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Alpha oscillations and aperiodic neural dynamics jointly predict visual temporal resolution, confidence, and dependence on prior experience

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eLife Assessment

This **important** study developed a novel paradigm combined with EEG recordings to examine the neural mechanisms underlying temporal integration in perception and its modulation by prior history (i.e., the serial dependence effect). The results provide **solid** evidence that two key EEG features, namely the individual alpha frequency and the aperiodic slope, jointly and independently shape perceptual integration and its reliance on prior information. While additional control analyses would further strengthen the main conclusions, the findings will be of broad interest to researchers studying perception, decision-making, inter-individual differences, and brain rhythms.

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Abstract

Perception requires integrating sensory input over time to construct coherent experiences. Alpha oscillations have been proposed to define the temporal resolution of perception, yet empirical evidence remains inconsistent. Here we combined a sustained visual integration paradigm with resting-state EEG to investigate how oscillatory and aperiodic neural dynamics jointly shape temporal perception. Participants (n=83) viewed alternating gratings that varied in alternation speed, producing the perception of either a fused plaid (integration) or two interchanging gratings (segregation). Faster individual alpha rhythms were associated with narrower temporal integration windows, and a steeper aperiodic spectrum predicted greater perceptual precision. Moreover, individuals with slower alpha frequencies and flatter spectra showed stronger reliance on prior judgments, suggesting reduced sensory precision and increased weighting of recent experience. Subjective confidence increased with faster alpha rhythms, reflecting the clarity of sensory evidence and its consistency with prior responses. Together, these findings show that the perceptual interpretation, confidence and previous experience effects in temporal integration reflect the joint influence of alpha rhythms and aperiodic neural activity. Mechanistically, faster alpha rhythms and lower neural noise may enhance perceptual resolution by generating more precise sampling frames per time unit, leading to finer temporal perception, reduced reliance on prior experience, and greater confidence.

Introduction

Temporal integration is a fundamental operation in vision: it allows the nervous system to accumulate sensory evidence over brief time intervals so that perception remains robust despite internal noise and external uncertainty[1]. Yet, we still lack a clear account of how the brain sets the temporal window within which sensory signals are bound. In other words, how does the system decide whether two sequential inputs should be integrated or segregated?

A prominent proposal is that rhythmic activity in the alpha band (~8–13 Hz) provides a temporal scaffold for perception. On this view, alpha oscillations define temporal excitation windows that allow for the integration and accurate processing of sensory information[2,3,4,5]. Accordingly, faster individual alpha frequencies (IAFs) would enable finer temporal resolution, whereas slower alpha rhythms would enlarge the integration window and promote binding. However, despite its conceptual appeal, the relationship between alpha oscillations and perception remains debated. Empirical evidence has been mixed, with several recent studies reporting null or even contradictory findings, calling into question the generality of this framework[6,7].

Several factors may underlie these inconsistencies, both methodological and theoretical[5,8,9,10]. One methodological issue is that most previous studies have relied on variants of the *two-flash fusion task*, in which participants judge whether two brief, identical flashes presented in close succession are perceived as one or two distinct events[2]. Within the framework of rhythmic perception, it is hypothesized that stimuli falling within the same alpha cycle are bound into a single percept. However, this interpretation of two flash perception is not unambiguous: because each flash can occur at different phases of the ongoing alpha rhythm, one stimulus might simply be processed suboptimally, yielding an apparent fused percept that reflects detection failure rather than genuine temporal integration[3,9,11,12,13]. One way to address this challenge is to use paradigms in which the stimuli are shown on screen for several seconds[9,10].

On a more theoretical level, there is disagreement over the fundamental mechanisms that link alpha oscillations to visual temporal perception. From a Bayesian perspective, for example, alpha frequency may shape perceptual inference by altering perceptual sensitivity or by adjusting top-down priors[6,14]. However, this framework often overlooks that such priors may be dynamically shaped by recent perceptual experience, which continuously updates internal models and biases the interpretation of incoming sensory information (i.e., serial dependence[15,16]). Critically, recent evidence shows that temporal binding mechanisms are not fixed within individuals but adaptively expand or contract based on prior perception, with events following a binding percept more likely to be experienced as a single unified event[17,18,19]. Interestingly, it has been hypothesized that serial dependence itself may be linked to alpha oscillations. One possibility is that these oscillations facilitate communication, binding current sensory input with recent perceptual history[16,20,21]. It is also plausible that the speed of alpha oscillations affects how strongly past experiences shape current perception. When IAF is slower, temporal resolution and sensory precision may decrease[22], making the brain's estimate of current sensory input more uncertain and thereby increasing reliance on prior experience to stabilize perception.

Another critical aspect that has often been overlooked in studies of temporal integration is its metacognitive dimension. Subjective confidence systematically influences pre- and post-perceptual processing across sensory domains[23,24,25]. Recent evidence suggests that faster alpha rhythms may enhance perceptual resolution by generating more sampling frames per time unit, and that more frequent sampling of sensory input may yield a more faithful representation of external events[22,26,27], thus enhancing perceptual and metacognitive abilities. In sum, the relationship between alpha oscillations and temporal perception may be more multi-layered, resisting a simple, single mechanistic explanation.

Another critical consideration is that the focus on oscillations may ignore a link to aperiodic activity, since the complex nature of visual temporal perception likely depends on multiple neural mechanisms, not only rhythmic oscillations[5,8,28]. Neural activity exhibits a prominent aperiodic *1/f* component reflecting nonrhythmic brain dynamics[29], and while there is growing evidence for the importance of taking aperiodic spectra into account[30], exactly how and why it influences temporal perception is still being explored[5,8]. Flatter spectra, indicating greater neural noise, may disrupt alpha-mediated pulsed inhibition, increasing processing variability and weakening temporal coupling[31,32]. It has been shown that aperiodic activity can influence how rhythmic oscillations organize sensory information over time[5,8]. Under the proposed framework, the association between alpha rhythms and temporal integration emerges only when internal noise is considered, with higher neural noise linked to greater variability of visual temporal processing and longer integration periods[5,8]. Thus, oscillatory and aperiodic neural dynamics may jointly shape visual

temporal integration, providing a more complete account of how the brain samples sensory input over time and potentially explaining recent null findings. In this study, we investigated this potential interaction between aperiodic structure and oscillatory dynamics, in the context of the different aspects and potential mechanisms involved in temporal perception.

To address this challenge, we developed a novel variation of a sustained visual stimulus paradigm[9], based on the perceptual fusion of consecutive visual patterns presented in a temporally extended stream (Fig. 1A). A large sample of participants (n = 83) viewed two low–spatial-frequency Gabor patches oriented in opposite directions (±45°) that alternated in the same spatial location in counterphase over one second. Rather than manipulating the interval between discrete flashes, we varied the duration of each Gabor presentation. This created a continuous visual flow in which shorter durations elicited the illusory perception of a single fused plaid (integration), whereas longer durations produced the perception of two alternating gratings (segregation). This design allowed us to estimate individual temporal integration thresholds while avoiding the confounds of traditional paradigms (e.g., detection failures), providing a more direct measure of perceptual integration[9]. An advantage of continuously presented stimulus streams that integration performance is not confounded with missing a rapidly presented stimulus[9]. Before the behavioral task, we recorded resting-state EEG in both eyes-open and eyes-closed conditions to examine how oscillatory and aperiodic neural dynamics jointly shape visual temporal integration. Critically, we considered the influence of prior perceptual judgment and subjective confidence, relating each of these factors to periodic and aperiodic activity. Including all of these measures of temporal integration performance allowed us to test a mechanistic framework in which faster alpha oscillations within a low-noise neural background enhance the rate and fidelity of visual sampling[5,8,22], thereby increasing temporal precision, reducing dependence on prior perception, and strengthening confidence, together shaping how the visual system dynamically integrates sensory information over time.

Results

Visual temporal binding is dynamically shaped by recent perceptual experience

The sustained stream of visual patterns in our temporal integration task elicited the illusory perception of a single fused plaid (integration) at shorter inter-stimulus intervals (ISIs), whereas longer ISIs induced the perception of two alternating gratings (segregation; Fig. 1A, 1B). This continuous task replicates classical findings from two-flash paradigms while avoiding their confounds[9], providing a more direct measure of perceptual binding. For each participant, we computed the proportion of separate responses across ISI levels and fitted a logistic psychometric function to derive two key parameters: the 50% threshold (Point of Subjective Equality, PSE) and the slope (b). The PSE reflects the temporal boundary between perceptual integration and segregation. The slope typically indexes perceptual sensitivity or internal noise, with steeper slopes indicating higher temporal precision[5,8]. Across participants, the mean temporal integration threshold was centered around ~80 ms (PSE = 77.71 ± 15.66 ms), closely aligning with the frequency of alpha-band oscillations.

