Resting-State EEG/MEG Aperiodic Components: Analysis Workflow, Application Advances, and Future Prospects

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Abstract

Power spectral analysis is a commonly employed method in EEG/MEG data processing. In recent years, a growing number of researchers have recognized that the aperiodic components of the power spectrum possess unique physiological significance and application value. With the international promotion and adoption of toolkits exemplified by the spectral parameter fitting algorithm (SpecParam), aperiodic analysis of resting-state EEG/MEG has garnered widespread attention. This article first introduces the conventional pipeline for conducting aperiodic analysis in high-density EEG/MEG. It then summarizes two major advances in applications: in developmental neuroscience, spectral flattening in older adults is highly correlated with declined cognitive performance and deteriorated sleep quality; in clinical applications, aperiodic parameters can serve as electrophysiological markers for multiple neuropsychiatric disorders. Currently, aperiodic analysis still lacks attention to whole-brain spatial distribution, and its neurophysiological generation mechanisms remain in the exploratory stage. Future research needs to incorporate innovative directions such as multimodal brain imaging techniques and experimental designs to further consolidate theoretical foundations and expand the scope of applications.

Full Text

Aperiodic Components of Resting-State EEG/MEG: Analysis Procedures, Application Advances, and Future Prospects

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Abstract

Power spectral analysis is a fundamental method in EEG/MEG data processing. In recent years, a growing number of researchers have recognized that the aperiodic components of power spectra hold unique physiological significance and practical value. With the global adoption of toolkits such as the Spectral Parameterization algorithm (SpecParam), aperiodic analysis of resting-state EEG/MEG has garnered substantial attention. This paper first introduces standardized procedures for aperiodic analysis in high-density EEG/MEG. Subsequently, we summarize two major empirical advances: in developmental neuroscience, age-related flattening of the power spectrum demonstrates robust associations with cognitive decline and deteriorated sleep quality among older adults; and in clinical applications, aperiodic parameters show promise as electrophysiological biomarkers for various neuropsychiatric disorders. Currently, aperiodic analysis still lacks sufficient exploration of whole-brain spatial distributions, and the neurophysiological generation mechanisms remain under investigation. Future research should integrate multimodal neuroimaging techniques and innovative experimental designs to strengthen theoretical foundations and expand clinical applications.

Keywords: aperiodic components, EEG/MEG, power spectrum, scale-free, resting-state

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1 Introduction

High spatiotemporal resolution brain imaging technologies have greatly advanced our understanding of brain structural organization and functional activity. Compared with other neuroimaging modalities, electroencephalography (EEG) and magnetoencephalography (MEG) offer superior temporal resolution and provide direct measurements of neural activity. As non-invasive whole-brain recording methods, EEG/MEG are widely favored by researchers. Resting-state EEG (rsEEG) and resting-state MEG focus on spontaneous neural activity generated during non-task states, offering advantages such as simple experimental paradigms, accessible equipment, and mature analysis pipelines. Previous studies have linked intracortical oscillatory activity to cognitive, memory, and developmental processes [**?**, **?**, **?**], and changes in oscillation frequency or amplitude may constitute markers of pathological neural activity in psychiatric, neurological, and developmental disorders [**?**, **?**].

Power spectral analysis is a common method in EEG/MEG data processing that transforms raw signals into frequency-domain power to quantify energy distribution across frequencies. In addition to spontaneous neural activity with specific center frequencies (i.e., periodic activity, including α and rhythms), the spectrum also contains aperiodic activity—also termed "non-rhythmic" or "arrhythmic" components—characterized by the absence of a dominant center frequency and "scale-free" properties due to its scale-invariant nature [**?**]. Re-

cent years have witnessed growing interest in extracting aperiodic components from power spectra. Aperiodic activity follows a 1/f-like distribution as a spectral feature independent of specific frequency bands. As shown in Figure 1a [Figure 1: see original paper], Donoghue et al. (2020) proposed the Spectral Parameterization algorithm (SpecParam, also known as Fitting Oscillations and One-Over-F, FOOOF), which obtains two parameters through linear fitting of log-transformed EEG spectra: (1) the **spectral exponent**, representing the trend of power distribution across frequencies and reflecting the steepness of power spectral decay (equivalent to the slope of linear fitting) [**?**]; and (2) the **offset**, reflecting overall power shifts across frequencies (equivalent to the intercept of linear fitting). Gao et al. (2017) used conductance modeling of excitatory neurons (E, represented by glutamate receptors) and inhibitory neurons (I, represented by GABA) to demonstrate that changes in aperiodic exponent depend on overall shifts in the excitation-inhibition (E:I) balance: when E > I, the exponent decreases and the power spectrum becomes flatter; when E < I, the exponent increases and the spectrum becomes steeper. This model was further validated in a neuropharmacological study [**?**]. The offset primarily reflects broadband power changes and is associated with alterations in perceptual and cognitive states. Using simultaneous EEG-fMRI, researchers have found that offset correlates with the blood oxygen level-dependent (BOLD) signal [**?**], and that spontaneous power fluctuations in aperiodic EEG activity can directly couple with whole-brain resting-state fMRI activity, suggesting that aperiodic EEG activity likely constitutes the neural basis of global fMRI signals [**?**].

Figure 1 illustrates the necessity of distinguishing aperiodic from periodic components in spectral analysis. Aperiodic analysis transforms signals from a single electrode into spectra (blue solid line), extracting (a.i) periodic components (the portion above the dashed line) and aperiodic components (the dashed line) within narrow bands (blue shading). The aperiodic component is characterized by two main parameters (a.ii): exponent and offset. Traditional spectral analysis may erroneously interpret certain changes as equivalent to (b) reduced oscillatory power when comparing conditions. However, several distinct scenarios can produce similar total power changes: (c) periodic activity may only alter peak frequency; or (d) offset or (e) exponent changes may occur with only aperiodic activity modifications.

