditions were broadly similar over posterior electrodes. Within the predefined N2 time window, the coherent − random difference waveform remained close to zero, indicating only a small modulation of the ERP signal by motion coherence. To quantify this effect, mean amplitudes within the posterior ROI were extracted for each participant and averaged across the N2 window (Figure 13A). The mean coherent − random difference was 0.174 μV, with a 95% confidence interval of [0.042, 0.306]. A one-sample t-test comparing this difference against zero yielded $t = 2.71$, with a one-tailed $p = .994$ under the a priori

prediction of a negative coherent-minus-random effect in this window. This result indicates that the predicted negative modulation of the posterior N2-like response by coherent motion was not observed in the present dataset. The scalp distribution of the coherent − random difference across the N2 time window is shown in Figure 13C. The topography revealed a posteriorly distributed pattern of activity consistent with visual cortical processing. However, the overall magnitude of the condition difference was small, in line with the waveform results. Overall, these findings suggest that although the motion stimuli elicited typical visual ERP responses, coherent motion did not produce a robust modulation of the posterior N2-like component within the predefined time window in the current sample.

4.4.1 Association between motion-related ERP responses and perceptual accuracy

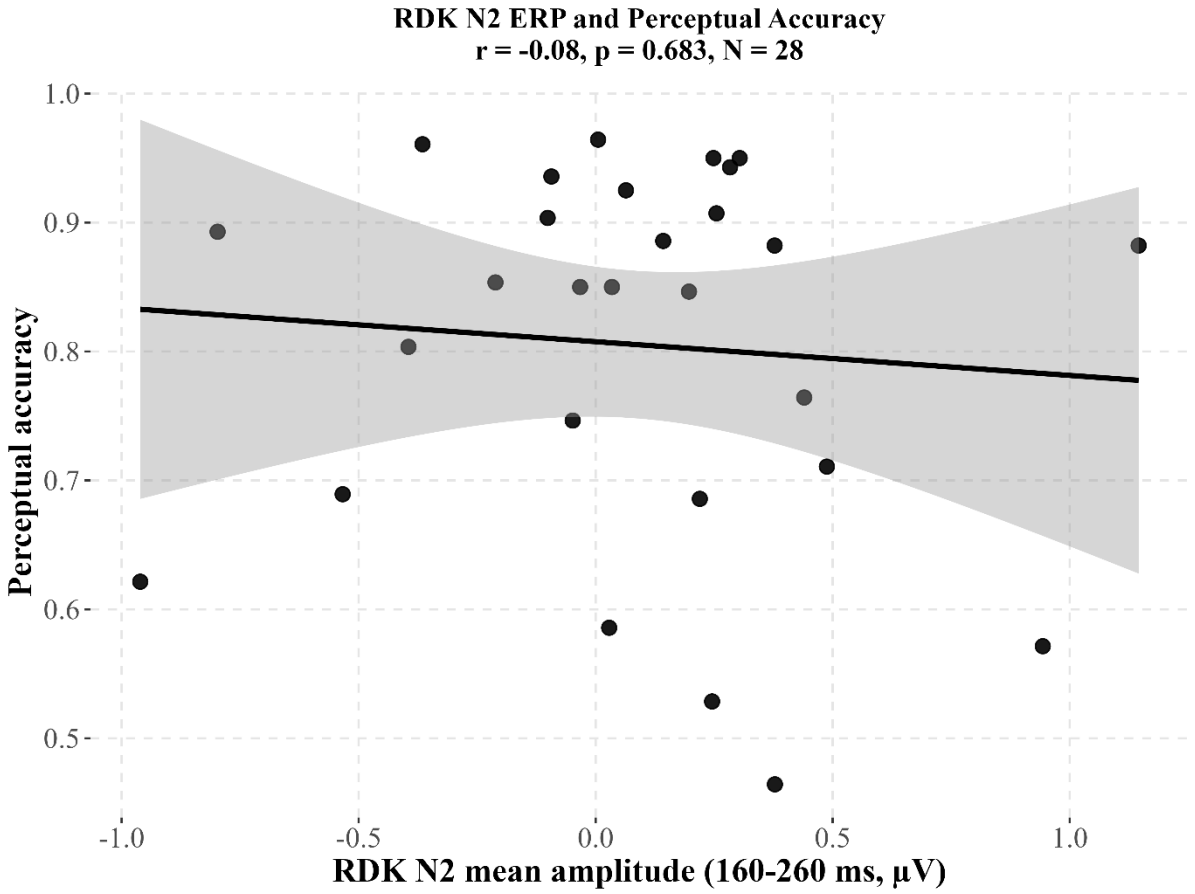

Figure 14. Association between motion-related RDK N2 amplitude and perceptual accuracy. Scatterplot showing the relationship between the posterior RDK N2 mean amplitude (160–260 ms) and perceptual accuracy in the motion coherence task. The solid line represents the linear fit, and the shaded area indicates the 95% confidence interval.

To examine whether the motion-related ERP response was related to behavioral performance, Pearson correlations were computed between the posterior RDK N2 mean amplitude (160–260 ms) and perceptual accuracy in the motion coherence task. As shown in Figure 14, no significant association was observed, $r = -.08$, $p = .683$, 95% CI [−.44, .30]. The direction of the effect was weakly negative, indicating that participants with more positive or less negative N2 amplitudes did not differ reliably in perceptual accuracy from those with more negative amplitudes. A Spearman rank correlation was also calculated as a robustness check and showed a similarly small, non-significant association, $\rho = -.11$, $p = .578$. Overall, these results suggest that individual differences in the posterior N2 mean amplitude were not reliably related to behavioral accuracy in the present sample.