Notably, visual temporal processing was not fixed but dynamically modulated by perceptual choice history. To assess this serial dependence effect, trials were binned according to the perceptual outcome of the preceding trial: i) t–1 integration (fused response in the previous trial) and ii) t–1 segregation (separate response in the previous trial). Separate psychometric functions were then fitted for each condition, yielding distinct PSE and slope estimates (Fig. 1B). A repeated-measures ANOVA on PSE values revealed a significant main effect of t–1 judgment ($F(1,82) = 187.15$, $p < 0.001$, $\eta^2p = 0.695$; Fig. 1C), indicating that integration responses were more likely to follow integration trials, whereas segregation judgments increased the likelihood of perceived segregation on the next trial (t–1 integration: M = 85.73, SD = 15.78; t–1 segregation: M = 68.59, SD = 14.58; $p < 0.001$; Cohen's d = 1.13). In contrast, no significant effect of t–1 judgment was found on the slope parameter ($F(1,82) = 0.34$, $p = 0.56$, $\eta^2p = 0.004$). These results show that recent

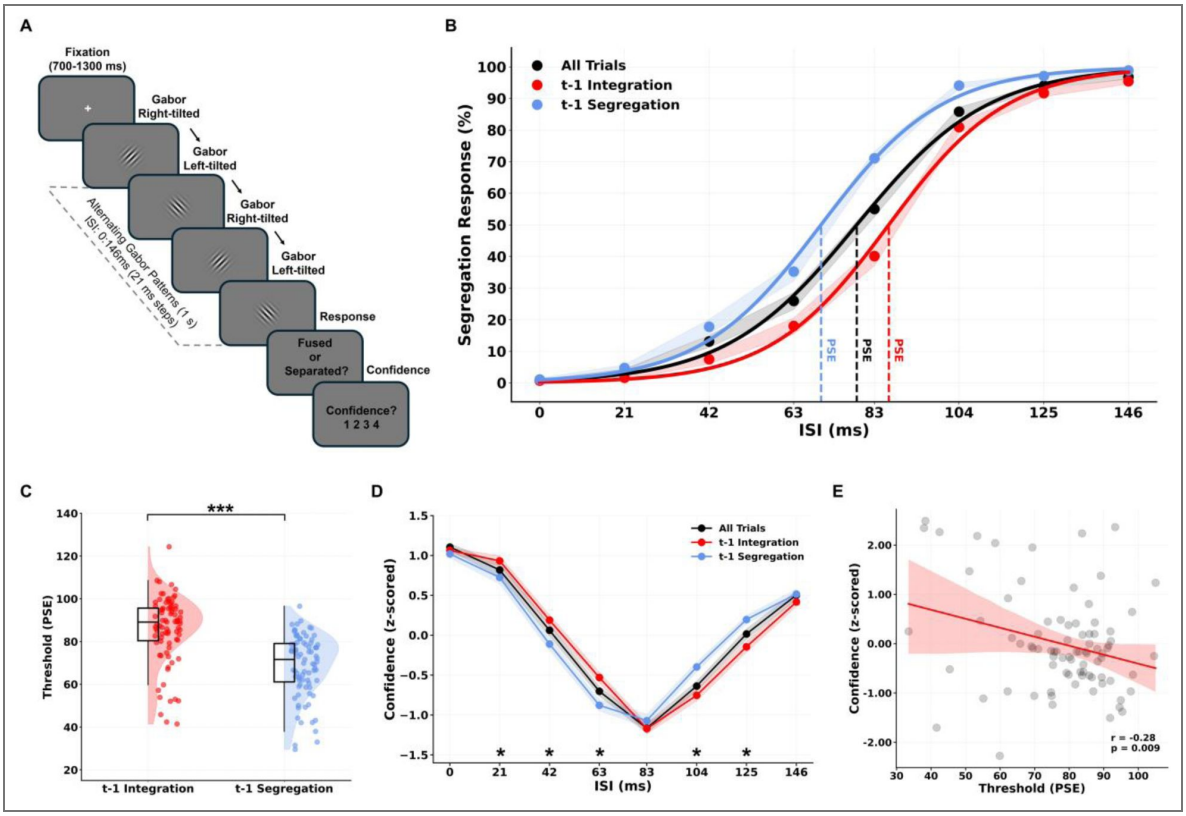

Figure 1. Visual temporal binding is dynamically shaped by sensory input, perceptual history and confidence.

(A) Schematic depiction of the sustained-stream temporal integration task. On each trial, two low–spatial-frequency Gabor patches of opposite orientation (±45°) alternated in counterphase for ~1 s with variable inter-stimulus intervals (ISIs, 0–146 ms, steps of 21 ms). Participants reported whether they perceived a fused plaid (integration) or separate gratings (segregation), followed by a confidence rating (1–4). (B) Psychometric functions showing the proportion of segregation responses as a function of ISI for all trials (black), trials following t–1 integration responses (red), and t–1 segregation responses (blue). Shaded areas denote SEM. The Point of Subjective Equality (PSE) was higher following t–1 integration trials, indicating a broader temporal binding window. (C) Individual PSE values as a function of previous perceptual outcome. Integration on the preceding trial biased perception toward integration on the current trial, indicating a stronger influence of recent perceptual choice-history on temporal binding processes (serial dependence effect). Black boxplots indicate the median and interquartile range (IQR), and individual dots represent participant-level data. (D) Mean z-scored confidence ratings as a function of ISI and t–1 judgment. Confidence decreased near the perceptual threshold (intermediate ISIs) and increased when temporal evidence clearly supported either integration or segregation. Confidence was higher after t–1 integration responses at short ISIs (21–63 ms) and higher after t–1 segregation trials at long ISIs (104–125 ms; $q < 0.05$, FDR-corrected), showing an interaction between prior experience and temporal evidence. (E) Across participants, mean confidence negatively correlated with temporal integration threshold (PSE; $r = -0.28$, $p = 0.009$; Parson Correlation Coefficient), indicating that individuals with narrower integration windows (higher temporal acuity) reported greater confidence. Together, these results show that visual temporal binding and metacognition are dynamically shaped by recent perceptual experience, reflecting an adaptive interplay between sensory evidence and perceptual history.

perceptual experience biases the temporal binding window without affecting precision. In line with recent evidence[18,19], this suggests that temporal integration mechanisms are flexible within individuals, adaptively expanding or contracting based on prior perceptual outcomes, reflecting a dynamic interplay between sensory evidence and perceptual history.

Confidence dynamically adjusts with temporal evidence and prior perceptual experience

After each temporal binding judgment, participants rated their subjective confidence on a four-point scale. As expected, confidence followed the temporal clarity of sensory evidence: participants reported lower confidence at intermediate ISIs, corresponding to perceptually ambiguous trials near the temporal integration threshold, and higher confidence at shorter and longer ISIs, where temporal evidence more clearly supported integration or segregation decisions. Across participants, mean subjective confidence was inversely related to the temporal integration threshold (PSE), revealing a negative linear correlation between confidence and PSE (r = –0.28, p = 0.009; Fig. 1E). Thus, individuals with narrower integration windows (i.e., higher temporal acuity) reported higher overall confidence in their perceptual judgments. In contrast, mean confidence was not significantly correlated with the slope of the psychometric curve (r = 0.15, p = 0.177). We next examined whether confidence was influenced by recent perceptual history. Trial-wise confidence ratings were sorted by ISI and by the perceptual outcome of the preceding trial (t–1 integration vs. t–1 segregation), and compared using permutation-based paired t-tests (10,000 permutations; FDR-corrected, q = 0.05). Confidence ratings were significantly higher following t–1 integration trials at short ISIs (21–63 ms; q < 0.05; Fig. 1D), whereas confidence was higher following t–1 segregation trials at long ISIs (104–125 ms; q < 0.05; Fig. 1D). No significant effects of prior perception emerged at the extremes of the temporal range (0 ms and 146 ms; q > 0.05; Fig. 1D) or near the point of subjective equality (83 ms; q > 0.05). Together, these findings indicate that confidence was enhanced when the current temporal evidence supported the same perceptual outcome as the previous trial, suggesting that recent perceptual states bias not only perceptual judgments but also their subjective certainty[33].

Alpha oscillations and aperiodic neural dynamics predict temporal integration

Alongside the temporal integration task, we recorded resting-state EEG activity (eyes-closed, EC; eyes-open, EO) from 64 scalp electrodes. In order to examine how oscillatory and aperiodic neural dynamics jointly shape visual temporal processing[8], we applied the FOOOF algorithm[30] to decompose each participant's power spectrum into oscillatory and aperiodic components (Fig. S1; see Supplementary). First, we tested the oscillatory sampling hypothesis, correlating resting-state IAF with behavioral measures of temporal integration (PSE and psychometric slope) using Pearson correlations with cluster-based correction (10,000 permutations). Faster IAFs, particularly over posterior–central sites, were associated with lower temporal thresholds (PSE) in both EC and EO conditions (p < 0.001; Fig. 2A), supporting the notion that faster alpha cycles correspond to narrower integration windows. By contrast, IAF was not significantly correlated with psychometric slope in either condition (p > 0.05; Fig. 2B). We then examined the contribution of aperiodic neural activity. Higher aperiodic exponents were significantly associated with steeper psychometric slopes in both EC and EO conditions (p < 0.001; Fig. 2D), indicating that a steeper (less flat) spectrum, reflecting lower neural noise, was linked to greater perceptual precision in temporal binding[8]. Additionally, higher aperiodic exponents were positively correlated with lower temporal thresholds (PSE) in the EO condition (p < 0.001; Fig. 2C), suggesting that reduced neural noise promoted finer temporal resolution. The absence of this effect in the EC condition further replicates our previous findings[9] and might reflect stronger alignment between neural dynamics and visual processing in EO. In order to check the specificity of alpha and aperiodic activity in temporal perception, we also correlated psychometric function measures with spectral power in the delta (1–4 Hz), theta (4–7 Hz), and beta (15–25 Hz) bands. No significant associations were found (p > 0.05). Additionally, because both IAF and the aperiodic exponent predicted

individual differences in PSE, we tested whether their effects were independent or mediated. Mediation analyses (see Method) revealed no significant indirect effect of IAF on temporal thresholds via the aperiodic exponent (β indirect = −0.043, CI [−0.154, 0.017]). Instead, IAF exerted a robust direct effect on PSE (β direct = −0.512, p < .001), alongside an independent contribution of the exponent (β = 0.236, p = .035), indicating that the aperiodic component acts in parallel rather than mediating the IAF–PSE relationship. Together, these findings corroborate previous evidence that visual temporal acuity emerges from the joint influence of oscillatory alpha dynamics and aperiodic neural mechanisms[8].