1.1 Advantages of Distinguishing Aperiodic and Periodic Components in Spectral Analysis

The electrophysiology field has long recognized the 1/f characteristic of EEG/MEG spectra [**?**]. Since 1/f noise is ubiquitous in nature (e.g., instrument noise, background noise), effective noise removal is crucial [**?**]. Early work considered aperiodic activity as mere noise and removed 1/f components through normalized power spectra or signal whitening preprocessing to avoid scale-free activity confounding periodic activity [**?**], but this approach overlooked physiologically meaningful aperiodic activity. Accumulating evidence

reveals that these activities have unique functional significance, and further discussion can clarify the neural activities and behavioral manifestations associated with different EEG signal components [**?**, **?**]. However, compared with extensive research on periodic activity, the properties and functions of aperiodic components remain poorly understood.

Figures 1c-e illustrate common pitfalls in EEG/MEG experimental studies when comparing two conditions. Traditional methods would detect significant differences in specific frequency bands across these conditions, yet the underlying realities differ substantially. When narrowband power changes occur, researchers typically assume altered energy at specific frequencies (Figure 1b). However, because periodic activity is nested within aperiodic activity, narrowband energy changes may not reflect genuine periodic activity alterations [**?**, **?**, **?**]. As shown in Figure 1c, peak frequency shifts may be misinterpreted as changes in energy and frequency bandwidth. Detected oscillatory changes might actually stem from aperiodic activity modifications, such as offset (Figure 1d) or exponent (Figure 1e) changes. Moreover, even without obvious periodic activity, traditional spectral analysis may still show total band power changes due to these aperiodic parameters. Ignoring these factors in spectral analysis can lead to misinterpretation of the physiological and psychological phenomena under investigation.

1.2 Main Content of This Paper

The international neuroelectrophysiology community has shown sustained interest in aperiodic analysis. Given the widespread adoption of spectral analysis in EEG/MEG research, more work is urgently needed to uncover the functional significance of "aperiodic activity" lurking beneath the tip of the iceberg. Resting-state EEG/MEG provides more stable background activity than task-based paradigms, facilitating aperiodic component extraction while reflecting individual baseline neural states. Compared with task-based EEG/MEG, resting-state databases are larger and more amenable to computational modeling, making them increasingly popular in current aperiodic analysis research. Furthermore, high-density EEG/MEG enables comprehensive whole-brain activity information, revealing inter-regional interactions and allowing macroscopic characterization of spatial distribution patterns and regularities of various components, laying the groundwork for subsequent cortical localization. Therefore, this paper systematically reviews research on aperiodic activity in the domain of resting-state high-density EEG/MEG: first, we summarize currently popular toolkits for single-electrode aperiodic analysis and compare their features; second, we innovatively propose analysis steps for whole-brain electrode-level aperiodic analysis tailored to high-density EEG/MEG coverage; third, we summarize major advances in aperiodic analysis across neuroscience, psychology, and psychiatry, particularly successful applications in developmental neuroscience and clinical practice; finally, we identify unexplored frontiers for aperiodic activity—focusing on whole-brain spatial distribution, exploring neural substrates through

multimodal techniques, and leveraging experimental design innovations.

2 Analysis Methods

2.1 Commonly Used Toolkits

Quantitative methods enable objective aperiodic analysis. Table 1 briefly introduces commonly used toolkits and their characteristics. Based on the signal fitting space, algorithms can be broadly categorized into two types. The first category comprises frequency-domain algorithms based on power spectra. The Spectral Parameterization algorithm (SpecParam; [**?**]) employs Gaussian mixture models and power-law functions to fit spectra, extracting both periodic and aperiodic parameters from electrophysiological data. Building on SpecParam, derivative algorithms include the time-resolved Spectral Parameterization Resolved in Time (SPRiNT; [**?**]) for identifying dynamic neural activity changes, and the Periodic/Aperiodic Parameterization of Transient Oscillations (PAPTO; [**?**]) for detecting instantaneous oscillatory events. Irregular-Resampling Auto-Spectral Analysis/Multiple-Resampling Cross-Spectral Analysis (IRASA/MRCSA; [**?**, **?**]) separates aperiodic components from mixed time series by exploiting differential robustness to resampling. The Better Oscillation detection/extended Better Oscillation detection (BOSC; [**?**]) and Multiple Oscillation Detection Algorithm (MODAL; [**?**]) extend previous algorithms by leveraging aperiodic activity to detect oscillatory activity. The second category comprises time-domain methods based on raw data. The -α model [**?**] employs probability distribution functions to fit periodic and aperiodic components, focusing primarily on α rhythm peaks. The -π model [**?**] demonstrates robustness against irregular spectral shapes by fitting periodic and aperiodic components separately.

Table 1 Commonly used aperiodic analysis toolkits and their main characteristics

Toolkit	Algorithm Principle	Fitting Space	Advantages	Limitations	Key References
SpecParam (FOOOF)	Gaussian fitting, log-power vs. frequency	No need to predefine specific frequency bands; controls aperiodic components	Fitting range limited when narrow-band low/high frequencies used Model-driven, heavily influenced by preset parameters Difficult to characterize indistinguishable overlapping peaks Cross-boundary oscillations increase exponent errors	[?]	