4.4.2 Associations Between Motion-Related ERP Responses and Schizotypy

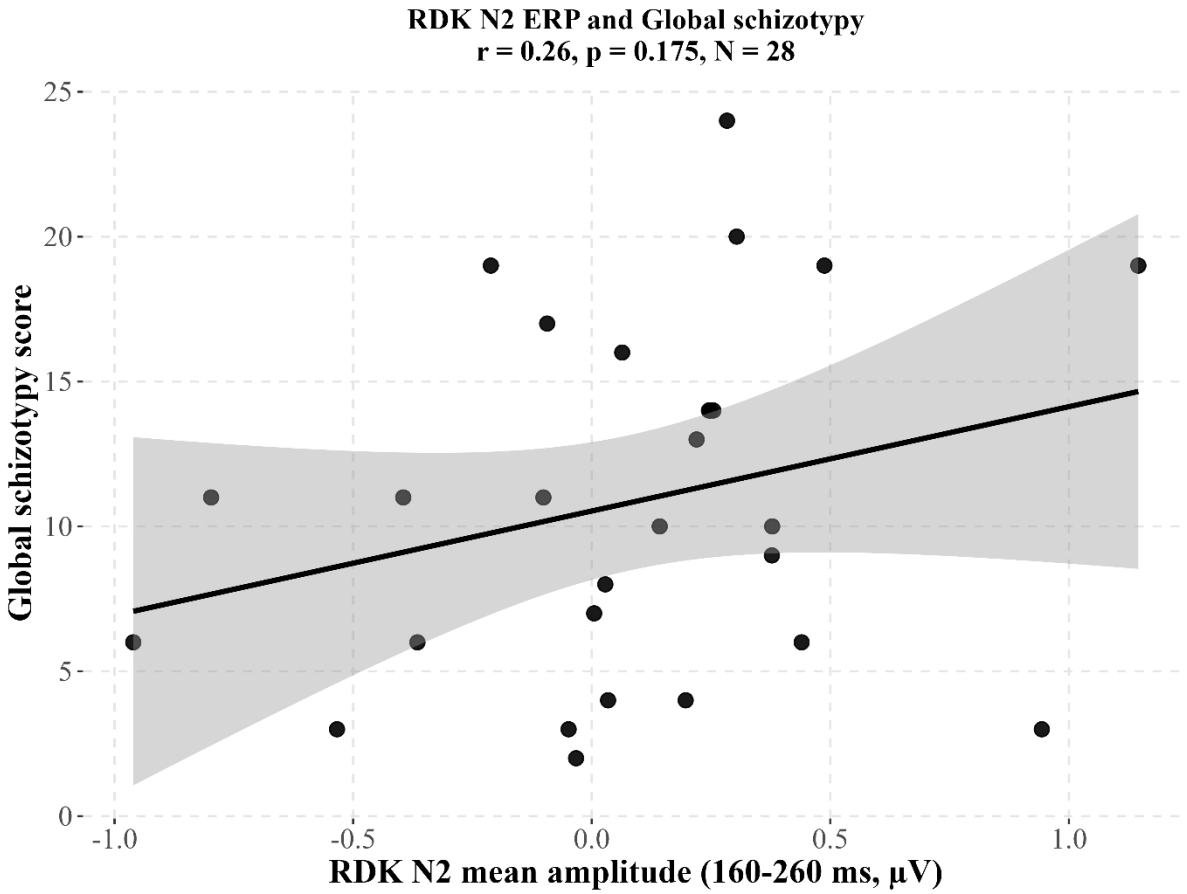

Figure 15. Association between motion-related RDK N2 amplitude and global schizotypy score. Scatterplot showing the relationship between the posterior RDK N2 mean amplitude (160–260 ms) and global schizotypy score. The solid line represents the linear fit, and the shaded area indicates the 95% confidence interval.

As an exploratory analysis, Pearson correlations were computed between the posterior RDK N2 mean amplitude (160–260 ms) and global schizotypy score. As shown in Figure 15, the association was positive but did not reach statistical significance, $r = .26$, $p = .175$, 95% CI [−.12, .58]. This pattern indicates that participants with more positive or less negative N2 amplitudes tended to show somewhat higher schizotypy scores, although this trend was weak and statistically unreliable in the present sample. A Spearman rank correlation was also calculated as a robustness check and showed a similarly small, non-significant association, $\rho = .29$, $p = .141$. Overall, these exploratory results do not provide reliable evidence for an association between the posterior RDK N2 mean amplitude and global schizotypy score.

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5. Discussion

5.1 Summary of Findings

The present study examined whether resting-state neural noise, indexed by EEG-derived aperiodic parameters (the 1/f exponent and offset), was related to schizotypal traits and perceptual accuracy in a motion coherence task. Across the primary correlational analyses, no statistically significant associations were observed between resting-state aperiodic measures, schizotypy scores, and overall perceptual accuracy. These null findings should be interpreted cautiously, however, because they are based on preliminary data from a relatively small sample ($N = 28$), which limited the study's sensitivity to detect small or moderate effects.

Although the main hypothesized associations were not supported, several trends were observed. At the global level, schizotypy scores showed a small positive, but non-significant, association with perceptual accuracy. At the subscale level, Cognitive Disorganization showed the largest positive trend with perceptual accuracy and a small positive association with the aperiodic exponent. At the same time, weak negative trends were observed between the aperiodic parameters and perceptual accuracy, suggesting that higher levels of resting-state neural noise may be associated with slightly poorer task performance. Because these effects were small, statistically non-significant, and did not survive correction for multiple comparisons, they should be interpreted as tentative patterns rather than reliable findings.

Beyond the correlational analyses, the moderation analysis provided partial support for the broader theoretical framework of the study. Specifically, the relationship between dot

numerosity and perceptual accuracy varied as a function of the aperiodic exponent, whereas the corresponding interaction with aperiodic offset was not statistically significant. This suggests that the exponent may capture an aspect of internal neural variability that becomes relevant when perceptual performance is examined under varying levels of externally introduced visual noise. However, because this interaction emerged in the absence of significant main effects linking aperiodic activity to schizotypy or overall task accuracy, it should be treated as preliminary.

The clearest and most robust finding concerned the neural measures themselves. Both the aperiodic exponent and offset showed strong correlations between pre-task and post-task resting-state recordings, indicating substantial within-session stability. Because both recordings were obtained under the same eyes-closed resting conditions and processed using the same preprocessing and spectral parameterization procedures, this high pre–post correspondence suggests that the aperiodic parameters capture relatively stable properties of large-scale cortical activity rather than transient task-induced fluctuations. In this sense, the aperiodic measures appeared more informative as stable neural characteristics than as direct predictors of schizotypal traits or perceptual performance in the present sample.

Task-related ERP analyses showed that the expected posterior N2-like coherent-motion effect was not robust in the present sample, and the N2 mean amplitude was not significantly associated with either perceptual accuracy or global schizotypy.

5.2 Interpretation

The absence of statistically significant associations should be interpreted cautiously considering the limited statistical power of the present dataset. With a relatively small behavioral–EEG sample ($N = 28$), the study may not have been sufficiently sensitive to detect subtle relationships among resting-state neural noise, schizotypy, and perceptual accuracy. Small or moderate effects may therefore have gone undetected. Although several analyses showed weak directional patterns, these did not reach statistical significance and should not be overinterpreted.