Neural predictors of serial dependence and subjective confidence in temporal binding

We next examined whether resting-state EEG activity predicts the strength of serial dependence during temporal binding. For each participant, we quantified the magnitude of serial dependence as the difference between the temporal thresholds (PSE) derived from the logistic fits following *t–1 integration* and *t–1 segregation* trials (ΔPSE = PSE t–1 integration – PSE t–1 segregation). This index captures how strongly the percept from the previous trial biases current temporal judgments. Similarly, we computed a slope difference index (Δslope = slope t–1 integration – slope t–1 segregation) to assess whether prior perceptual history affects perceptual precision and internal noise. Correlating these behavioral indices with resting-state EEG measures (IAF and aperiodic exponent) revealed distinct neural signatures of serial dependence. Faster IAFs, particularly over posterior–central electrodes, were associated with lower ΔPSE values in the EO condition (p < 0.001; cluster-based corrected; Fig. 3A), indicating that individuals with faster alpha rhythms (i.e., finer temporal resolution) were less influenced by prior experience, relying more on current sensory evidence. This relationship was absent in the EC condition (p > 0.05), and no significant associations emerged between IAF and Δslope in either condition (p > 0.05). Conversely, lower exponents were linked to higher ΔPSE values in the EO condition (p < 0.001; Fig. 3B), suggesting that individuals with noisier neural activity rely more heavily on prior perceptual outcomes to stabilize perceptual decisions under uncertainty. This association was not significant in the EC condition (p > 0.05), nor was any reliable relationship found between the aperiodic exponent and Δslope in either condition. Additionally, a mediation analysis (see Method) on the relationship between resting-state IAF and serial dependence strength (ΔPSE) revealed no significant indirect effect (β = 0.07, CI [−0.04, 0.22]). Both faster alpha rhythms (higher IAF; β direct = −0.43, p < .001) and aperiodic activity (β = −0.39, p < .001) independently predicted the degree of reliance on prior perceptual history.

Finally, we tested whether EEG measures predicted subjective confidence in temporal binding judgments. Faster IAFs over posterior–central sites were associated with higher mean confidence ratings in the EO condition (p < 0.001, cluster-corrected; Fig. 3C), indicating that individuals with faster alpha cycles not only exhibited finer temporal resolution but also greater subjective certainty in their perceptual decisions. No significant relationships were observed between confidence and IAF in the EC condition, or between confidence and aperiodic activity in either condition (p > 0.05). Together, these results demonstrate that oscillatory and aperiodic neural dynamics jointly shaped both the perceptual and metacognitive facets of temporal integration, where faster alpha oscillations promoted sharper temporal sampling and higher confidence in perceptual judgments, reducing dependence on the immediate past.

Discussion

The perceptual system segments the continuous flow of sensory inputs into discrete events to construct a coherent experience of an otherwise chaotic visual world. This temporal parsing has long been linked to the intrinsic speed of alpha-band oscillations[2] and more recently to the aperiodic structure of EEG spectra[8]. However, recent studies have reported contradictory findings that challenge a direct link between alpha oscillations and individual differences in perceptual resolution[6]. Here, by combining a novel continuous temporal integration paradigm with resting-state EEG, we replicate the classical two-flash findings while overcoming their key limitations that

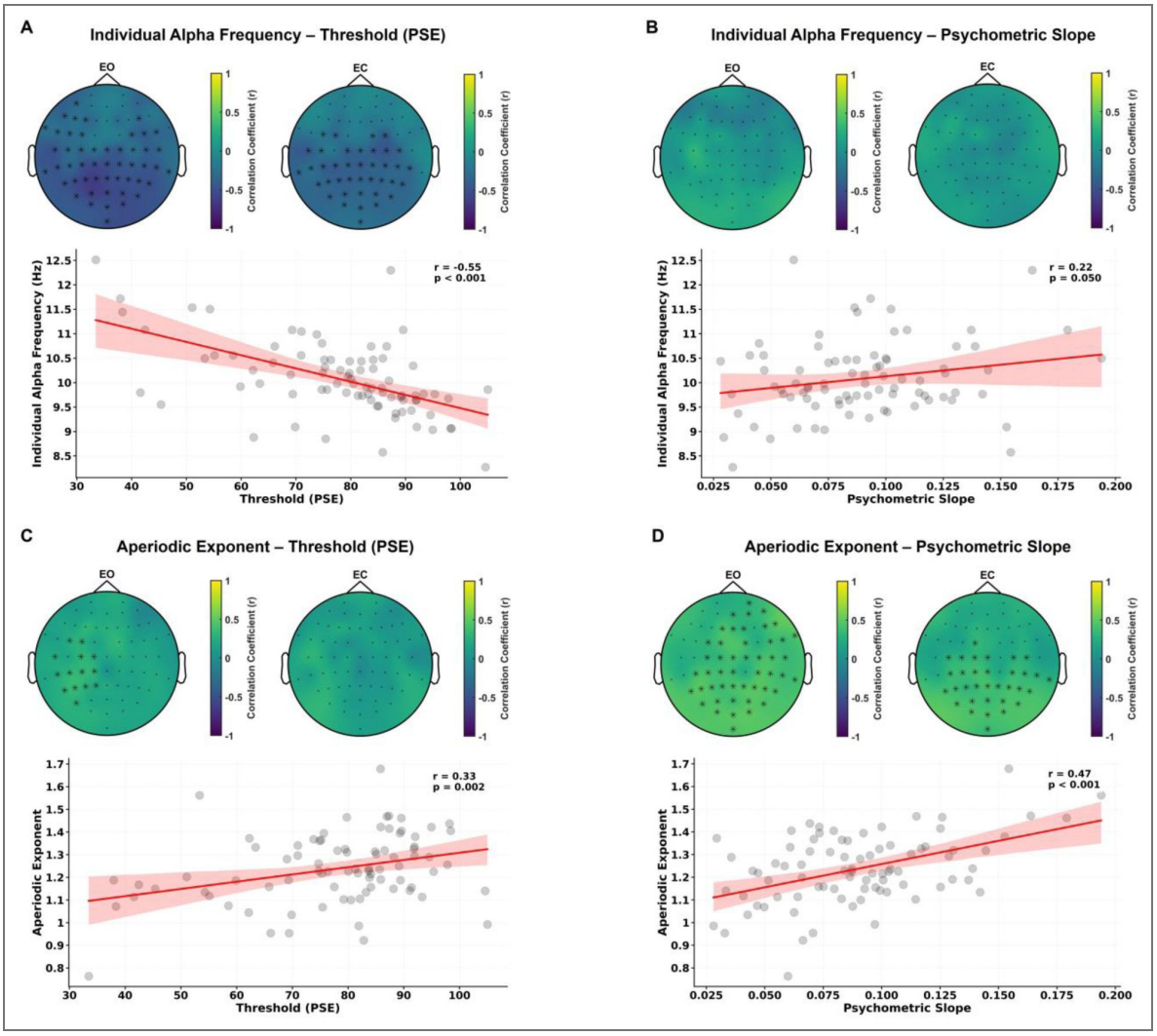

Figure 2. Oscillatory and aperiodic neural dynamics predict visual temporal integration performance.

(A) Topographical maps show the scalp distribution of correlations between individual alpha frequency (IAF) and temporal threshold of the psychometric function (PSE) during eyes-open (EO) and eyes-closed (EC) resting-state conditions. Faster IAFs over posterior–central sites were significantly associated with lower temporal thresholds ($p < 0.001$, cluster-corrected), indicating finer temporal resolution and narrower integration windows. Scatterplot shows the pooled correlation across participants over posterior-central electrodes. (B) Correlations between IAF and psychometric slope revealed no significant effects in either resting-state condition ($p > 0.05$), suggesting that alpha frequency primarily modulates temporal binding boundaries rather than perceptual precision. (C) Topographies and scatterplot depict positive correlations between aperiodic exponent and temporal threshold in the EO condition ($p < 0.001$, cluster-corrected), indicating that steeper aperiodic spectra (i.e., lower neural noise) were linked to finer temporal resolution. No reliable associations were found in the EC condition. (D) Higher aperiodic exponents were robustly correlated with steeper psychometric slopes in both EO and EC conditions ($p < 0.001$, cluster-corrected), showing that reduced neural excitation supports greater perceptual sensitivity and more stable temporal integration. Together, these results reveal that visual temporal acuity depends jointly on alpha oscillations and aperiodic activity, with faster alpha rhythms and steeper aperiodic slopes facilitating more precise temporal sampling of sensory input.