Toolkit	Algorithm Principle	Fitting Space	Advantages	Limitations	Key References
SPRiNT	Gaussian fitting, log-power vs. frequency	Combines SpecParam with STFT for time-resolved parameterization	Overestimates peak bandwidth, underestimates peak count Performance degrades with aperiodic knee	[?]	
PAPTO	Gaussian fitting, log-power vs. frequency	Sensitive to transient β rhythm activity in cortex	-	-	[?]
IRASA/MRCSA	Resampling method	Log-power vs. log-frequency	Can estimate periodic components at frequency boundaries MRCSA analyzes cross-spectrum of simultaneously recorded signals	Assumes invariant aperiodic component Lacks systematic preprocessing to remove spectral peak interference	[?, ?]

Toolkit	Algorithm Principle	Fitting Space	Advantages	Limitations	Key References
MODAL	Frequency sliding method	Log-power vs. log-frequency	Correctly rejects non-oscillatory transient events	Assumes invariant aperiodic component Lacks systematic preprocessing steps	[?]
-α model	Probability distribution fitting	Time domain	Focuses on α rhythm peak	Single-modal and multi-modal	[?]
-π model	Probability distribution fitting	Time domain	Robust to irregular spectral shapes Unbiased identification of all periodic signal types	-	[?]

Note: "-" indicates not applicable or not discussed in references; "√" indicates parameterization possible during spectral separation; "×" indicates parameterization not possible. Readers are recommended to consult [?] for detailed comparison of SpecParam (FOOOF) and IRASA characteristics and limitations.

Overall, frequency-domain algorithms currently dominate while time-domain methods remain scarce. Compared with methods that only separate periodic and aperiodic components (e.g., IRASA), Donoghue et al.' s (2020) SpecParam algorithm enables separate modeling of both components, obtaining relevant parameters while achieving separation. Compared with other parameterization methods (e.g., eBOSC), SpecParam' s automation and widespread adoption facilitate rapid entry for beginners. The algorithm requires no predefinition of specific frequency bands of interest; peaks in the power spectrum are character-

ized by their specific center frequency, power, and bandwidth, allowing further investigation of adjusted periodic parameters after removing 1/f signal interference. For each electrode' s periodic components, quantifying center frequency, periodic power, and periodic bandwidth helps elucidate their roles across the lifespan in cognitive and behavioral functions [**?**]. Parameters obtained using SpecParam demonstrate good test-retest stability [**?**], making it the predominant analysis tool in recent aperiodic research.

2.2 Standardized Procedure for High-Density EEG/MEG Aperiodic Analysis

Since aperiodic analysis has primarily been applied in single-electrode or few-electrode neuroscience studies, unified guidelines for standardized use in whole-brain high-density EEG/MEG—particularly resting-state EEG/MEG—are still lacking. Below, using the mainstream SpecParam toolkit and a sleep deprivation dataset [**?**], we illustrate the computational process for aperiodic components in within-subject experimental designs.

The sleep deprivation dataset recorded 5-minute eyes-open resting-state EEG from 61 scalp electrodes in 71 subjects under normal sleep and sleep-deprived conditions. While SpecParam operates at the single-electrode level, we propose a standardized high-density EEG/MEG aperiodic/periodic analysis framework [**?**] to enable more rigorous whole-brain discussion of aperiodic activity and its parameters. This framework integrates SpecParam while addressing multi-electrode configurations and group-level statistical inference commonly encountered in high-density EEG/MEG research (Figure 2 [Figure 2: see original paper]), maximizing utilization of information from all electrodes.

Figure 2 Standardized high-density EEG/MEG aperiodic/periodic analysis framework. **Step 1:** (a.i) Estimate parameters at single-electrode level using SpecParam; each electrode yields (a.ii) periodic parameters, (a.iii) aperiodic parameters, goodness-of-fit R^2, and residual error. The periodic parameter with maximum power across all fitted peaks is selected as the representative value for each electrode. **Step 2:** Subject-level assessment; exclude subjects with excessive poorly-fitted electrodes. (b.i-ii) Average aperiodic parameters and representative periodic parameters across all electrodes to obtain subject-level parameterization results. **Step 3:** (b.iii) Group-level statistics. With both aperiodic and periodic components for each subject, descriptive statistics or hypothesis testing can be applied.

2.2.1 Preprocessing and Power Spectrum Calculation Preprocessing of eyes-open resting-state EEG data was performed in MATLAB R2021b (The MathWorks) and EEGLAB (2021, http://sccn.ucsd.edu/). Raw data were band-pass filtered at 0.2–47 Hz. The 5-minute EEG recordings were segmented into 75 epochs of 4 seconds each. Visual inspection identified and rejected artifact-contaminated epochs (mean = 1.46, SD = 2.02) and bad electrodes (mean = 2.03, SD = 2.36), with bad electrodes interpolated using spherical spline inter-

polation. Independent component analysis (ICA) removed muscle and ocular artifacts. Data were finally re-referenced to the average of all electrodes.

Power spectral density (PSD) for each subject and electrode was computed using Welch' s method (4-s Hamming window, no overlap). Given the increasing maturity of EEG source localization techniques—and the fact that source localization is routine for MEG—we recommend performing source localization on raw signals before computing power spectra for high-density (64+ channels) EEG/MEG data. The exact low-resolution electromagnetic tomography (eLORETA) method can be used for EEG/MEG source localization to construct cortical electrical neuroactivity, calculating PSD for each vertex (dipole) on the cortical surface. For simplicity, we present only scalp electrode power spectral analysis here.

2.2.2 Electrode-Level SpecParam Fitting Aperiodic fitting at the single-electrode (or single cortical dipole) level was implemented in MATLAB R2021b using SpecParam version 1.0.0 from Donoghue et al. (2020) (example code available in supplementary materials). Inputting each electrode' s PSD into SpecParam yields periodic and aperiodic parameter estimates.