From a theoretical perspective, the findings suggest that the relationship between neural noise, schizotypal traits, and perceptual processing may be more nuanced than initially hypothesized. The present results do not support a simple linear association in which greater resting-state

neural noise directly predicts either higher schizotypy scores or lower perceptual accuracy. One possible explanation is that resting-state aperiodic activity reflects a baseline property of cortical network organization that does not necessarily translate directly into observable behavioral differences under relatively stable task conditions. This interpretation is consistent with work suggesting that aperiodic activity indexes broad features of large-scale neural dynamics, while its behavioral significance depends strongly on state, context, and task demands rather than appearing as a uniform trait–outcome relationship across conditions (Donoghue et al., 2020; Gyurkovics et al., 2021; Voytek et al., 2015). In healthy populations, perceptual systems may also operate within a functional range in which compensatory mechanisms help maintain performance despite variability in underlying neural activity (Di Ponzio et al., 2024; Voytek et al., 2015).

Although resting-state aperiodic exponent did not significantly predict overall perceptual accuracy, it did moderate the relationship between dot numerosity and performance. This pattern is broadly consistent with theoretical accounts of stochastic resonance and nonlinear sensory processing, according to which internal variability may become functionally relevant under specific levels of external noise rather than exerting a uniform effect across all conditions (McDonnell & Abbott, 2009; McDonnell & Ward, 2011). However, this result should be interpreted cautiously. The interaction was observed only for the exponent and not for the offset, and it emerged in the absence of significant main effects linking resting-state neural noise to schizotypy or overall task accuracy. For this reason, the present findings provide only partial and preliminary support for the proposed internal–external noise framework.

A further issue concerns the distinction between trait-like and state-dependent aspects of neural noise. The strong pre–post stability observed for the aperiodic exponent and offset suggests that these parameters capture relatively stable characteristics of resting-state cortical dynamics. At the same time, perceptual performance in the motion task may depend more strongly on neural processes that occur during stimulus processing than on resting-state activity measured beforehand (Østergaard et al., 2024). In this sense, resting-state aperiodic activity may reflect relatively stable baseline characteristics of cortical dynamics, whereas perceptual performance may be shaped more directly by moment-to-moment neural responses to the task (Donoghue et al., 2020; Gyurkovics et al., 2021; Østergaard et al., 2024). This interpretation helps explain why the aperiodic measures showed strong pre–post stability but only weak associations with behavior and schizotypy.

Although the motion-related N2 was included as a task-evoked index of coherent motion processing supported by previous research by Manning et al., 2019, the expected coherent-minus-random posterior negativity was not robust in the present sample, and individual differences in N2 amplitude were not significantly related to perceptual accuracy. This suggests that the present dataset did not capture a strong or behaviorally informative motion-sensitive ERP effect, despite the theoretical relevance of the N2 in RDK paradigms (Manning et al., 2019; Wei et al., 2019).

Within the broader psychosis-continuum framework, the present findings further suggest that resting-state neural noise differences alone may not be sufficient to produce measurable behavioral differences in non-clinical populations. Schizotypal traits in healthy individuals reflect mild variation in cognitive and perceptual tendencies (Ettinger et al., 2014) that do not necessarily translate into detectable performance differences in a relatively simple task. This is consistent with dimensional models of schizotypy, which emphasize continuity with psychosis-related traits without implying that non-clinical variation will always produce clear behavioral impairment (Barrantes-Vidal et al., 2020; Ettinger et al., 2014). Neural noise may become behaviorally relevant only when combined with greater vulnerability, more demanding perceptual conditions, or additional neurobiological factors.

5.3 Comparison to Previous Studies

The present study extends previous research on neural noise, perceptual performance, and schizotypy by testing these questions with a more direct electrophysiological measure of neural variability. Earlier behavioral work has suggested that psychophysical stochastic resonance reflects an interaction between internal and external noise, such that performance is not expected to vary linearly with stimulus noise but may instead peak at intermediate levels (Battaglini et al., 2023; Di Ponzio et al., 2024; McDonnell & Abbott, 2009). Building on this framework, recent work proposed that schizotypal traits may be associated with altered performance under varying levels of external noise, using behavioral performance as an indirect way of inferring differences in internal neural noise (Cessa et al., 2025). The present study moves beyond behavioral proxy measures by examining resting-state aperiodic EEG activity directly. However, because most of the observed associations were small and non-significant, the current findings should not be taken as clear support for stochastic-resonance

accounts. Rather, they provide a more cautious test of whether electrophysiological indices of neural variability are related to schizotypy and perceptual performance.

This ERP pattern also differs from previous RDK studies in which posterior N2 amplitude scaled more clearly with motion coherence and was interpreted as a marker of coherent motion processing, suggesting that the motion-sensitive ERP effect may have been weaker or less reliably captured in the present sample (Manning et al., 2019; Niedeggen & Wist, 1999).

Within the broader electrophysiological literature, alterations in aperiodic neural activity have been reported across a wide range of clinical populations, including schizophrenia-spectrum conditions, ADHD, autism, depression, Parkinson's disease, and neurodegenerative disorders. At the same time, this literature is marked by substantial heterogeneity in the direction, magnitude, and anatomical distribution of reported effects. Donoghue's (2025) systematic review of 177 reports across 38 disorders concluded that aperiodic measures often relate to diagnosis, symptoms, or treatment status, but also emphasized that findings vary considerably as a function of clinical heterogeneity, recording state, frequency range, analytic approach, medication status, and other covariates. Importantly, the same review cautioned that the available evidence does not yet support a simple or universally specific biomarker interpretation of aperiodic activity.

Against this background, the absence of statistically significant global associations in the present study is not necessarily inconsistent with previous work. Many stronger effects in the literature have been reported in clinical populations, where symptom severity, neural alteration, and functional impairment are more pronounced (Abbasi et al., 2023; Earl et al., 2024; Peterson et al., 2023; Spencer et al., 2023). In contrast, the current sample consisted of non-clinical participants varying along the schizotypy continuum, where any neural and behavioral differences would be expected to be subtler. This interpretation is consistent with dimensional models of schizotypy, which propose continuity with psychosis-related traits while also implying that non-clinical variation may not always produce clear behavioral or neurophysiological effects (DeRosse & Karlsgodt, 2015).

The present findings suggest that aperiodic activity may be more informative when perceptual performance is examined across varying levels of external noise than when it is examined in relation to overall behavioral accuracy or schizotypy scores (Di Ponzio et al., 2024; McDonnell & Abbott, 2009). In the present study, resting-state aperiodic measures were not significantly

associated with schizotypy or overall perceptual accuracy, but the aperiodic exponent did moderate the relationship between dot numerosity and task performance. Because this effect was observed in a very small sample and in the absence of significant main effects, it should be interpreted cautiously. More broadly, small samples are likely to be underpowered to detect subtle or moderate effects reliably (Button et al., 2013). This limitation is especially important in schizotypy research, where studies examining individual differences typically aim for samples well above the present one, often around 100–150 participants or more (Cella et al., 2013; Fonseca-Pedrero et al., 2015). Consistent with this, our own power analysis based on the existing behavioral data indicated that approximately 90 participants would be required to detect reliable effects, underscoring that the present dataset should be considered highly preliminary. Rather than supporting a strong mechanistic conclusion, the current results suggest only that aperiodic activity may become behaviorally relevant under some conditions. This possibility is broadly compatible with behavioral work showing that the effects of noise on performance can depend on the level of externally introduced noise rather than appearing as a simple uniform effect across conditions (Di Ponzio et al., 2024; McDonnell & Abbott, 2009).