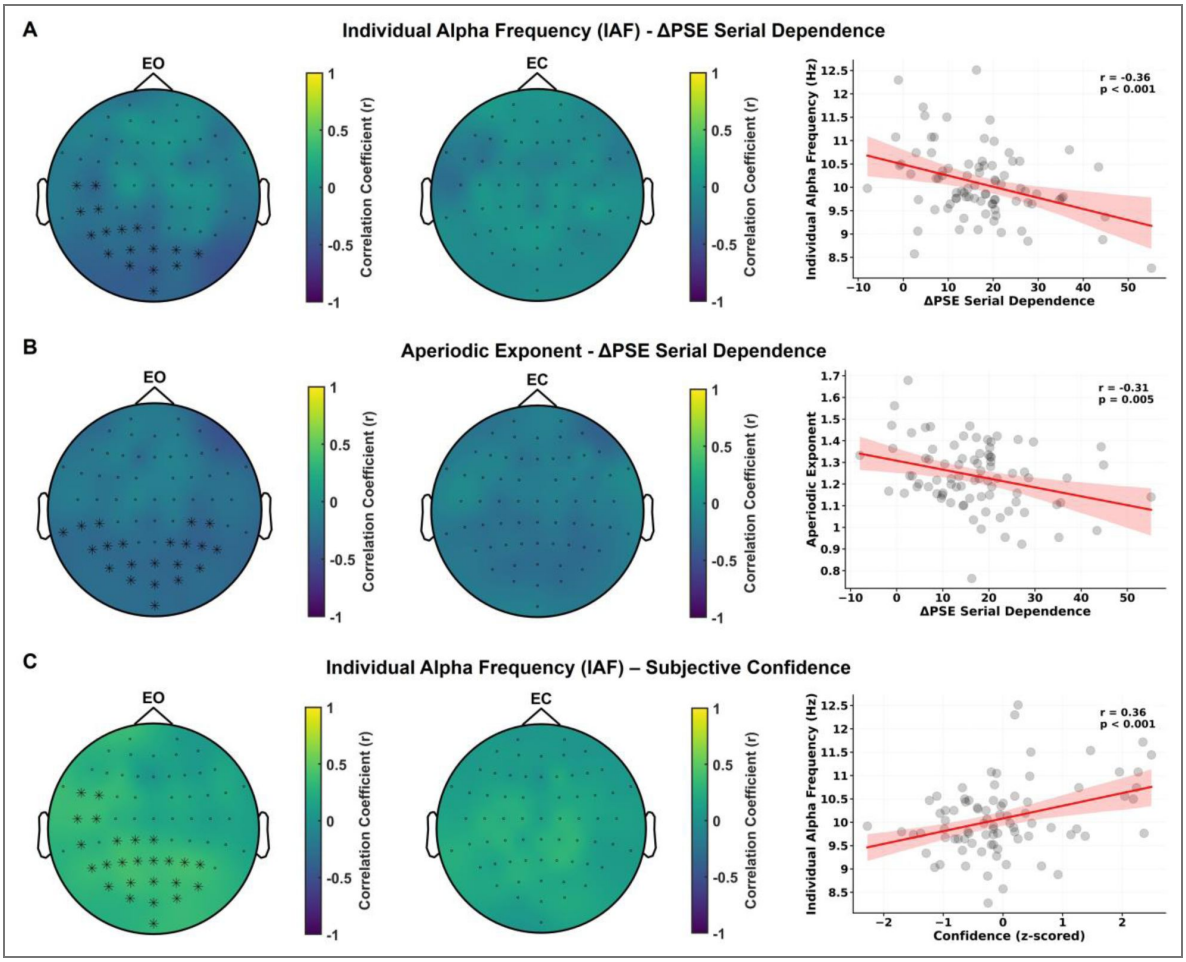

Figure 3. Resting-state neural dynamics predict individual differences in serial dependence and confidence.

(A) Topographies show correlations between individual alpha frequency (IAF) and serial dependence strength (ΔPSE = PSE t–1 integration – PSE t–1 segregation) for eyes-open (EO) and eyes-closed (EC) conditions. Faster IAFs over posterior–central electrodes were associated with lower ΔPSE in the EO condition ($p < 0.001$, cluster-corrected), indicating that individuals with faster alpha rhythms (i.e., higher temporal acuity) relied less on prior perceptual outcomes. No significant effects were observed in the EC condition ($p > 0.05$). (B) Correlations between the aperiodic exponent and ΔPSE revealed that flatter spectra (lower exponents, greater neural noise) were linked to higher ΔPSE values in the EO condition ($p < 0.001$, cluster-corrected), suggesting greater dependence on perceptual history to stabilize noisy sensory representations. This relationship was absent in the EC condition ($p > 0.05$). (C) Mean subjective confidence (z-scored) correlated positively with IAF in the EO condition ($p < 0.001$, cluster-corrected), showing that individuals with faster alpha cycles exhibited not only higher temporal acuity but also greater confidence in their perceptual judgments. No significant correlations were found for EC or for aperiodic activity ($p > 0.05$). Together, these findings demonstrate that oscillatory and aperiodic neural mechanisms jointly shape perceptual and metacognitive aspects of temporal integration: slower alpha rhythms and flatter spectra bias perception toward reliance on prior experience, whereas faster alpha oscillations enhance temporal precision and subjective certainty.

can confound genuine perceptual binding from failure to fully process both stimuli. We replicated the finding that oscillatory and aperiodic activity jointly predict the threshold and slope of the psychophysical curve[5,8], now using a sustained visual stream, as well as linking it for the first time to previous perception effects and confidence judgments. Our results reveal that visual temporal integration arises from a multilevel process governed by the interplay of rhythmic and aperiodic neural activity, perceptual history, and subjective confidence, moving beyond a simple account of the role of alpha oscillations in temporal integration.

First, our findings provide support for, but also a more complex understanding of the link between brain rhythms and visual perception. Individuals with faster resting-state alpha rhythms did indeed show faster temporal integration thresholds, in line with previous findings using brief flashes[2,3,4,5,8,13,26,34]. However, the speed of alpha frequency did not predict the steepness of the psychometric function (slope), suggesting that rhythmic activity alone does not determine perceptual precision or internal noise during temporal binding[35,36]. Interestingly, our findings revealed that this aspect of temporal processing was captured by the aperiodic component of neural activity[5,8]. Consistent with a recent framework[8]., higher aperiodic exponents were associated with steeper psychometric slopes and lower temporal thresholds, indicating that a steeper spectrum (i.e., lower neural noise) was linked to both greater perceptual precision and finer temporal resolution. These results are also consistent with the view that aperiodic activity indexes the neural excitation–inhibition balance[37] and modulates oscillatory synchronization relevant for the temporal organization of perception[5,8,38,39]. In this framework, alpha speed may determine the temporal resolution of perception, whereas the aperiodic structure can regulate its reliability by modulating the excitation–inhibition balance, thus enhancing its precision[8].

It is interesting that the aperiodic structure of electrophysiological signals has been related to various aspect of cognition and perception[40], such as speed of processing[41,42], working memory[43], emotional processing and arousal[44,45], as well as numerous psychopathologies[46], and aging[30,31,46].

The current findings explain in more detail how and why resting state EEG can predict individual performance in temporal perception tasks. Our findings reveal that visual temporal integration judgments are strongly perceptual history-dependent and shaped by both alpha rhythmicity and aperiodic neural activity. When we separately examined temporal integration thresholds for trials preceded by an integration response and those preceded by a segregation response, we found that temporal binding judgments were biased toward the previous perceptual outcome. Specifically, a previous integration response increased the likelihood of perceiving a subsequent stimulus as a single unified event, and vice-versa for segregation responses. These results demonstrate that recent perceptual experience flexibly biases the temporal binding window, consistent with recent evidence showing that temporal perception reflects a dynamic interplay between the temporal structure of sensory evidence and perceptual history[17,18,19]. Recent work has suggested that alpha oscillations may also support serial dependence processes[16,21]. In this study, faster resting-state alpha rhythms and higher aperiodic exponents were associated with a lower magnitude of serial dependence effect, indicating reduced influence of prior perceptual outcomes and a greater reliance on current sensory evidence, potentially due to increased sensory precision[22,27]. Conversely, individuals with slower alpha rhythms and lower aperiodic exponents showed stronger serial dependence, suggesting that when temporal resolution and sensory precision decrease the brain compensates by weighting prior perceptual information more heavily to stabilize perceptual experience under sensory uncertainty[16].

After each temporal binding judgment, participants rated their confidence, which mirrored the clarity of temporal evidence: confidence was lowest near the temporal integration threshold and highest at short and long inter-stimulus intervals, where evidence more clearly supported either integration or segregation. Additionally, subjective confidence was inversely related to individual temporal thresholds, indicating that observers with narrower integration windows (i.e., higher temporal acuity) reported higher overall confidence in their perceptual judgments. Crucially, confidence also modulated the interaction between prior perceptual history and current temporal evidence. Confidence ratings were significantly higher following integration judgments at short inter-stimulus intervals and higher following segregation responses at long intervals. These

findings suggest that confidence is enhanced when current sensory evidence supports the same perceptual outcome as the previous trial, suggesting that recent perceptual states bias not only perceptual judgments but also subjective certainty[33]. Finally, we tested whether neural dynamics predicted subjective confidence in temporal binding judgments. Our findings showed that faster alpha rhythms were associated with higher confidence, indicating that individuals with faster alpha cycles not only exhibited finer temporal resolution and less reliance on previous experience, but also greater certainty in their perceptual decisions, supporting previous evidence linking alpha-band oscillations to both temporal resolution and confidence in perceptual decisions[23,24,47].

Overall, the alpha rhythm was distinctly associated with multiple facets of visual temporal processing, from temporal thresholds and serial dependence to subjective confidence. One potential explanation for this multilevel influence of alpha oscillatory speed on temporal binding is that faster alpha rhythms operating within a neural background of lower noise may enhance temporal resolution through more efficient sensory evidence accumulation[5,8,26,27,34,48,49,50,51]. Recent evidence suggests that faster alpha rhythms promote greater perceptual resolution by generating more sampling frames per time unit, thereby increasing the amount of accumulated sensory evidence[22,26,27]. Consequently, more accurate and higher-rate sampling of visual input may yield a more faithful representation of external events, resulting in higher temporal precision, reduced reliance on prior perceptual experience, and greater subjective confidence in perceptual decisions, as observed in the current study.

Together, these results support and expand on our recently proposed framework linking alpha oscillatory speed and aperiodic neural dynamics in perceptual integration[5,8], showing also a link to decisional and metacognitive facets. By linking rhythmic sampling with the stability of the underlying neural background, this framework highlights that temporal perception emerges from the coordinated interplay between oscillatory precision, neural noise regulation, and the brain's predictive use of recent perceptual history. Beyond temporal processing, this account provides a broader model for how rhythmic and aperiodic neural dynamics jointly sustain the continuity of conscious visual experience across time.

Methods

Participants

A total of 83 volunteers (46 females, mean age=23.4 years, SD=2.58) participated in the experiment and received compensation. Participants presented normal or corrected-to-normal vision. Exclusion criteria were self-reported neurological and attention disorders, epilepsy, and photosensitivity. The sample size was determined a priori based on a recent meta-analysis of 27 studies examining the relationship between individual alpha frequency and temporal resolution[2]. The meta-analysis reported a pooled population correlation of r = 0.394 (95% CI [0.332, 0.465]; SE = 0.034). Using this estimate as the expected effect size, an a priori power analysis (two-tailed, α = 0.05) indicated that a minimum of N = 49 participants would be required to achieve 80% power to detect r = 0.394, and N = 69 for the lower bound of the confidence interval (r = 0.332). To ensure sufficient power to detect effects within this plausible range, we recruited 83 participants, which provided approximately 96% power for r = 0.394. Power analyses were conducted using G*Power 3.1[52]. The experiment was conducted in accordance with the Declaration of Helsinki and approved by the New York University Abu Dhabi Human Research Protection Program Internal Review Board (IRB).