Detailed algorithm steps are shown in Figure 3 [Figure 3: see original paper] [**?**]. Pre-processing parameters must be set before execution: (1) **peak_{{{width}}*{{limits}}*: *Default [0.5, 12] Hz, defining possible peak width range. This study used [1, 12] Hz. Unless otherwise specified, default values were used for subsequent steps. (2) max_n*{peaks}**: Default Inf, maximum number of peaks to fit. This study used 8. (3) **min_{{{peak}}*{{height}}*: *Default 0.0, absolute threshold for peak detection as the minimum height (above aperiodic component) for any extracted peak. Defined in absolute units of power spectrum (log-power), commonly set to 0.1. This absolute threshold remains constant during iteration. (4) peak*{threshold}**: Default 2.0, relative threshold for peak detection based on standard deviation of flattened spectrum; extracted peaks must exceed this threshold. This relative threshold is recalculated during each iteration. (5) **aperiodic_{mode}**: Default 'fixed' , selecting the fitting method for aperiodic component. The 'fixed' condition assumes a single 1/f component characteristic where energy across all frequencies in log-log space falls on a straight line. However, across wide frequency ranges (>~40 Hz), aperiodic components typically exhibit "bending" requiring a 'knee' parameter.

Figure 3 SpecParam algorithm steps at single-electrode level: (a) Initial aperiodic fitting: Fit and estimate aperiodic component from raw PSD; (b) Flatten spectrum: Subtract aperiodic estimate from raw PSD, with residual assumed to be mixture of periodic components and noise; (c.i) Peak detection: Use iterative process to find peaks in flattened spectrum. Identify residual maximum and fit Gaussian curve around peak; (c.ii) Subtract fitted Gaussian and continue fitting; (c.iii) Iteration stops when next identified point falls below ab-

solute/relative thresholds or fitted peak count exceeds maximum; (d) Create full-peak fit: After determining oscillation count from peaks above noise threshold, perform multi-Gaussian fit on flattened spectrum from (b) to obtain joint power of all periodic components (orange dots), including three parameters per peak: center frequency, power, and width; (e) Create peak-removed spectrum: Subtract joint power from (d) from raw PSD; (f) Refit aperiodic component: Refit aperiodic component on peak-removed spectrum to obtain exponent and offset; (g) Combine joint power from (d) with refitted aperiodic component from (f) for final fit.

In summary, each electrode yields: (1) two aperiodic parameters—exponent and offset; and (2) 3×m periodic parameters (where m ≤ max_n_{peaks}), with each periodic peak providing three parameters: single-peak center frequency, single-peak power, and single-peak width.

2.2.3 Subject-Level Parameter Integration Subjects were excluded if more than one-third of electrodes showed poor fit quality ($R^2 < 0.9$). For each subject' s aperiodic parameters, representative values were computed by averaging across all electrodes (Figure 2b). For periodic components, the center frequency corresponding to maximum power across all electrodes was selected as the subject' s representative periodic center frequency. Based on this center frequency, the closest-matching single peak was identified in each electrode according to the nearest-center-frequency principle, then averaged to obtain periodic component power and periodic component width. Note that periodic component center frequency, power, and width represent integrated information at the subject level derived from single-electrode peak parameters.

2.2.4 Group-Level Statistical Analysis Following these steps, each subject possessed two aperiodic parameters (exponent and offset) and three periodic parameters (periodic center frequency, periodic power, periodic width). For this within-subject design, paired-sample t-tests were performed on aperiodic and periodic parameters between normal sleep and sleep-deprived conditions. To analyze scalp distribution of aperiodic components, paired-sample t-tests were conducted for each electrode with Bonferroni correction for multiple comparisons. In high-density EEG/MEG, electrode-wise multiple comparisons can also be addressed using cluster-based permutation tests [**?**].

In this example, aperiodic offset increased significantly after sleep deprivation, while aperiodic exponent differences were non-significant (Figures 4c-d [Figure 4: see original paper]). Electrode-wise paired-sample t-tests revealed that offset differences were primarily localized to multiple occipital electrodes (Figure 4c).

Figure 4 Scalp topographic distributions for normal sleep versus sleep deprivation. (a) Topographic maps of offset for both conditions; (b) Topographic maps of exponent for both conditions; (c)(d) Electrode-wise paired-sample t-tests between conditions, with electrodes showing $p < 0.05$ marked in red. (Source: [**?**])

2.3 Summary

This section compared features of commonly used aperiodic analysis toolkits and, based on SpecParam, introduced considerations for multi-electrode information integration and group-level statistical analysis in high-density EEG/MEG. This approach not only maximizes electrode-level information utilization but also allows flexible selection of electrode-level or subject-level analyses according to research questions, enhancing data utilization efficiency.

3 Applications of Resting-State Aperiodic Analysis Across Populations

Fundamentally, the aperiodic exponent serves as a metric for how quickly the power spectrum changes with frequency, thus representing an index of neural variability; offset reflects overall upward/downward shifts in power across the spectrum. Recent work has leveraged aperiodic activity and its parameters to reflect psychologically relevant physiological processes. Resting-state aperiodic component analysis currently finds primary application in neuroscience and psychology, including wakeful resting states, sleep states, and neurodevelopmental questions. In clinical applications, aperiodic parameters demonstrate potential value as electrophysiological biomarkers for group comparisons. Below, we review current mainstream findings by population type.

3.1.1 Wakeful Resting State

Resting-state EEG/MEG is typically divided into eyes-open and eyes-closed conditions, with both exponent and offset being larger in eyes-closed than eyes-open states [**?**, **?**], and these condition differences are highly stable [**?**, **?**].