In the present sample, the aperiodic exponent and offset showed strong within-session stability, but their associations with schizotypy and overall perceptual accuracy were weak, and only one moderation effect emerged. Given the small sample size and the predominantly non-significant results, the present data do not support strong claims about the biomarker value of aperiodic activity or about its physiological interpretation. Instead, these findings are better interpreted considering recent methodological discussions emphasizing that aperiodic measures should not be treated too straightforwardly as direct indicators of excitation–inhibition balance or as broadly applicable biomarkers, because findings vary across disorders, analytic approaches, and recording contexts (Donoghue, 2025).

5.4 Clinical Relevance

Although the present findings do not support most of the hypothesized trait-level associations, they may still help inform future clinical research on neural noise and psychosis vulnerability. The strong pre–post stability of the aperiodic exponent and offset suggests that these measures capture relatively stable characteristics of large-scale cortical activity within individuals. In this respect, aperiodic EEG parameters may be useful for describing individual differences in neural

organization, even when they do not map directly onto behavioral performance or schizotypal traits (Donoghue et al., 2020; He, 2014; Voytek et al., 2015).

At the same time, the present results do not support the idea that resting-state aperiodic activity functions as a standalone marker of psychosis vulnerability. This interpretation is consistent with recent literature showing that aperiodic neural activity varies across disorders and is shaped by multiple methodological and physiological factors rather than mapping cleanly onto a single diagnostic category (Donoghue, 2025; Gyurkovics et al., 2021). From a clinical perspective, this supports a multifactorial account of vulnerability, in which aperiodic neural activity is better understood as one component within a broader profile that also includes cognitive, behavioral, and other neurobiological factors (Barrantes-Vidal et al., 2020; DeRosse & Karlsgodt, 2015; Ettinger et al., 2014).

These findings therefore suggest that the clinical relevance of neural noise is likely to emerge most clearly when aperiodic measures are interpreted alongside other markers and within task contexts that place meaningful demands on perception. Rather than supporting strong biomarker claims, the present study supports continued investigation of EEG-derived aperiodic activity as part of a broader and more context-sensitive model of psychosis vulnerability.

5.5 Limitations

Several limitations should be considered when interpreting the present findings. First, and most importantly, the main behavioral–EEG sample was small ($N = 28$), resulting in limited statistical power. This reduced the study's sensitivity to detect small or moderate effects (Button et al., 2013), and increases the possibility of non-significant findings despite the presence of true underlying relationships. As data collection is ongoing, the current results should therefore be regarded as preliminary.

Second, the use of a single perceptual paradigm may limit the generalizability of the findings. More importantly, the present task may also have lacked sufficient sensitivity to detect the hypothesized effects. The paradigm was adapted from Di Ponzio et al., 2024 but did not include the staircase-based thresholding procedure used in that study to calibrate task difficulty before the constant-stimuli block. Because the present version used a fixed task structure, and overall accuracy was relatively high, the task may have been too easy for many participants. This likely

reduced sensitivity to individual differences and may have obscured subtle associations between neural noise, schizotypy, and perceptual accuracy.

A further limitation concerns the interpretation of resting-state aperiodic activity itself. Although EEG-derived exponent and offset parameters provide a useful and biologically grounded index of large-scale neural variability, they capture only one aspect of neural dynamics (Donoghue et al., 2020; Gyurkovics et al., 2021; Voytek et al., 2015). Other features, including oscillatory activity, task-evoked responses, and large-scale network interactions, may also be important for understanding the relationship between neural noise, schizotypy, and perception. More broadly, the present study focused primarily on resting-state measures, which may not fully capture the moment-to-moment neural processes most directly involved in perceptual decision-making during the task.

5.6 Future Directions

The present findings point to several directions for future research. First, increasing the sample size will be essential for improving statistical power and obtaining more precise estimates of the relationships among resting-state neural noise, schizotypal traits, and perceptual accuracy. Because the current behavioral–EEG sample was relatively small, larger datasets will be needed to determine whether the weak patterns observed here reflect reliable effects or sampling variability. Continued data collection and replication in independent samples will therefore be important for establishing the robustness of these associations.

Second, longitudinal designs may help clarify the temporal role of aperiodic neural activity in psychosis-related traits and perceptual processing. The current cross-sectional design cannot determine whether resting-state neural noise precedes perceptual differences, emerges alongside them, or reflects broader developmental changes in cortical organization. Following participants over time may help establish whether aperiodic parameters function primarily as stable markers of individual neural organization, early indicators of vulnerability, or both. This direction is particularly relevant given recent work suggesting that developmental changes in aperiodic activity may be informative for later neurocognitive outcomes (Wilkinson et al., 2025).

Third, future work would benefit from using a broader range of behavioral paradigms. Although the motion coherence task is well suited for studying perceptual decision-making

under visual noise, it captures only one aspect of sensory processing. Neural noise may be related to other domains, such as perceptual uncertainty, attentional control, working memory, or multisensory integration, in ways that were not assessed in the present study. Employing multiple tasks may therefore provide a more comprehensive picture of how neural noise relates to cognition and schizotypal traits.

Finally, future research should integrate aperiodic EEG parameters with other neural indices. Although exponent and offset provide useful information about broadband cortical dynamics, perceptual processing is also shaped by oscillatory activity, task-evoked responses, and large-scale network interactions (Donoghue et al., 2020; Gyurkovics et al., 2021; Voytek et al., 2015). Combining resting-state aperiodic measures with ERP components, oscillatory analyses, or multimodal neuroimaging approaches may provide a more complete account of how neural noise contributes to perception and psychosis-related traits.

5.7 Conclusion

The present study examined whether internal neural noise, indexed by EEG-derived aperiodic activity, was related to schizotypal traits and perceptual accuracy in a visual motion discrimination task. Across the primary correlational analyses, no statistically significant associations were observed between resting-state aperiodic parameters, schizotypy scores, and perceptual accuracy in this non-clinical sample.