Stimuli and Experimental Design

We designed a novel visual temporal integration task to measure individual integration performance while avoiding confounds associated with brief, discrete two-flash paradigms. Stimuli were generated and presented in MATLAB (MathWorks) using Psychtoolbox on a gamma-corrected monitor (refresh rate: 144 Hz). Observers viewed the display binocularly from a distance of 70 cm in a dimly lit room. On each trial, two Gabor patches were presented at the center of the screen, alternating over ~1 s in the same spatial location. Each Gabor had a low spatial frequency

(1.94 cycles/degree; λ = 0.52°) and a Gaussian envelope (σ = 0.62°), presented at full contrast, with orientations of +45° (right-tilted) and −45° (left-tilted). Each Gabor was rendered with a circular aperture and converted to a texture. These two orthogonal Gabors alternated rapidly to manipulate temporal perception. The key manipulation was the duration of each Gabor presentation (i.e., the inter-stimulus interval, ISI) rather than the interval between discrete events. The Gabors alternated in counterphase with an ISI ranging from 0 to 146 ms in 21-ms steps. Each ISI level was repeated 30 times, yielding 240 experimental trials presented in random order. For ISI = 0, a "fully fused" control was shown by presenting a precomputed fused texture with slight spatial jitter to prevent adaptation. The order of presentation (which orientation appeared first) was randomized across trials. This manipulation produced a continuous visual stream in which short presentation durations elicited the illusory percept of a single fused plaid (integration), whereas longer durations induced the perception of two alternating gratings (segregation). Because the stimuli had distinct orientations but occupied the same retinal location within an uninterrupted sequence, this paradigm dissociated genuine temporal binding from simple detection failures. At the beginning of the experimental session, resting-state EEG activity was recorded while participants relaxed for 3 minutes with eyes closed (EC condition) and 3 minutes with eyes open (EO condition). Before the task, participants received on-screen instructions and completed a short practice block to familiarize with the procedure. Each trial began with a central fixation cross (500 ms), followed by the ~1 s alternation sequence. Immediately after stimulus offset, participants made a two-alternative forced choice indicating their percept: fused/single pattern (key F) or separate/alternating patterns (key S). They then rated their confidence on a four-point scale (1 = not confident at all, 2 = not very confident, 3 = quite confident, 4 = very confident). A short break was provided halfway through the session.

Data Analysis

Behavioral Analyses and Psychometric Function

For each participant, we first computed the proportion of separate responses for each inter-stimulus interval (ISI) level and fitted a psychometric logistic function to the percentage of separate responses as a function of ISI. The fitting was performed individually using a nonlinear least-squares method (mean adjusted $R^2 = 0.938$; all participants $R^2 > 0.85$). We used a logistic equation and a nonlinear least squares method to fit the proportion of separate responses as a function of ISIs. The formula applied was as follows: $y = 1/(1 + exp(b \times (t - x)))$. In this equation, x represents the ISI, and y denotes the proportion of separate responses. The lower bound of y was set at 0, and the upper bound was set at 1. The only free parameters of the function were b (the slope of the function) and t (the 50% threshold), both of which were constrained to assume positive values above zero. Individual 50% threshold and psychometric slope values were obtained by fitting the psychometric logistic curve. The threshold (t) corresponds to the Point of Subjective Equality (PSE)—the temporal delay at which participants were equally likely to report a fused or separate percept. Within this framework, a lower PSE reflects greater temporal segregation (narrower integration window), whereas a higher PSE indicates an increased tendency to bind. The slope parameter (b) indexes the steepness of the psychometric function, providing an estimate of perceptual sensitivity or sensory noise: steeper slopes reflect higher temporal precision, whereas shallower slopes indicate noisier, less precise perceptual decisions. To assess the influence of perceptual history on temporal binding, we implemented a serial dependence analysis. Trials were divided into two bins based on the perceptual outcome of the preceding trial: t–1 segregation (previous trial perceived as separate) and t–1 integration (previous trial perceived as fused). To ensure statistical robustness, we verified that the number of trials per ISI was comparable across bins and that all participants contributed sufficient data for stable curve fitting. Separate logistic functions were then fitted for t–1 integration (mean adjusted $R^2 = 0.918$) and t–1 segregation trials (mean adjusted $R^2 = 0.92$), yielding distinct PSE and slope estimates for each condition. The difference in PSE between the two bins (ΔPSE = PSE t–1 integration – PSE t–1 segregation) was used as a quantitative index of serial dependence strength, reflecting the extent to which percepts from the preceding trial biased current perceptual judgments. In parallel, an analogous measure was derived for the psychometric slope (Δslope = t–1

integration minus t–1 segregation) to assess potential carry-over effects on response precision. Finally, we computed the average confidence rating for each participant and ISI level, separately for all trials, t–1 integration trials, and t–1 segregation trials.

EEG analysis

Resting-state EEG was recorded in two conditions, eyes closed (EC) and eyes open (EO), each lasting 3 min. Signals were acquired from 64 active scalp electrodes using BrainVision Recorder (Brain Products), sampled at 1000 Hz, and referenced online to FCz. Impedances were kept below 10 kΩ. Participants were instructed to relax, minimize movements, and fixate (EO) or keep their eyes closed (EC). Preprocessing was performed in MATLAB. For each participant, noisy channels were identified by visual inspection and interpolated using spherical splines. Oculomotor artifacts were removed by independent component analysis (ICA). The reference was kept at FCz for all subsequent analyses. We intentionally avoided re-referencing to the average reference because broadband noise or a single noisy channel would otherwise be spread over all channels and distort the estimation of the aperiodic (1/f) component[8]. For spectral analysis, continuous resting-state data were segmented into 1-s epochs. Remaining segments were submitted to Welch's method, yielding a power spectral density (PSD) estimate. Similar to our recent studies[5,8], to separate oscillatory from aperiodic activity, we applied the "fitting oscillations and one-over-f" (FOOOF) algorithm[30] to the PSD of each participant, condition (EC, EO), and electrode. FOOOF models the log-power spectrum as the sum of (i) an aperiodic component following a 1/f function (offset and exponent) and (ii) a set of Gaussian peaks capturing periodic oscillations. We fitted spectra in the 1–70 Hz range to avoid oscillations and spectral plateau crossing the fitting range borders. Default settings were used (peak width limits: 0.5–12 Hz; minimum peak height: 0; maximum number of peaks: Inf; peak threshold: 2), as in previous works[30,53]. The aperiodic exponent (slope) from this fit was taken as our index of aperiodic neural activity and, by extension, of excitation/inhibition balance[31,37]. Alpha power was defined as the spectral peak within this frequency range in both the full and aperiodic-corrected spectra. The individual alpha frequency (IAF) was identified as the frequency of the maximum spectral peak within the 8–13 Hz range. For control analyses, we additionally computed the power of delta (1–4 Hz), theta (4–7 Hz), and beta (15–25 Hz) oscillations to examine potential relationships with temporal perception outside the alpha band.

Statistical Analysis

After computing individual temporal thresholds (PSE) and slopes, we examined choice-history effects (i.e., serial dependence) using a repeated-measures ANOVA on PSE values, with the preceding trial type (t–1 judgment: integration vs. segregation) as a within-subjects factor. Greenhouse–Geisser corrections were applied where necessary to adjust for violations of sphericity, and all post-hoc p-values were Holm-corrected for multiple comparisons. To quantify serial dependence strength at the individual level, we computed a PSE difference index (ΔPSE = PSE t–1 integration – PSE t–1 segregation) and a slope difference index (Δslope = slope t–1 integration – slope t–1 segregation). Larger ΔPSE and Δslope values reflect stronger dependence on the previous perceptual judgment. These single-value indices served as summary measures of serial dependence strength, used in subsequent correlational analyses with EEG-derived parameters.

For confidence analyses, trial-wise confidence ratings were extracted for each participant and sorted according to ISI and preceding trial type (All trials, t–1 integration, t–1 segregation). Confidence scores were z-scored within participants (row-wise normalization) to preserve within-subject relative variability while removing between-subject scale biases. Differences in confidence between t–1 integration and t–1 segregation trials were assessed using permutation-based paired-sample t-tests conducted separately for each ISI. In each permutation (N = 10,000), participant-wise differences were randomly sign-flipped and a new t-statistic was computed to form an empirical null distribution. Two-tailed empirical p-values were defined as the proportion of permuted t-values with absolute magnitude greater than or equal to the observed t-statistic. To correct for

multiple comparisons across ISIs, p-values were adjusted using the Benjamini–Hochberg False Discovery Rate (FDR) procedure (q = 0.05). Effect sizes were calculated as Cohen's d for paired samples.

For EEG data, we first assessed differences between the eyes-closed (EC) and eyes-open (EO) resting-state conditions. For each electrode, we conducted two-sided dependent-sample t-tests using nonparametric, cluster-based permutation methods[54] to control for multiple comparisons (10,000 permutations). This analysis was performed separately for the aperiodic exponent and individual alpha frequency (IAF).