Personality traits represent stable patterns of emotion, cognition, and behavior [**?**], and their neural underpinnings have been extensively investigated, particularly in resting states. Jach et al. (2020) used multivariate pattern analysis (MVPA) to demonstrate that personality traits could be predicted from frequency-band activities, but this result relied on traditional spectral analysis. Pacheco et al. (2024) further incorporated aperiodic components and found that aperiodic analysis increased predictive effect sizes. Moreover, periodic and aperiodic components may represent different aspects of personality: while periodic activity predicts all personality domains, agreeableness specifically requires aperiodic features for improved prediction.

Recent work also highlights the importance of aperiodic activity in higher cognitive functions, including task performance [**?**], arousal level [**?**], and advanced cognitive processing. Higher cognitive functions are mediated by complex oscillatory patterns, with individuals adjusting cognitive control styles between persistence and flexibility according to task demands [**?**, **?**]. Resting-state EEG activity can serve as a neural marker reflecting these functional variations [**?**]. Facing different persistence/flexibility demands, neural signal transmission changes

accordingly, manifesting as altered E:I balance, which can be indexed by aperiodic exponent changes. During more flexible processing, cortical network states update more frequently to adapt to tasks (larger exponent); during persistent tasks, transitions between cortical network states must be minimized (smaller exponent) [?]. Pi et al. (2024) extended this relationship to individual differences, using resting-state EEG aperiodic activity to predict cognitive control styles. Individuals with smaller resting-state exponents showed increased exponents under high-persistence conditions, while those with larger resting-state exponents showed no task-related differences. These group differences corresponded to performance across task conditions, demonstrating that individuals can adjust cognitive control modes by modulating aperiodic activity levels. Thus, aperiodic activity represents not only stable background neural activity but also reflects individual differences in cognitive adaptation.

3.1.2 Sleep State

Separating aperiodic components in sleep states enhances understanding of sleep neurophysiology. Transitions between wakefulness and sleep exhibit distinct electrophysiological features reflecting global brain state changes [?]. Furthermore, sleep EEG activity correlates with age, sex, and cognitive ability [?, ?, ?].

The spectral exponent is highly sensitive to relative ratio changes in excitatory and inhibitory neural activity. Early research demonstrated significant differences in aperiodic exponents between wakefulness and slow-wave sleep, most pronounced below 10 Hz but absent above 70 Hz [?]. Schneider et al. (2022) analyzed different human sleep stages and found, after controlling for individual differences, that spectral exponent could serve as a sleep stage marker. Wakefulness showed the largest exponent, suggesting enhanced inhibitory activity may characterize reduced arousal states. Exponent progressively decreased with deepening non-rapid eye movement (NREM) sleep [?, ?], reaching minimum values during slow-wave sleep. Spatial analyses further revealed strongest sleep-state dependency in prefrontal regions [?]. Medial prefrontal and medial temporal cortices showed greater sleep-stage effects than lateral prefrontal cortex—regions most relevant to sleep-dependent memory consolidation [?, ?].

Nocturnal synaptic excitability modulation constitutes a physiological mechanism of neural network plasticity that promotes memory consolidation during sleep [?, ?], reflected in aperiodic activity. Aperiodic activity drives broadband power decreases during sleep, with spectral exponent increasing post-sleep. Rapid eye movement (REM) sleep mediates this nocturnal down-regulation of spectral exponent, which becomes smaller in NREM stages following REM. Correspondingly, sleep deprivation attenuates nocturnal regulation of aperiodic activity, producing flatter spectra compared to normal sleep [?], providing electrophysiological evidence for sleep deprivation-induced memory and learning impairments [?, ?].

3.1.3 Neurodevelopment

Neural oscillations are highly sensitive to developmental changes. With brain maturation, δ and band power decreases while α and β band power increases, with significant sex differences in certain brain regions [**?**, **?**, **?**]. Similar to periodic activity, aperiodic activity shows developmentally relevant changes [**?**, **?**]. Across the lifespan, individual differences in spectral exponent correlate with age-related cognitive decline, where smaller exponents predict poorer cognitive performance [**?**, **?**, **?**]. During rapid developmental periods (early childhood and adolescence), both exponent and offset show significant age-related decreases [**?**, **?**]. In later life stages, Pathania et al. (2022) confirmed these age-related individual differences by linking resting-state spectral exponent to a battery of cognitive and motor tasks, finding that frontal exponent mediated age-related cognitive changes. Decreased aperiodic exponent indicates increased E:I ratio and reduced population-level neural synchronization during aging [**?**, **?**]. Throughout development, whole-brain maxima of exponent and offset shift from posterior to anterior regions [**?**], with maximum wake-sleep aperiodic exponent changes located in frontal cortex, matching the later maturation of higher-order cognitive and executive functions. Wake-sleep aperiodic activity also differentiates progressively during development, with classic sleep-stage slow-wave activity correlating strongly with aperiodic exponent [**?**]. Older adults show flatter spectra than younger adults, potentially explaining reduced information processing capacity and consistent with poor sleep quality and frequent awakenings. Human brain development exhibits sexual dimorphism also reflected in aperiodic parameters: females show earlier brain maturation patterns than age-matched adolescent males [**?**, **?**]. Parameterized PSD reveals significantly lower aperiodic offset in females, though males' higher early offset declines at a greater rate over time [**?**].