At the same time, the findings do not indicate that neural noise is irrelevant to perception. The moderation analysis showed that the relationship between dot numerosity and perceptual accuracy varied as a function of the aperiodic exponent, suggesting that the behavioral relevance of internal neural variability may depend on external sensory conditions rather than appearing as a simple global effect (McDonnell & Abbott, 2009; McDonnell & Ward, 2011). In addition, the strong pre–post stability of the aperiodic parameters indicates that these measures capture relatively stable characteristics of large-scale cortical dynamics.

Taken together, the findings suggest that resting-state aperiodic EEG activity is unlikely to operate as a single predictor of schizotypal traits or perceptual performance in non-clinical populations. Instead, neural variability may be one component within a broader system shaping perception and psychosis-related traits. Despite the modest sample size, the study contributes by moving beyond behavioral proxies and directly quantifying neural noise using

electrophysiological measures, thereby providing a basis for future work using larger samples, longitudinal designs, and more explicit models of internal–external noise interaction.

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6. References

Abbasi, S., Wolff, A., Çatal, Y., & Northoff, G. (2023). Increased noise relates to abnormal excitation-inhibition balance in schizophrenia: A combined empirical and computational study. *Cerebral Cortex*, *33*(20), 10477–10491. https://doi.org/10.1093/cercor/bhad297

Aggarwal, S., & Ray, S. (2025). Changes in Higuchi Fractal Dimension Across Age in Healthy Human EEG Are Anticorrelated With Changes in Oscillatory Power and 1/ *f* Slope. *European Journal of Neuroscience*, *62*(2), e70193. https://doi.org/10.1111/ejn.70193

Arieli, A., Sterkin, A., Grinvald, A., & Aertsen, A. (1996). Dynamics of Ongoing Activity: Explanation of the Large Variability in Evoked Cortical Responses. *Science*, *273*(5283), 1868–1871. https://doi.org/10.1126/science.273.5283.1868

Arnett, A. B., Peisch, V., & Levin, A. R. (2022). The role of aperiodic spectral slope in event-related potentials and cognition among children with and without attention deficit hyperactivity disorder. *Journal of Neurophysiology*, *128*(6), 1546–1554. https://doi.org/10.1152/jn.00295.2022

Asai, T., Sugimori, E., Bando, N., & Tanno, Y. (2011). The hierarchic structure in schizotypy and the five-factor model of personality. *Psychiatry Research*, *185*(1–2), 78–83. https://doi.org/10.1016/j.psychres.2009.07.018

Barlow, H. B. (1956). Retinal Noise and Absolute Threshold. *Journal of the Optical Society of America*, *46*(8), 634. https://doi.org/10.1364/JOSA.46.000634

Barrantes-Vidal, N., Racioppi, A., & Kwapil, T. R. (2020). Schizotypy, schizotypal personality, and psychosis risk. In *Risk Factors for Psychosis* (pp. 81–99). Elsevier. https://doi.org/10.1016/B978-0-12-813201-2.00005-3

Basar-Eroglu, C., Schmiedt-Fehr, C., Marbach, S., Brand, A., & Mathes, B. (2008). Altered

oscillatory alpha and theta networks in schizophrenia. *Brain Research*, *1235*, 143–152. https://doi.org/10.1016/j.brainres.2008.06.114

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using **lme4**. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

Battaglini, L., Casco, C., Fertonani, A., Miniussi, C., Di Ponzio, M., & Vicovaro, M. (2023). Noise in the brain: Transcranial random noise stimulation and perceptual noise act on a stochastic resonance-like mechanism. *European Journal of Neuroscience*, *57*(12), 2097–2111. https://doi.org/10.1111/ejn.15965

Brake, N., Duc, F., Rokos, A., Arseneau, F., Shahiri, S., Khadra, A., & Plourde, G. (2024). A neurophysiological basis for aperiodic EEG and the background spectral trend. *Nature Communications*, *15*(1), 1514. https://doi.org/10.1038/s41467-024-45922-8

Button, K. S., Ioannidis, J. P. A., Mokrysz, C., Nosek, B. A., Flint, J., Robinson, E. S. J., & Munafò, M. R. (2013). Power failure: Why small sample size undermines the reliability of neuroscience. *Nature Reviews Neuroscience*, *14*(5), 365–376. https://doi.org/10.1038/nrn3475

Cella, M., Serra, M., Lai, A., Mason, O. J., Sisti, D., Rocchi, M. B. L., Preti, A., & Petretto, D. R. (2013). Schizotypal traits in adolescents: Links to family history of psychosis and psychological distress. *European Psychiatry*, *28*(4), 247–253. https://doi.org/10.1016/j.eurpsy.2012.04.002

Cessa, R., Contemori, G., Battaglini, L., Cenk, E., & Bertamini, M. (2025). *Stochastic resonance and internal noise in schizotypal traits: A random dot kinematograms paradigm*. Open Science Framework. https://osf.io/nvydj

Chapman, L. J., Chapman, J. P., Kwapil, T. R., Eckblad, M., & Zinser, M. C. (1994). Putatively psychosis-prone subjects 10 years later. *Journal of Abnormal Psychology*, *103*(2), 171–183. https://doi.org/10.1037/0021-843X.103.2.171

Chen, R., Liu, W., Wang, J.-J., Zhou, D.-D., & Wang, Y. (2024). Aperiodic components and aperiodic-adjusted alpha-band oscillations in children with ADHD. *Journal of Psychiatric Research*, *173*, 225–231. https://doi.org/10.1016/j.jpsychires.2024.03.042

Dave, S., Brothers, T. A., & Swaab, T. Y. (2018). 1/f neural noise and electrophysiological indices of

contextual prediction in aging. *Brain Research*, *1691*, 34–43. https://doi.org/10.1016/j.brainres.2018.04.007

Denfield, G. H., Ecker, A. S., Shinn, T. J., Bethge, M., & Tolias, A. S. (2018). Attentional fluctuations induce shared variability in macaque primary visual cortex. *Nature Communications*, *9*(1), 2654. https://doi.org/10.1038/s41467-018-05123-6

Deodato, M., & Melcher, D. (2024). Aperiodic EEG Predicts Variability of Visual Temporal Processing. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, *44*(40), e2308232024. https://doi.org/10.1523/JNEUROSCI.2308-23.2024

DeRosse, P., & Karlsgodt, K. H. (2015). Examining the Psychosis Continuum. *Current Behavioral Neuroscience Reports*, *2*(2), 80–89. https://doi.org/10.1007/s40473-015-0040-7

Di Ponzio, M., Battaglini, L., Bertamini, M., & Contemori, G. (2024). Behavioural stochastic resonance across the lifespan. *Cognitive, Affective, & Behavioral Neuroscience*, *24*(6), 1048–1064. https://doi.org/10.3758/s13415-024-01220-w