Next, for each channel and resting-state condition, we examined EEG–behavior relationships by computing Pearson's correlation coefficients between EEG measures and behavioral indices. Using the same nonparametric cluster-based permutation framework[54] (10,000 permutations), we correlated the aperiodic exponent and IAF with the temporal integration threshold (PSE) and psychometric slope derived from the behavioral data across all trials. To assess whether EEG parameters predicted the strength of serial dependence, we further correlated EEG measures with ΔPSE (t–1 integration - t–1 segregation). We also tested whether EEG features were related to metacognitive aspects of temporal perception. For this, mean confidence ratings were computed for each participant and correlated with EEG spectral measures (aperiodic exponent and IAF) using Pearson's correlations with cluster-based nonparametric correction (10,000 permutations). Finally, as control analyses, we correlated behavioral measures (PSE, slope, ΔPSE, Δslope, and confidence) with resting-state oscillatory power in the delta (1–4 Hz), theta (4–7 Hz), alpha (8–13 Hz), and beta (15–25 Hz) bands to evaluate potential relationships outside the alpha-frequency range. Although a priori hypotheses specified the expected direction of effects, all statistical tests were two-sided. All EEG analyses were implemented in MATLAB using custom scripts in combination with the FieldTrip Toolbox[55] and the FOOOF-mat toolbox[30]. To examine how oscillatory and aperiodic neural dynamics jointly contribute to perceptual behavior, we conducted a series of mediation analyses using the *lavaan* package (version 0.6–19) in RStudio[56]. All variables were z-standardized prior to analysis to facilitate the interpretation of path coefficients. Structural equation models were estimated using maximum likelihood estimation with Full Information Maximum Likelihood (FIML). The significance and confidence intervals of indirect effects were assessed using 10,000 bias-corrected bootstrap resamples, from which 95% confidence intervals (CIs) were derived. Path coefficients are reported as standardized regression weights (β). Separate mediation models were specified to test directional hypotheses regarding how resting-state EEG parameters predicted behavioral measures. We first tested whether the relationship between oscillatory alpha speed and temporal thresholds could be explained by aperiodic neural activity, by estimating mediation models in both directions: IAF - aperiodic exponent - PSE and the reverse aperiodic exponent - IAF - PSE. These analyses examined whether either oscillatory speed or the aperiodic component served as an intermediary mechanism linking resting-state EEG dynamics to temporal integration precision. Next, we applied the same bidirectional framework to serial dependence strength (ΔPSE), testing IAF - aperiodic exponent - ΔPSE and aperiodic exponent - IAF - ΔPSE, to assess whether these neural parameters jointly contribute to the degree of reliance on prior perceptual experience. Finally, we estimated a parallel mediation model including the aperiodic exponent, serial dependence strength (ΔPSE), and confidence as simultaneous mediators of the association between IAF and PSE. This comprehensive model was used to assess whether the relationship between oscillatory dynamics and temporal integration could be explained by the combined or independent contributions of neural noise, reliance on prior perceptual history, and subjective confidence. All models were tested on EEG values averaged over posterior electrode clusters showing significant correlations in the eyes-open (EO) condition. Effects were considered significant when the 95% bootstrap confidence interval of the indirect effect did not include zero. Model fit was evaluated using standard indices (CFI, TLI, RMSEA, SRMR), and explained variance (R^2) was reported for each dependent variable.

Supplementary Information

EEG activity in eyes-closed and eyes-open Resting-State

To characterize the spectral components of neural activity, we applied the FOOOF algorithm (Donoghue et al., 2020) to decompose each participant's power spectrum into oscillatory and aperiodic components (Fig. S1A). We first compared EC and EO conditions using two-sided dependent-sample t-tests with cluster-based permutation correction for multiple comparisons (10,000 permutations; Maris & Oostenveld, 2007). The analyses revealed no significant difference in individual alpha frequency (IAF) between conditions ($p > 0.05$; Fig. S1B). In contrast, the aperiodic exponent was significantly higher across widespread scalp regions in the EC condition compared to EO ($p < 0.001$; Fig. S1C), consistent with previous reports of increased aperiodic activity during eyes-closed rest (Dehghani et al., 2010; Donoghue et al., 2020; Deodato & Melcher, 2024).

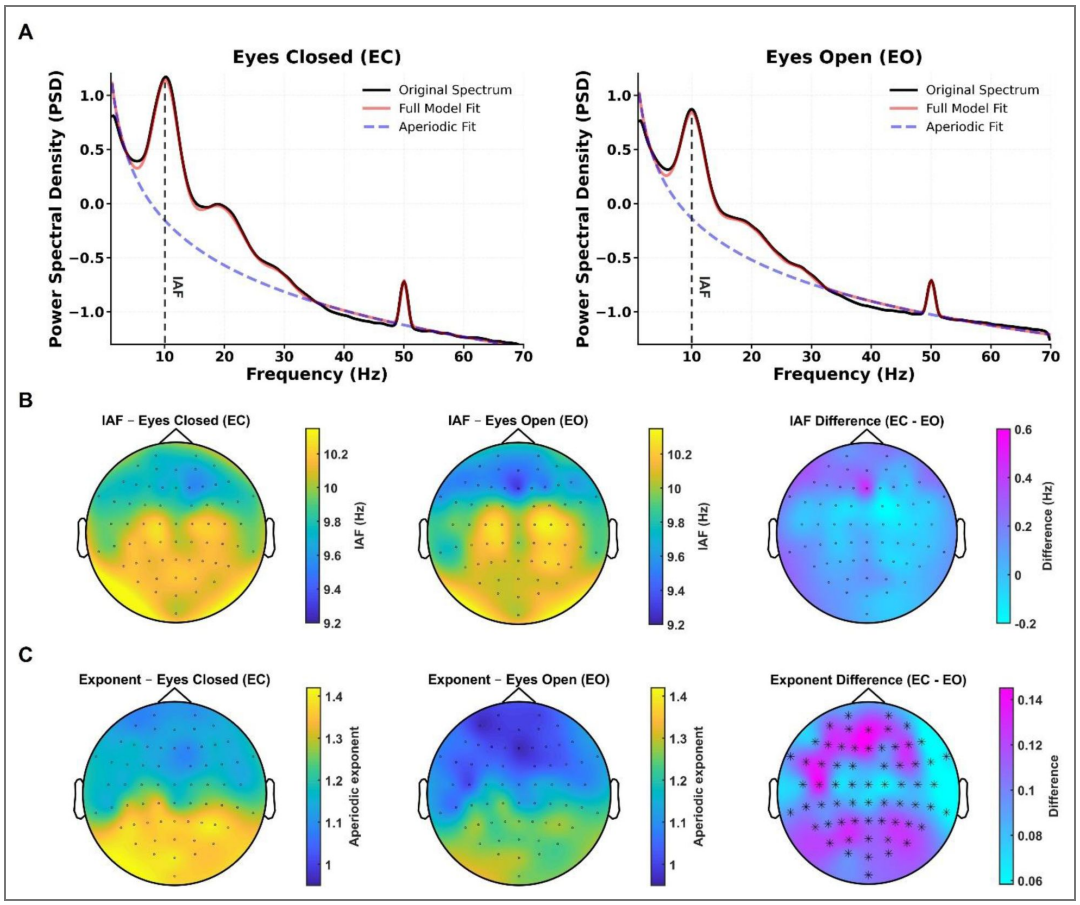

Figure S1. Resting-state EEG decomposition and comparison of oscillatory and aperiodic neural activity across eyes-closed and eyes-open conditions. (A) Representative FOOOF spectral parameterization of resting-state EEG averaged over posterior–occipital electrodes for the eyes-closed (EC, left) and eyes-open (EO, right) conditions. The algorithm decomposes the original power spectral density (PSD; black line) into its aperiodic 1/f component (blue dashed line) and periodic oscillatory peaks (red line). Individual alpha frequency (IAF; vertical dashed line) and the aperiodic fit. (B) Topographical distributions of IAF during EC (left) and EO (middle) resting-state conditions, and their scalp-level difference map (EC–EO, right). No significant differences in IAF were observed between conditions ($p > 0.05$, cluster-corrected). (C) Topographical distributions of the aperiodic exponent during EC (left) and EO (middle), and the corresponding difference map (EC–EO, right). Aperiodic exponents were significantly higher during EC relative to EO ($p < 0.001$, two-tailed, cluster-based correction; black asterisks indicate significant electrodes), consistent with stronger aperiodic activity under eyes-closed rest.

Mediation analyses linking neural dynamics and temporal binding

Our results revealed that both IAF and the aperiodic exponent predicted individual differences in temporal thresholds (PSE) and their modulation by prior perceptual experience (ΔPSE). However, it was important to also check whether these effects were independent, or that one mediated the other. We conducted mediation analyses testing whether the effects of IAF on behavioral measures were mediated by aperiodic activity. Path coefficients were estimated with maximum likelihood and evaluated using 10,000 bias-corrected bootstrap resamples (95% confidence intervals). Analyses were performed on the average electrode activity showing the strongest correlations in the EO condition, as identified in previous results.

The first mediation analysis indicated no significant indirect effect of IAF on temporal thresholds via the aperiodic exponent (β indirect = −0.043, CI [−0.154, 0.017]). Instead, IAF exerted a robust direct effect on PSE (β direct = −0.512, $p < .001$), with an additional independent contribution of the exponent (β = 0.236, $p = .035$; R^2 PSE = .36). Thus, the IAF's influence on temporal integration is not mediated by aperiodic activity but rather operates in parallel through an IAF-specific pathway. A second mediation analysis on the relationship between resting-state IAF and serial dependence strength (ΔPSE) also revealed no significant indirect effect (β = 0.07, CI [−0.04, 0.22]). Both faster alpha rhythms (higher IAF; β direct = −0.43, $p < .001$) and aperiodic activity (β = −0.39, $p < .001$) independently predicted the degree of reliance on prior perceptual history. Finally, a parallel mediation model including confidence, aperiodic exponent, and ΔPSE as simultaneous mediators of the IAF–PSE relationship showed no reliable indirect pathways, whereas the direct effect of IAF on PSE remained robust (β = −0.48, $p < .001$; R^2 PSE = .37).

Data availability

Data are shared open-access at *https://osf.io/4wdmc/*.

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Additional information

Author contributions

Conceptualization, G.M., M.D., D.M.; Methodology G.M., M.D., D.M.; Formal Analysis, G.M.; Software, G.M.; Visualization, G.M.; Funding Acquisition, D.M.; Writing - Original Draft Preparation, G.M. D.M.; Writing – Review & Editing, G.M., M.D., D.M.; Supervision, D.M.