α rhythm is among the most prominent components linking periodic activity to cognitive performance [**?**], yet the relationship between α oscillations and cognition remains inconclusive [**?**, **?**, **?**]. This inconsistency may arise from mixing of α oscillations with aperiodic activity in traditional analyses [**?**]. As shown in Figures 1c-e, periodic component changes may actually result from aperiodic component alterations [**?**, **?**], a problem overlooked in many early studies. Aperiodic component analysis provides a novel perspective to resolve these controversies. Finley et al. (2024) found that individual α frequency and resting-state aperiodic exponent jointly predicted cognitive decline from middle to old age, both decreasing with age and relating to poorer executive function and working memory in later life. Reanalysis of adjusted periodic components revealed that α peak center frequency remained age-related, but α peak power no longer differed significantly between age groups [**?**]. This confounding effect of aperiodic components on α total power changes was also confirmed in childhood and adolescent samples [**?**, **?**]. Notably, adjusted α oscillations no longer predicted cognitive speed, whereas aperiodic exponent robustly predicted individual processing speed [**?**]. Thus, in neurodevelopment, decomposing periodic

and aperiodic components clarifies their relative contributions.

3.2 Neuropsychiatric Disorders

Recent research has explored the substantial value of aperiodic components in disease-related neural changes. Specific EEG/MEG features correlate with neurological disorders, with patient power spectrum changes relative to healthy populations serving as potential biomarkers [**?**, **?**].

Healthy neural development requires environmental shaping [**?**], particularly adequate sensory input during critical periods. In vision, for example, congenital blindness reduces α oscillations detected by EEG [**?**, **?**] but increases γ rhythm activity in MEG [**?**], reflecting increased neural excitability [**?**, **?**]. Compared with sighted individuals, congenital blindness induces changes partly attributable to aperiodic activity. Individuals with restored vision show recovery of disease-related oscillatory activity, but aperiodic abnormalities persist, suggesting irreversible changes in visual cortex E:I ratio [**?**].

Similarly, many neuropsychiatric disorders disrupt brain development, progressing to cognitive, motor, and autonomic dysfunction. Comparisons of patient and healthy control resting-state EEG/MEG reveal abnormal activity in specific bands (e.g., β and γ) and significant aperiodic exponent changes, correlating with poorer behavioral performance. While periodic power changes generally reflect abnormal neural circuits, aperiodic exponent changes may further indicate altered E:I ratios.

Table 2 lists nine clinical studies investigating aperiodic components. Despite mechanistic heterogeneity across diseases, most show increased aperiodic exponent in patients. Given the hypothesis linking neural excitability and neurotransmitter signaling to spectral exponent, most neuropsychiatric manifestations can be categorized as either hyperexcitability (steeper slope, e.g., Parkinson' s disease; [**?**]) or hypoexcitability (flatter slope, e.g., pediatric Fragile X syndrome; [**?**]). When associating structural brain changes with spectral changes, both slope patterns may represent compensatory mechanisms: (1) decreased resting excitability to maintain normal firing rates, or (2) additional excitability recruitment during difficult tasks in individuals with abnormal neural connectivity. However, current associations between aperiodic exponent and pathological mechanisms remain correlational, with insufficient evidence for causal relationships.

Table 2 Aperiodic analysis in neuropsychiatric disorders

Study	Population & Disorder	Adjusted Periodic Component	Aperiodic Component	Key Findings	Reference
Rett syndrome (N=57) vs. healthy controls (N=57)	-	SpecParam	↑ Exponent	Increased δ power correlated with lower cognitive assessment	[?]
Pediatric Fragile X (N=11) vs. age-matched (N=12) & cognitive-matched (N=12)	-	SpecParam	↑ Exponent	Frontal γ power mixed higher than healthy controls	[?]
Parkinson's disease (medicated/withdrawn; N=15) vs. healthy controls (N=15)	-	SpecParam	↑ Exponent	-range power higher in Parkinson's group	[?]
ADHD (N=33) vs. healthy controls (N=33)	-	SpecParam	↑ Exponent	β power higher in ADHD group	[?]

Study	Population & Disorder	Adjusted Periodic Component	Aperiodic Component	Key Findings	Reference
First-episode schizophrenia spectrum (N=43) vs. healthy controls (N=29)	-	SpecParam	↑ Exponent	-	[?]
Alzheimer's disease (N=36) vs. frontotemporal dementia (N=23) vs. healthy controls (N=29)	-	SpecParam	-	Alzheimer's showed higher power than frontotemporal dementia	[?]
Alzheimer's disease (N=43) vs. healthy controls (N=49)	-	SpecParam	-	Significant power reduction in Alzheimer's; changes related to aperiodic EEG activity	[?]

Study	Population & Disorder	Adjusted Periodic Component	Aperiodic Component	Key Findings	Reference
Generalized epilepsy	(N=51) vs. healthy controls (N=49)	SpecParam	↑ Exponent	Negative correlation between exponent and α power reduced in epilepsy	[?]
Lewy body dementia	(N=21) vs. Parkinson's (N=28) vs. mild cognitive impairment (N=27) vs. healthy controls (N=22)	SpecParam	↑ Exponent	Lewy body dementia showed higher power than other groups	[?]

Note: "-" indicates non-significant or unreported findings; "↑" indicates increase; "↓" indicates decrease.

Aperiodic analysis revolutionizes traditional spectral analysis. Previous associations between periodic activity and disease severity yielded contradictory findings. Based on aperiodic analysis, researchers hypothesize these discrepancies stem from aperiodic confounding: after removing aperiodic components, β power in subthalamic nucleus correlates more strongly with Parkinson' s motor symptoms [?], and aperiodic exponent independently predicts Parkinson'

s symptom severity [?]. In neurodevelopmental disorders more closely linked to electrophysiology (e.g., ADHD, autism spectrum disorder), aperiodic exponent shows even greater group differences than traditional diagnostic criteria [?, ?]. Temporally, Belova et al. (2021) found exponent sensitive not only to resting-state or long-term changes but also to short-term dynamics, highlighting advantages in reflecting brain pathology. Separating periodic and aperiodic components also helps identify sources of disease-related neural signal changes. For example, in Alzheimer' s disease, [?] clarified that neural activity changes derive entirely from periodic contributions, independent of aperiodic activity. Aperiodic component analysis enables more precise physiological interpretation and defines different power spectrum components and their changes.