Dinstein, I., Heeger, D. J., & Behrmann, M. (2015). Neural variability: Friend or foe? *Trends in Cognitive Sciences*, *19*(6), 322–328. https://doi.org/10.1016/j.tics.2015.04.005

Donoghue, T. (2025). A Systematic Review of Aperiodic Neural Activity in Clinical Investigations. *European Journal of Neuroscience*, *62*(7), e70255. https://doi.org/10.1111/ejn.70255

Donoghue, T., Haller, M., Peterson, E. J., Varma, P., Sebastian, P., Gao, R., Noto, T., Lara, A. H., Wallis, J. D., Knight, R. T., Shestyuk, A., & Voytek, B. (2020). Parameterizing neural power spectra into periodic and aperiodic components. *Nature Neuroscience*, *23*(12), 1655–1665. https://doi.org/10.1038/s41593-020-00744-x

Earl, R. J., Ford, T. C., Lum, J. A. G., Enticott, P. G., & Hill, A. T. (2024). Exploring aperiodic activity in first episode schizophrenia spectrum psychosis: A resting-state EEG analysis. *Brain Research*, *1840*, 149052. https://doi.org/10.1016/j.brainres.2024.149052

Ettinger, U., Meyhöfer, I., Steffens, M., Wagner, M., & Koutsouleris, N. (2014). Genetics, Cognition, and Neurobiology of Schizotypal Personality: A Review of the Overlap with Schizophrenia. *Frontiers in Psychiatry*, *5*. https://doi.org/10.3389/fpsyt.2014.00018

Faisal, A. A., Selen, L. P. J., & Wolpert, D. M. (2008). Noise in the nervous system. *Nature Reviews*

Neuroscience, *9*(4), 292–303. https://doi.org/10.1038/nrn2258

Federmann, L. M., Sindermann, L., Primus, S., Raimondo, F., Oexle, K., Goltermann, J., Winkelmann, J., Nöthen, M. M., Amunts, K., Mühleisen, T. W., Cichon, S., Eickhoff, S. B., Hoffstaedter, F., Dannlowski, U., Patil, K. R., & Forstner, A. J. (2025). Neurobiological correlates of schizophrenia-specific and highly pleiotropic genetic risk scores for neuropsychiatric disorders. *Translational Psychiatry*, *15*(1), 230. https://doi.org/10.1038/s41398-025-03440-1

Findling, C., & Wyart, V. (2021). Computation noise in human learning and decision-making: Origin, impact, function. *Current Opinion in Behavioral Sciences*, *38*, 124–132. https://doi.org/10.1016/j.cobeha.2021.02.018

Fonseca-Pedrero, E., Ortuño-Sierra, J., Sierro, G., Daniel, C., Cella, M., Preti, A., Mohr, C., & Mason, O. J. (2015). The Measurement Invariance of Schizotypy in Europe. *European Psychiatry*, *30*(7), 837–844. https://doi.org/10.1016/j.eurpsy.2015.07.005

Fonseca-Pedrero, E., Pérez-Albéniz, A., Lucas-Molina, B., Al-Halabí, S., & Debbané, M. (2025). Schizotypal Traits, Psychopathology, and Reflective Functioning Impairments During Adolescence: A Bayesian Network Approach. *Schizophrenia Bulletin*, *51*(Supplement_2), S214–S225. https://doi.org/10.1093/schbul/sbae041

Fox, J., & Weisberg, S. (2019). *An R companion to applied regression* (Third edition). SAGE.

Freche, D., Naim-Feil, J., Hess, S., Peled, A., Grinshpoon, A., Moses, E., & Levit-Binnun, N. (2020). Phase-Amplitude Markers of Synchrony and Noise: A Resting-State and TMS-EEG Study of Schizophrenia. *Cerebral Cortex Communications*, *1*(1), tgaa013. https://doi.org/10.1093/texcom/tgaa013

Goldstein, E. B., & Cacciamani, L. (2022). *Sensation and perception* (Eleventh edition, student edition). Cengage.

Guo, D., Perc, M., Liu, T., & Yao, D. (2018). Functional importance of noise in neuronal information processing. *EPL (Europhysics Letters)*, *124*(5), 50001. https://doi.org/10.1209/0295-5075/124/50001

Gyurkovics, M., Clements, G. M., Low, K. A., Fabiani, M., & Gratton, G. (2021). The impact of 1/f

activity and baseline correction on the results and interpretation of time-frequency analyses of EEG/MEG data: A cautionary tale. *NeuroImage*, *237*, 118192. https://doi.org/10.1016/j.neuroimage.2021.118192

Hasanaj, G., Jaeger, I., Karsli, B., Schulz, E., Boudriot, E., Roell, L., Korman, M., Kallweit, M. S., Dengl, F., Klimas, N., Fischer, K., Hanken, K., Meisinger, V., Moussiopoulou, J., Yakimov, V., Karch, S., Hasan, A., Schmitt, A., Falkai, P., … Keeser, D. (2025). Periodic and Aperiodic Alterations of Resting-State EEG in Schizophrenia Spectrum Disorders: Cognitive and Clinical Insights. *European Journal of Neuroscience*, *62*(7), e70263. https://doi.org/10.1111/ejn.70263

He, B. J. (2014). Scale-free brain activity: Past, present, and future. *Trends in Cognitive Sciences*, *18*(9), 480–487. https://doi.org/10.1016/j.tics.2014.04.003

He, B. J., Zempel, J. M., Snyder, A. Z., & Raichle, M. E. (2010). The Temporal Structures and Functional Significance of Scale-free Brain Activity. *Neuron*, *66*(3), 353–369. https://doi.org/10.1016/j.neuron.2010.04.020

Hu, D. K., Li, L. Y., Lopour, B. A., & Martin, E. A. (2020). Schizotypy dimensions are associated with altered resting state alpha connectivity. *International Journal of Psychophysiology*, *155*, 175–183. https://doi.org/10.1016/j.ijpsycho.2020.06.012

Kitajo, K., Nozaki, D., Ward, L. M., & Yamamoto, Y. (2003). Behavioral Stochastic Resonance within the Human Brain. *Physical Review Letters*, *90*(21), 218103. https://doi.org/10.1103/PhysRevLett.90.218103

Koshiyama, D., Miyakoshi, M., Tanaka-Koshiyama, K., Joshi, Y. B., Sprock, J., Braff, D. L., & Light, G. A. (2021). Abnormal phase discontinuity of alpha- and theta-frequency oscillations in schizophrenia. *Schizophrenia Research*, *231*, 73–81. https://doi.org/10.1016/j.schres.2021.03.007