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Peer reviews

Reviewer #1 (Public review):

Summary

Alpha oscillations have been previously proposed to shape the temporal resolution of visual perception, with a higher alpha frequency providing a finer resolution. This study goes beyond by investigating three additional processes that could influence joint visual temporal perception: the aperiodic neural signal, the integration of recent perceptual experience (serial dependence), and subjective confidence. To address their question, they developed a novel task where two Gabor patches oriented in opposite directions are presented in a continuous stream. This allows for testing for robust perceptual integration while avoiding bias from suboptimal perception. Behavioral analyses revealed an association between confidence and individual temporal integration thresholds, and demonstrated that serial dependence biases visual temporal integration as well as its associated confidence. EEG analyses first replicated the previous findings showing that faster IAF provides higher temporal resolution. Interestingly, the aperiodic neural signal was associated with both perceptual and temporal precision. Finally, the authors show that serial dependence is reduced in individuals with faster IAF and enhanced in participants exhibiting a stronger aperiodic component. Together, these findings highlighted that visual temporal integration

arises from an interplay between alpha oscillations, the aperiodic signal, serial dependance and subjective confidence.

Strengths:

(1) The novel task proposed in the study represents a substantial improvement over the two-flash fusion task previously used to investigate the role of alpha oscillations in visual temporal perception.

(2) Serial dependence has attracted increasing interest in vision research in recent years. Testing whether recent visual inputs also influence temporal resolution is, therefore, a valuable and timely approach. In this regard, the authors provide evidence for a serial dependence effect.

(3) Although the functional role of brain oscillations has been extensively studied over the past decade, the role of the aperiodic neural signal has long been overlooked. This study revealed that the aperiodic component plays a role in perceptual precision and temporal resolution, thus providing evidence for an important role of the aperiodic neural signal.

(4) The mediation analysis demonstrates that the aperiodic and oscillatory neural components act independently, providing important insights for future studies aimed at understanding their respective role.

Weaknesses

It would have been valuable to record EEG continuously during the experiment to investigate how spontaneous alpha oscillations and aperiodic signal dynamically influence the temporal integration, serial dependance and confidence on a trial-by-trial basis.

Appraisal

The authors employed a novel and thoughtfully designed task, combined with appropriate analyses, to address their research question. Their results are convincing and provide strong support for their conclusions.

Impact

This study provides valuable insights into the role of the aperiodic neural signal in visual temporal integration. This is important because its contribution has likely been underestimated, and future research will likely uncover increasing evidence of its impact across multiple cognitive functions.

It was also very interesting to observe how alpha oscillations are associated with serial dependence and confidence, extending beyond their well-known role in visual temporal resolution. This opens intriguing avenues for future research on the functional role of alpha oscillations.

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Reviewer #2 (Public review):

Summary:

This paper examines resting-state electroencephalography (EEG), the electrophysiological underpinnings of the temporal integration window in perception, and its modulation by priors (serial dependence) as measured through the perceptual fusion point of two continuous alternating stimuli. The study also includes a measure of perceptual confidence. Separating periodic from aperiodic EEG activity, the results show that the faster the

individual alpha-frequency at rest and the steeper the aperiodic slope (previously linked to higher sampling/ lower noise), the lower the perceptual fusion point (corresponding to narrower integration windows), with independent contributions of the period and aperiodic activity to the integration window. The data also reveal that the point of fusion depends on prior history, and that the strength of this effect depends on individual alpha frequency and aperiodic slope: the lower the individual alpha frequency and the aperiodic slope, the stronger the serial dependence, with the two contributions being again independent. Higher alpha frequency also led to higher confidence. The results are interpreted to suggest that speed of alpha oscillations and aperiodic slope of the power spectrum (presumably reflecting rate/fidelity of visual sampling and the level of background noise) jointly shape the perceptual measure under study: high rate/ fidelity and low noise promote temporal precision in integration, while lower rate/fidelity and higher noise lead to a higher reliance on prior history. It is concluded that it is the interaction between two EEG features that shapes temporal integration and hence perceptual fusion.

Strengths:

The strength lies in the use of a continuous visual stream of two alternating stimuli whose timing shapes fusion or separation of the two stimulus precepts, avoiding some of the pitfalls of previous fusion probes through discrete (not continuous) stimulus pairs (missed detection of one stimulus of the pair may be misinterpreted as fusion). The results seem robust (based on n=83 participants), the results are interesting, and the interpretations are sound.

Weaknesses:

The main weakness lies in the reliance on resting state EEG for correlation with the behavioural measures. This captures trait-based relationships, but does miss out on the brain activity dynamics within/across trials, which could be used for a direct readout of evidence accumulation to a decision, for capturing spontaneous fluctuations of the processes under study, etc. Also, in terms of resting state EEG, both eyes-closed (EC) and eyes-open (EO) data have been recorded, but their links to perceptual fusion point/ confidence seem somewhat inconsistent across the results. This is a bit confusing. Are the EO and EC signals in any way related/ correlated, and if not, what are they supposed to represent? Would an analysis of these EEG measures during task performance (e.g., in a pre-stimulus = baseline time window) provide more consistent results? These points could be resolved by additional analyses and/or more elaborate discussions.

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Reviewer #3 (Public review):

Summary:

In this study, the authors seek to explain what influences the temporal resolution of visual perception and its associated metacognitive monitoring, interindividual differences in such processes, and the neural mechanisms associated with these interindividual differences. More specifically, they investigated the factors influencing the perception of a rapid alternating stream of visual patterns as a single fused percept versus two segregated stimuli, and how these factors relate to stable features of ongoing brain activity. They introduce a novel sustained-stream temporal integration paradigm designed to address limitations of traditional two-flash tasks, and combine this with resting-state electroencephalography (EEG) to examine how individual alpha peak frequency and the aperiodic component of the power spectrum relate to temporal integration thresholds, perceptual history effects, and subjective confidence. Their overarching aim is to move beyond a purely oscillatory account of temporal sampling and to test whether periodic (alpha) and non-periodic (aperiodic) neural dynamics jointly shape perceptual decisions.

Strengths:

The study has several notable strengths. First, the experimental paradigm represents a thoughtful and innovative refinement of earlier approaches. By presenting alternating gratings within a continuous stream and varying the duration of each element rather than introducing discrete blank intervals, the authors mitigate well-known confounds of classical two-flash paradigms, particularly the possibility that "fusion" reports reflect missed detections rather than genuine temporal integration. The psychometric functions are well characterized, and the sample size is large for an individual-differences EEG study, with an a priori power analysis supporting the adequacy of the sample. Second, the use of spectral parameterization to separate oscillatory alpha peak frequency from the aperiodic component of the spectrum is methodologically rigorous and timely, as this distinction is increasingly recognized as important to avoid confounds in oscillatory activity estimation and the measurement of neural noise/excitatory-inhibitory balance (i.e., the aperiodic component of the power spectrum). The present work contributes to this emerging direction by relating both to behavioral indices within the same dataset. Third, the integration of perceptual thresholds, serial dependence, and subjective confidence within a unified framework provides a richer account of temporal perception than studies focusing on a single measure. In particular, the demonstration that resting alpha frequency predicts integration thresholds and that the aperiodic exponent relates to variability of the psychometric function is broadly consistent with the authors' central claims.

Weaknesses:

(1) At the same time, several aspects of the interpretation require caution. One conceptual issue concerns the interpretation of the psychometric slope parameter as an index of "temporal precision." The manuscript consistently equates steeper slopes with higher perceptual precision or lower internal noise. However, the slope of a binary psychometric function does not uniquely index sensory temporal resolution. It reflects the steepness of the transition between response categories and can arise from multiple sources, including variability in sensory encoding, instability of decision criteria, lapse rates, or other decisional processes. Even in the literature cited by the authors, slope is often described more generally as reflecting perceptual variability or sensory and/or decision noise rather than a pure measure of perceptual precision. An abrupt transition from "fused" to "segregated" responses, therefore, does not necessarily imply finer temporal resolution at the sensory level; it may instead reflect more consistent categorization or reduced decisional variability. The present data convincingly demonstrate relationships between spectral measures and the steepness of behavioral transitions, but they do not by themselves establish that this steepness reflects perceptual temporal precision rather than broader sources of behavioral variability.

(2) A related concern involves the causal language used to describe the relationship between neural measures and behavior. The EEG metrics are derived from resting-state recordings and therefore reflect stable, trait-like individual differences. Nonetheless, the Discussion sometimes adopts mechanistic phrasing suggesting that slower alpha rhythms or flatter spectra lead the brain to compensate by weighting prior information more heavily, or that neural noise is being "regulated." Such formulations imply within-task adaptive processes that are not directly measured. The results demonstrate robust between-participant associations, but further research is needed to establish whether individuals regulate neural noise or adjust prior weighting dynamically.

(3) Another point that merits clarification concerns the control analyses. The authors appropriately use spectral parameterization to dissociate oscillatory alpha peak frequency from the aperiodic component in the main analyses; however, their subsequent control analyses examining other frequency bands appear to rely on conventional band-power measures. Because band power can be influenced by the aperiodic background, null effects in other bands are difficult to interpret without similarly accounting for aperiodic structure.

(4) In addition, the temporal structure of the stimulus stream introduces an interpretational nuance. Varying the duration of each Gabor in a continuous alternation produces quasi-periodic stimulation rates, and several of these ISIs fall within the alpha frequency range. Rhythmic visual stimulation at alpha-range frequencies is known to produce strong stimulus-locked responses and can interact with intrinsic alpha rhythms in a frequency-dependent manner (Keitel et al., 2019; Gulbinaite et al., 2017). Although the present study does not record EEG during task performance and therefore cannot directly assess stimulus-driven steady-state responses, this aspect of the design complicates a purely intrinsic sampling interpretation. The observed relationship between resting alpha frequency and integration thresholds may reflect intrinsic sampling speed, but it could also be influenced by how closely an individual's alpha rhythm aligns with alpha-range temporal structure in the stimulus.