Currently, hypotheses regarding hyper- and hypo-excitability in neuropsychiatric disorders require further validation. Limited by early-stage research quantity, the generalizability and replicability of aperiodic findings await verification. Additionally, patient EEG acquisition is more susceptible to noise (e.g., ocular and muscle artifacts; [?]), necessitating development of more robust, noise-resistant algorithms.

3.3 Summary

In summary, aperiodic parameters—particularly the exponent—demonstrate associations with higher cognitive functions, arousal states, and neurodevelopment, enabling electrophysiological interpretation of neural mechanisms underlying behavior. In clinical domains, the destructive impact of neuropsychiatric disorders on brain function and behavior necessitates objective electrophysiological biomarkers, for which aperiodic analysis provides a novel perspective. Parameterization of periodic and aperiodic components also clarifies contributions from different components, effectively explaining previously contradictory findings. In all population types, aperiodic analysis shows broad application prospects.

4 Future Directions

Although empirical aperiodic analysis research remains in its infancy, it has opened new avenues for traditional spectral analysis in neuroelectrophysiology. However, limitations exist: aperiodic parameters currently lack mature and comprehensive systematic validation regarding spatial distribution and psychometric properties. Future research should address the following aspects.

4.1 Spatial Distribution Patterns

Some researchers have begun investigating spatial distribution characteristics of aperiodic components in resting-state EEG [?] and MEG [?, ?]. In healthy adults, posterior regions generally show larger aperiodic exponents (steeper spectra). Offset also decreases from posterior (occipital) to anterior (frontal) directions, being lowest in prefrontal and medial temporal cortices. When fitting

human brain activity using piecewise linear models (with a knee around 10 Hz), low-frequency slope is steepest in anterior regions and shallowest in sensorimotor and visual cortices, while high-frequency slope remains steepest in posterior regions (excluding occipital cortex), with negative correlations between cortical patterns of the two slopes [**?**]. Although spatial patterns of aperiodic parameters resemble those of periodic peak frequencies, periodic peak frequency gradients are largely independent of aperiodic parameters [**?**]. Due to variability in electrode/channel selection across EEG/MEG studies with different research purposes and populations, and because aperiodic activity origins may not be limited to specific brain regions [**?**], future aperiodic analysis studies should report whole-scalp aperiodic activity to enable selective comparison across electrode configurations and assess spatial group differences in aperiodic parameters.

Given EEG' s limited spatial resolution, future research should consider simultaneous EEG-fMRI [**?**] to enhance spatial resolution. Evidence suggests broadband power fluctuations in aperiodic neural population activity may constitute the neural basis of whole-brain resting-state fMRI activity [**?**]. Additionally, aperiodic parameters correlate highly with BOLD signals at rest [**?**]. As an indirect measure of neural activity, BOLD also represents E:I balance [**?**]. Although individuals lack explicit tasks during rest, certain brain regions remain active —the default mode network (DMN; [**?**, **?**]). In periodic oscillation research, spontaneous α and β activity has been linked to anterior and posterior cingulate cortices, associated with attention and cognitive activity, respectively [**?**]. Researchers have attempted to correlate eyes-open aperiodic parameters with DMN, but correlation coefficients were small [**?**], possibly because eyes-open conditions generate stronger external attention and weaker DMN functional connectivity than eyes-closed conditions [**?**]. During rest, particularly eyes-open, individuals' attention and arousal fluctuate, involving top-down or bottom-up attention networks corresponding to different arousal states and excitability levels [**?**]. Eyes-closed conditions may enhance top-down sensory activity and mental imagery [**?**], showing increased arousal and decreased exponent. Currently, simultaneous EEG-fMRI evidence from eyes-closed conditions and eyes-open/closed comparisons are lacking, preventing clear specification of state effects on aperiodic activity. Furthermore, task-irrelevant stimuli (e.g., scanner noise) increase fMRI signal-related aperiodic activity in auditory cortex, reflecting active suppression of irrelevant stimuli [**?**]. Future simultaneous EEG-fMRI studies should focus on eyes-open/closed states and effects of environmental stimuli on cross-modal signal associations.

4.2 Free Parameter Determination and Group Analysis

Recent aperiodic research shows higher prevalence and broader application of SpecParam compared with other algorithms. Notably, using SpecParam requires presetting multiple free parameters (Figure 2). While [**?**] provides defaults suitable for most experimental data, practical applications require parameter adjustments to prevent overfitting or poor fit. Free parameter determination can

reference settings from similar published samples, using data-driven approaches to iteratively optimize model fit [?].

After determining model parameters, the pipeline described herein yields corresponding aperiodic and periodic parameters. For group-level statistics, our framework provides a within-subject design example; other studies can select statistical procedures based on experimental design. Critical is deriving subject-level parameters from electrode-level data. Aperiodic parameters can be directly averaged, but periodic parameters require algorithmic design based on experimental hypotheses. Our framework demonstrates extraction of maximum-power periodic components without assuming specific numbers or frequency distributions of periodic components.