Koychev, I., El-Deredy, W., Haenschel, C., & Deakin, J. F. W. (2010). Visual information processing deficits as biomarkers of vulnerability to schizophrenia: An event-related potential study in schizotypy. *Neuropsychologia*, *48*(7), 2205–2214. https://doi.org/10.1016/j.neuropsychologia.2010.04.014

Kraikivski, P. (2021). Implications of Noise on Neural Correlates of Consciousness: A Computational Analysis of Stochastic Systems of Mutually Connected Processes. *Entropy*, *23*(5), 583. https://doi.org/10.3390/e23050583

Kramer, M. A., & Chu, C. J. (2024). A General, Noise-Driven Mechanism for the 1/f-Like Behavior of Neural Field Spectra. *Neural Computation*, *36*(8), 1643–1668. https://doi.org/10.1162/neco_a_01682

Krystecka, K., Stanczyk, M., Magnuski, M., Szelag, E., & Szymaszek, A. (2024). Aperiodic activity differences in individuals with high and low temporal processing efficiency. *Brain Research Bulletin*, *215*, 111010. https://doi.org/10.1016/j.brainresbull.2024.111010

Kumral, D., Şansal, F., Cesnaite, E., Mahjoory, K., Al, E., Gaebler, M., Nikulin, V. V., & Villringer, A. (2020). BOLD and EEG signal variability at rest differently relate to aging in the human brain. *NeuroImage*, *207*, 116373. https://doi.org/10.1016/j.neuroimage.2019.116373

Lacquaniti, F., La Scaleia, B., & Zago, M. (2023). Noise and vestibular perception of passive self-motion. *Frontiers in Neurology*, *14*, 1159242. https://doi.org/10.3389/fneur.2023.1159242

Lin, A., Maniscalco, B., & He, B. J. (2016). Scale-Free Neural and Physiological Dynamics in Naturalistic Stimuli Processing. *Eneuro*, *3*(5), ENEURO.0191-16.2016. https://doi.org/10.1523/ENEURO.0191-16.2016

Lombardi, F., Herrmann, H. J., & De Arcangelis, L. (2017). Balance of excitation and inhibition determines 1/f power spectrum in neuronal networks. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, *27*(4), 047402. https://doi.org/10.1063/1.4979043

Manning, C., Kaneshiro, B., Kohler, P. J., Duta, M., Scerif, G., & Norcia, A. M. (2019). Neural dynamics underlying coherent motion perception in children and adults. *Developmental Cognitive Neuroscience*, *38*, 100670. https://doi.org/10.1016/j.dcn.2019.100670

Manyukhina, V. O., Prokofyev, A. O., Galuta, I. A., Goiaeva, D. E., Obukhova, T. S., Schneiderman, J. F., Altukhov, D. I., Stroganova, T. A., & Orekhova, E. V. (2022). Globally elevated excitation–inhibition ratio in children with autism spectrum disorder and below-average intelligence. *Molecular Autism*, *13*(1), 20. https://doi.org/10.1186/s13229-022-00498-2

Mason, O., Claridge, G., & Jackson, M. (1995). New scales for the assessment of schizotypy.

Personality and Individual Differences, *18*(1), 7–13. https://doi.org/10.1016/0191-8869(94)00132-C

Mason, O., Linney, Y., & Claridge, G. (2005). Short scales for measuring schizotypy. *Schizophrenia Research*, *78*(2–3), 293–296. https://doi.org/10.1016/j.schres.2005.06.020

Matthews, P., Raul, P., Ward, L. M., & Van Boxtel, J. J. A. (2024). Stochastic resonance in the sensory systems and its applications in neural prosthetics. *Clinical Neurophysiology*, *165*, 182–200. https://doi.org/10.1016/j.clinph.2024.07.004

Mazerolle, M. J. (2009). *AICcmodavg: Model Selection and Multimodel Inference Based on (Q)AIC(c)* (p. 2.3-4) [Dataset]. https://doi.org/10.32614/CRAN.package.AICcmodavg

McCarthy, J. B. (2015). The Continuum of Psychosis Proneness and Schizotypal Traits: A Comment on Loas, *et al.* (2013). *Psychological Reports*, *116*(3), 914–919. https://doi.org/10.2466/02.19.PR0.116k30w2

McCleod, M., Borneman, S., & Malaia, E. (2024). *Neurocomputational Phenotypes in Female and Male Autistic Individuals* (Version 1). arXiv. https://doi.org/10.48550/ARXIV.2405.04248

McDonnell, M. D., & Abbott, D. (2009). What is stochastic resonance? Definitions, misconceptions, debates, and its relevance to biology. *PLoS Computational Biology*, *5*(5), e1000348. https://doi.org/10.1371/journal.pcbi.1000348

McDonnell, M. D., & Ward, L. M. (2011). The benefits of noise in neural systems: Bridging theory and experiment. *Nature Reviews Neuroscience*, *12*(7), 415–425. https://doi.org/10.1038/nrn3061

Miller, K. J., Sorensen, L. B., Ojemann, J. G., & Den Nijs, M. (2009). Power-Law Scaling in the Brain Surface Electric Potential. *PLoS Computational Biology*, *5*(12), e1000609. https://doi.org/10.1371/journal.pcbi.1000609

Moss, F. (2004). Stochastic resonance and sensory information processing: A tutorial and review of application. *Clinical Neurophysiology*, *115*(2), 267–281. https://doi.org/10.1016/j.clinph.2003.09.014

Muthukumaraswamy, S. D., & Liley, D. Tj. (2018). 1/f electrophysiological spectra in resting and drug-induced states can be explained by the dynamics of multiple oscillatory relaxation

processes. *NeuroImage*, *179*, 582–595. https://doi.org/10.1016/j.neuroimage.2018.06.068

Nandi, M. K., Sarracino, A., Herrmann, H. J., & De Arcangelis, L. (2022). Scaling of avalanche shape and activity power spectrum in neuronal networks. *Physical Review E*, *106*(2), 024304. https://doi.org/10.1103/PhysRevE.106.024304

Niedeggen, M., & Wist, E. R. (1999). Characteristics of visual evoked potentials generated by motion coherence onset. *Cognitive Brain Research*, *8*(2), 95–105. https://doi.org/10.1016/S0926-6410(99)00009-9

Nomi, J. S., Bolt, T. S., Ezie, C. E. C., Uddin, L. Q., & Heller, A. S. (2017). Moment-to-Moment BOLD Signal Variability Reflects Regional Changes in Neural Flexibility across the Lifespan. *The Journal of Neuroscience*, *37*(22), 5539–5548. https://doi.org/10.1523/JNEUROSCI.3408-16.2017