Conclusion:

Despite these limitations, the study achieves many of its primary aims. The sustained-stream paradigm reliably elicits graded temporal integration behavior and robust serial dependence effects. Individual alpha frequency is convincingly associated with integration thresholds, and the aperiodic exponent relates to behavioral variability measures. These findings support the broader conclusion that temporal perception reflects an interaction between rhythmic neural dynamics and the background spectral structure of ongoing activity. The work is likely to have a meaningful impact for researchers studying perceptual timing, perceptual history, individual differences in brain rhythms, and the functional role of aperiodic neural activity.

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Author Response:

> *(1) Clarification of the distinction between resting-state trait measures and ongoing neural dynamics*

All the Reviewers commented that this study provides a useful characterization of the relationship between trait-based resting-state neural dynamics and behavioral measures. At the same time, we agree that including ongoing EEG dynamics during task performance would have added important complementary information. In particular, task-related EEG would allow a more direct characterization of the relationship between ongoing neural activity and behavioral indices at the single trial level, thereby helping to clarify the role of ongoing neural dynamics in evidence accumulation and perceptual decision-making. It

would also enable testing how pre-stimulus alpha oscillations and aperiodic activity dynamically influence temporal integration, serial dependence, and confidence on a trial-by-trial basis.

However, we would like to emphasize that the primary aim of the present study was to investigate trait-level resting-state neural dynamics, which are known to be relatively stable and consistent within individuals, such as individual alpha frequency (e.g., Grandy et al., 2013; Wiesman & Wilson, 2019; Gray & Emmanouil, 2020) and aperiodic neural dynamics (Demuru and Fraschini, 2020; Pathania et al., 2021; Euler et al., 2024), and to examine whether these stable neural characteristics predict behavioral measures indexing temporal perception. Accordingly, the present study was designed to address how stable individual differences in resting-state neural dynamics shape temporal performance, rather than within-task neural fluctuations during the temporal task. We agree that combining resting-state and task-related EEG would be a valuable direction for future work, but this lies beyond the scope of the current dataset, as EEG was not recorded during task performance. Furthermore, we agree with the Reviewers that some of the wording in the Discussion can be clarified to emphasize the trait-level, rather than trial-level, nature of the task and potential interpretations.

Additionally, we agree that the relationship between eyes-open (EO) and eyes-closed (EC) resting-state EEG, and their differential associations with behavior, warrants further discussion. In our data, EO resting-state activity emerged as a stronger predictor of behavioral performance than EC. Conceptually, resting-state EO and EC should not be considered interchangeable measures of the same underlying neural activity, but rather as related yet distinct brain states, with overlapping neural generators expressed under different state constraints. EC is typically associated with stronger posterior alpha activity and a more internally oriented mode, whereas EO reflects a more visually engaged and vigilant state, closer to the conditions under which perceptual judgments are formed. This may explain why, in our findings, brain–behavior associations are more evident in EO, consistent with the greater similarity between the EO condition and the task context. In this sense, EO may emphasize exteroceptive processing and visual readiness, whereas EC reflects a more internally oriented configuration. This difference in functional weighting could account for the stronger behavioral correlations observed in EO in the present study. The distinction between these resting states has been emphasized in previous EEG and neuroimaging work showing differences in power, topography, and large-scale network organization (e.g., Marx et al., 2004). Additionally, these state-related differences may reflect physiological changes related to sensory processing (El Boustani et al., 2009) and arousal (Lendner et al., 2020). Accordingly, the present dissociation may arise because EO provides a resting-state measure that is more proximal to the sensory and excitability conditions engaged during task performance (for similar findings, see also Deodato and Melcher, 2024). However, we agree with the reviewers that further clarification of these state-related differences is warranted. In the revised manuscript, we will (i) expand the Discussion to more clearly articulate the conceptual distinction between EO and EC and their expected links to perceptual and confidence measures, (ii) systematically describe EO–EC differences across all EEG measures analyzed, and (iii) quantify the relationship between EO and EC indices to directly assess the extent to which they share trait-like variance across individuals.

In the revised manuscript, we will clarify these points by adjusting the text, strengthening the conceptual framing, and expanding the Discussion, including a more detailed outline of future research directions.

> *(2) Functional interpretation of psychometric measures*

The Reviewers raised an important point regarding the interpretation of the psychometric parameters investigated in our study. In particular, we agree that the slope of a binary psychometric function does not provide a direct measure of sensory temporal resolution or

perceptual sensitivity, and that our original wording may have overstated this interpretation. Rather, the slope reflects the steepness of the transition between response categories and indexes overall behavioural variability, which can arise from multiple sources, including variability in sensory encoding, decision criteria, and occasional response errors (e.g., Wichmann and Hill 2001; Prins 2012).

We therefore agree that interpreting steeper slopes as necessarily reflecting "temporal precision" may be overly specific, and that there are other possible interpretations. In the revised manuscript, we will adopt more cautious terminology and describe the slope more generally as indexing behavioral variability in the transition between perceptual reports, which may reflect a combination of sensory and decisional factors. Importantly, our results demonstrate robust relationships between neural measures and the consistency or sharpness of perceptual categorization, rather than uniquely isolating sensory temporal resolution. While, in standard psychophysical frameworks, the slope is related to internal variability in the sensory representation, this relationship depends on model assumptions and does not uniquely isolate sensory precision (e.g., Prins, 2016). Following the reviewers' suggestion, we will also refine our psychometric modeling by incorporating a lapse parameter. We agree with the Reviewer that accounting for occasional stimulus-independent errors (e.g., lapses) can improve parameter estimation and prevent biases in slope and threshold estimates when lapse rates are implicitly fixed to zero (Wichmann & Hill, 2001). In the revised manuscript, we will therefore (i) clarify the terminology used to describe psychometric parameters and (ii) report additional analyses including lapse rates.

In addition, we agree that complementary modeling approaches could help disentangle perceptual and decisional contributions to the observed effects by providing access to latent parameters of perceptual decision-making. For example, within a signal detection framework, one could test whether EEG measures relate to perceptual sensitivity versus decision criterion, while sequential sampling models such as the diffusion model (e.g., Ratcliff and McKoon, 2008) could assess whether neural measures are associated with parameters such as drift rate, decision boundary, starting bias, or trial-to-trial variability. However, several characteristics of the present paradigm limit the direct applicability of these approaches. First, the task relies on a continuous manipulation of sensory evidence across stimulus durations (ISIs), and behavioral responses are summarized through psychometric functions rather than modeled at the single-trial level. As a result, the current framework does not provide direct access to trial-by-trial latent decision variables required by these models. Second, reaction times were not collected, which constrains the application of sequential sampling models that rely on joint modeling of accuracy and response times. Finally, while the task involves categorical judgments (integration vs. segregation), it does not include explicit signal-absent or catch trials, which can help constrain sensitivity and criterion estimates within classical signal detection formulations. Despite these limitations, we agree that these approaches could still provide useful insights. In the revised manuscript, we will explore whether alternative modeling approaches (e.g., signal detection-based metrics or Bayesian psychometric modeling) can help further characterize the contributions of perceptual sensitivity, decision criterion, and response variability to our behavioral measures. While these analyses will necessarily remain exploratory given the structure of the current dataset, they may provide initial insights into whether the observed effects reflect perceptual or decisional dynamics. A more definitive dissociation, however, is beyond the scope of the present study and will be an important direction for future work.

> *(3) Control analyses and robustness of EEG–behavior relationships*

The Reviewers raised interesting points regarding the interpretation of our control analyses and the potential influence of stimulus structure on the observed EEG–behavior relationships. We agree that these aspects require clarification and additional analyses to strengthen the robustness of our findings.

First, regarding the control analyses across frequency bands, we acknowledge that while our main analyses appropriately dissociate oscillatory and aperiodic components using spectral parameterization, the control analyses were based on conventional band-power measures. As correctly noted by the reviewers, band-limited power estimates can be influenced by the aperiodic background, which complicates the interpretation of null effects in the other frequency bands. In the revised manuscript, we will address this issue by extending our spectral parameterization approach to these control analyses. Specifically, we will recompute band-specific measures after removing the aperiodic component, allowing a clearer comparison across frequency bands and a more robust assessment of the specificity of alpha-related effects. Preliminary analyses suggest that these updated results are likely to be consistent with our initial findings, thereby reinforcing the robustness of the reported effects.

Another important point raised by the reviewers concerns the temporal structure of the stimulus stream. We agree that the continuous alternation of Gabor stimuli at varying durations introduces quasi-periodic stimulation rates that may induce entrainment of neural oscillations. Notably, some inter-stimulus intervals correspond to frequencies within the alpha range, which raises the possibility that the observed relationship between resting alpha frequency and integration thresholds may not solely reflect intrinsic sampling speed, but could also be influenced by the degree of alignment between an individual's alpha rhythm and the temporal structure of the stimulus. As highlighted in prior work (e.g., Gulbinaite et al., 2017; Keitel et al., 2019; Gallina et al., 2023; Duecker et al., 2024), rhythmic stimulation in the alpha range can interact with intrinsic alpha oscillations and modulate both neural and perceptual processing. Although our study does not include EEG recordings during task performance and therefore cannot directly assess stimulus-locked responses or neural entrainment, we agree that this factor should be explicitly considered in the interpretation of our findings. To address this point, in the revised manuscript we will perform additional control analyses to assess the robustness of the observed relationships while accounting for potential rhythmic stimulation confounds. Specifically, we will explore whether the strength of behavioral effects and their relationship with EEG measures depends on the alignment between each participant's individual alpha frequency and the effective stimulation rate induced by the stimulus presentation. In addition, we will test whether the association between resting-state alpha frequency and behavioral measures is disproportionately driven by stimulus durations corresponding to alpha-range temporal frequencies. These analyses will help determine whether the observed effects primarily reflect intrinsic sampling properties or are modulated by resonance-like interactions between endogenous rhythms and stimulus timing. We will also address all additional recommendations raised by the reviewers in the revised manuscript.

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