4.3 Psychometric Properties of Aperiodic Analysis

Good measurement indices require strong psychometric properties—validity and reliability. As noted, numerous studies link aperiodic exponent to perceptual and cognitive behaviors (e.g., working memory; [?, ?, ?, ?]), reflecting validity potential, with demonstrated value in clinical and neurodevelopmental research [?]. Additionally, good within-subject signal stability (test-retest reliability) is essential.

Traditional spectral analysis reliability is well-established, with high test-retest reliability in eyes-open/closed resting states using intraclass correlation coefficients [?, ?]. Aperiodic component test-retest reliability ranges from fair to excellent (0.50–0.95; [?]), with offset being more stable than exponent. Eyes-open reliability is poorer, attributable to increased ocular artifacts [?] and potential unconscious visual processing during eyes-open states, creating a "task state" that affects aperiodic components [?]. Reliability is also state-dependent, with tasks susceptible to emotional or arousal fluctuations showing lower reliability [?, ?].

Although researchers have begun exploring aperiodic parameter reliability across states, psychometric performance requires further validation compared with periodic parameters. Spatial-level investigation combining fMRI could focus on specific brain regions and corresponding scalp electrodes to comprehensively evaluate psychometric properties, providing stronger theoretical and practical foundations for aperiodic parameters as biomarkers.

4.4 Physiological Significance of Aperiodic Components

E:I balance between excitatory and inhibitory neurons is crucial for neural homeostasis and oscillation generation [?, ?], ensuring normal information transmission [?, ?]. E:I imbalance during developmental critical periods associates with various central nervous system pathologies [?, ?, ?]. Higher aperiodic exponent is thought to reflect increased inhibition or decreased excitation [?]. For example, ADHD' s low neural stability may relate to increased neural noise. Peripheral bodily rhythms (e.g., respiration, cardiac rhythm) also regulate behavior,

cognition, and underlying neural oscillations, coordinating cortical excitability [?, ?, ?]. Kluger et al. (2023) linked respiration to aperiodic brain activity, finding exponent changes phase-locked to respiratory cycles, indicating spontaneous E:I balance states are influenced by peripheral bodily signals.

Neural circuit excitation and inhibition are typically mediated by fast glutamatergic and slower GABAergic inputs [?, ?]. Magnetic resonance spectroscopy (MRS) can measure in vivo neurotransmitter concentrations, with many studies reporting relationships between neurotransmitter levels and psychophysical performance in specific brain regions [?, ?]. Based on E:I imbalance theory, neurotransmitters can serve as biomarkers for neuropsychiatric disorders [?, ?, ?]. This theoretical indirect evidence can link aperiodic parameters to neurotransmitters, but direct evidence remains lacking. Hormones, as another regulatory substance, also relate to internal information transmission. Gaižauskaitė et al. (2024) investigated effects of female hormonal status on resting-state EEG periodic and aperiodic parameters based on gonadal hormone mechanisms, finding no significant group differences. However, given significant within-individual spectral parameter fluctuations across menstrual cycles, direct associations between aperiodic components and neurotransmitters or hormones cannot be excluded.

5 Conclusion

As data analysis techniques advance, aperiodic analysis of EEG/MEG has gained widespread attention in neuroelectrophysiology, with successful applications in developmental neuroscience and neuropathology. This paper reviewed progress in aperiodic component analysis across eyes-open/closed resting states, sleep states, neurodevelopment, and clinical disorders, and discussed future directions including spatial distribution, parameter settings, group-level analysis, test-retest reliability, and physiological significance. Extensive applications and emerging algorithms reflect researchers' increasingly nuanced understanding of neurophysiological signals, laying foundations for further functional exploration. Current aperiodic component analysis still lacks focus on whole-brain spatial distribution, and its neurophysiological generation mechanisms remain exploratory. Future research should integrate multimodal techniques and experimental designs to strengthen theoretical foundations and expand applications.

Code Example (MATLAB)

```
% Calculate power spectra with Welch's method
[psds, freqs] = pwelch(data, 500, [], [], s_{rate});

% FOOOF settings
settings = struct('peak_{{{width}}_{{limits}}}',[1,12], ...
```

```
                    'max_n_{peaks}',8,'min_{{{peak}}_{{height}}}', 0.1, ...
                    'peak_{threshold}', 2.0,'aperiodic_{mode}','fixed');
f_{range} = [1, 30];

% Run FOOOF across a group of power spectra
import py.fooof.*
fooof_{results} = fooof_{group}(freqs, psds, f_{range}, settings);
```

Notes: 1. Before running, install the Python toolkit via PIP; see official website (https://specparam-tools.github.io/index.html) for detailed installation instructions. 2. The `settings` variable (lines 4-6) stores all preset parameters; unspecified parameters retain default values. SpecParam fitting performance is sensitive to preset parameters. Typically, peak detection absolute and relative thresholds remain at defaults, while other parameters require adjustment based on raw data spectral characteristics (e.g., [**?**] provides data-driven methods). When raw data are unsuitable for SpecParam, parameter adjustment alone cannot fully resolve fitting issues. Readers are recommended to consult [**?**] for specific handling of overlapping peaks and other problems. 3. The `fooof_{results}` output (line 10) contains five parameters: `aperiodic_{params}`: aperiodic parameters [offset, exponent]; `peak_{params}`: periodic parameters [center frequency, peak power, peak bandwidth]; `gaussian_{params}`: Gaussian fitting parameters; `error`: fitting residual; `r_{squared}`: goodness-of-fit.

Author Contributions

Lei Xu, Hu Jingyi: Conceived the review topic;
Hu Jingyi, Bai Duo: Conducted literature search and organization;
Hu Jingyi, Bai Duo: Drafted the manuscript;
Hu Jingyi, Bai Duo, Lei Xu: Revised the final version.

Note: Figure translations are in progress. See original paper for figures.