Østergaard, F. G., Penninx, B. W. J. H., Das, N., Arango, C., Van Der Wee, N., Winter-van Rossum, I., Luis Ayuso-Mateos, J., R. Dawson, G., Marston, H., & Kas, M. J. H. (2024). The aperiodic exponent of neural activity varies with vigilance state in mice and men. *PLOS ONE*, *19*(8), e0301406. https://doi.org/10.1371/journal.pone.0301406

Ostlund, B. D., Alperin, B. R., Drew, T., & Karalunas, S. L. (2021). Behavioral and cognitive correlates of the aperiodic (1/f-like) exponent of the EEG power spectrum in adolescents with and without ADHD. *Developmental Cognitive Neuroscience*, *48*, 100931. https://doi.org/10.1016/j.dcn.2021.100931

Pathania, A., Euler, M. J., Clark, M., Cowan, R. L., Duff, K., & Lohse, K. R. (2022). Resting EEG spectral slopes are associated with age-related differences in information processing speed. *Biological Psychology*, *168*, 108261. https://doi.org/10.1016/j.biopsycho.2022.108261

Peterson, E. J., Rosen, B. Q., Belger, A., Voytek, B., & Campbell, A. M. (2023). Aperiodic Neural Activity is a Better Predictor of Schizophrenia than Neural Oscillations. *Clinical EEG and Neuroscience*, *54*(4), 434–445. https://doi.org/10.1177/15500594231165589

Ping, A., Guan, L., Gu, H., Jiang, Z., Deng, W., Chen, H., Zeng, K., & Li, X. (2025). *Enhancing Neural Synchrony with Endogenous-like 1/f Noise Stimulation*. Biophysics. https://doi.org/10.1101/2025.04.30.651370

Pinneo, L. R. (1966). On noise in the nervous system. *Psychological Review*, *73*(3), 242–247. https://doi.org/10.1037/h0023240

Pisarchik, A. N., & Hramov, A. E. (2023). Coherence resonance in neural networks: Theory and experiments. *Physics Reports*, *1000*, 1–57. https://doi.org/10.1016/j.physrep.2022.11.004

Polner, B., Faiola, E., Urquijo, M. F., Meyhöfer, I., Steffens, M., Rónai, L., Koutsouleris, N., & Ettinger, U. (2021). The network structure of schizotypy in the general population. *European Archives of Psychiatry and Clinical Neuroscience*, *271*(4), 635–645. https://doi.org/10.1007/s00406-019-01078-x

Reeves, A., Wu, S., & Schirillo, J. (1998). The effect of photon noise on the detection of white flashes. *Vision Research*, *38*(5), 691–703. https://doi.org/10.1016/S0042-6989(97)00201-0

Rosenblum, Y., Bovy, L., Weber, F. D., Steiger, A., Zeising, M., & Dresler, M. (2023). Increased Aperiodic Neural Activity During Sleep in Major Depressive Disorder. *Biological Psychiatry Global Open Science*, *3*(4), 1021–1029. https://doi.org/10.1016/j.bpsgos.2022.10.001

Scarciglia, A., Bonanno, C., & Valenza, G. (2025). Physiological noise: A comprehensive review on informative randomness in neural systems. *Physics of Life Reviews*, *53*, 281–293. https://doi.org/10.1016/j.plrev.2025.04.001

Scarciglia, A., Magliaro, C., Catrambone, V., Bonanno, C., Ahluwalia, A., & Valenza, G. (2025). Distinctive regional patterns of dynamic neural noise in cortical activity. *Journal of Neural Engineering*, *22*(2), 026052. https://doi.org/10.1088/1741-2552/adc33c

Shadlen, M. N., & Newsome, W. T. (1998). The Variable Discharge of Cortical Neurons: Implications for Connectivity, Computation, and Information Coding. *The Journal of Neuroscience*, *18*(10), 3870–3896. https://doi.org/10.1523/JNEUROSCI.18-10-03870.1998

Smyrnis, A., Mantas, A., Klein, C., & Smyrnis, N. (2023). *1/F Noise in Human Cognition as the Signature of Predictive Processing and Not Self-Organized Criticality*. SSRN. https://doi.org/10.2139/ssrn.4618531

Snyder, A. Z., & Raichle, M. E. (2012). A brief history of the resting state: The Washington University perspective. *NeuroImage*, *62*(2), 902–910. https://doi.org/10.1016/j.neuroimage.2012.01.044

Spencer, K. M., Nakhnikian, A., Hirano, Y., & Levin, M. (2023). The contribution of gamma bursting to spontaneous gamma activity in schizophrenia. *Frontiers in Human Neuroscience*, *17*, 1130897. https://doi.org/10.3389/fnhum.2023.1130897

Sun, Y., Farzan, F., Barr, M. S., Kirihara, K., Fitzgerald, P. B., Light, G. A., & Daskalakis, Z. J. (2011). Gamma oscillations in schizophrenia: Mechanisms and clinical significance. *Brain Research*, *1413*, 98–114. https://doi.org/10.1016/j.brainres.2011.06.065

Tran, T. T., Rolle, C. E., Gazzaley, A., & Voytek, B. (2020). Linked Sources of Neural Noise Contribute to Age-related Cognitive Decline. *Journal of Cognitive Neuroscience*, *32*(9), 1813–1822. https://doi.org/10.1162/jocn_a_01584

Voytek, B., Kramer, M. A., Case, J., Lepage, K. Q., Tempesta, Z. R., Knight, R. T., & Gazzaley, A. (2015). Age-Related Changes in 1/*f* Neural Electrophysiological Noise. *The Journal of Neuroscience*, *35*(38), 13257–13265. https://doi.org/10.1523/JNEUROSCI.2332-14.2015

Waschke, L., Donoghue, T., Fiedler, L., Smith, S., Garrett, D. D., Voytek, B., & Obleser, J. (2021). Modality-specific tracking of attention and sensory statistics in the human electrophysiological spectral exponent. *eLife*, *10*, e70068. https://doi.org/10.7554/eLife.70068

Wei, Y., Okazaki, Y. O., So, R. H. Y., Chu, W. C. W., & Kitajo, K. (2019). Motion sickness-susceptible participants exposed to coherent rotating dot patterns show excessive N2 amplitudes and impaired theta-band phase synchronization. *NeuroImage*, *202*, 116028. https://doi.org/10.1016/j.neuroimage.2019.116028

Wilkinson, C. L., Chung, H., Dave, A., Tager-Flusberg, H., & Nelson, C. A. (2025). Changes in Early Aperiodic EEG Activity Are Linked to Autism Diagnosis and Language Development in Infants With Family History of Autism. *Autism Research*, *18*(7), 1356–1368. https://doi.org/10.1002/aur.70063