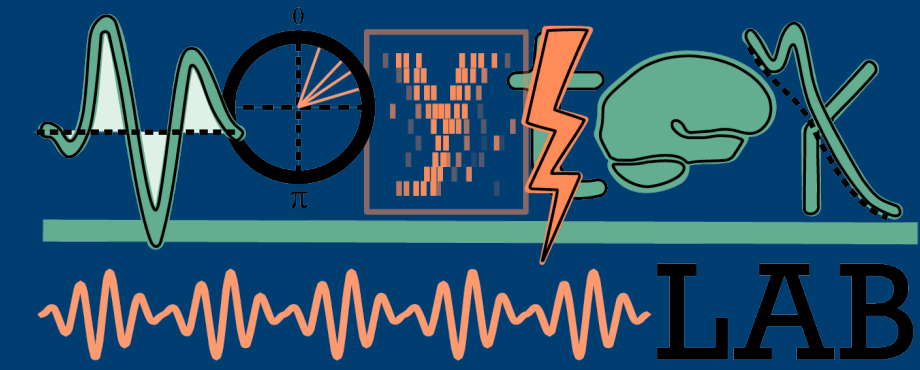




NeuroVlm: A Neuroscience Vision-Language Model

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From words to brain maps: An *efficient* and *versatile* vision-language model for neuroscience.

Introduction

Over the past decades, tens of thousands of neuroimaging studies have created an extensive corpus pairing natural language descriptions with brain activation coordinates, forming a rich multimodal dataset.

Recent advances in generative and predictive models [1, 2, 3, 4] now enable leveraging this vast knowledge base to fill scientific gaps and accelerate scientific discovery. Alongside advances in vision-language models ([5]), these methods may be adapted for neuroscience use cases. However, most state-of-the-art vision-language models require billions of parameters and / or extensive computational resources, limiting their accessibility and practicality.

In this work, we introduce NeuroVlm, a vision-language model that aligns neuroscientific text with coordinate-based brain activation maps. The model supports natural language queries, retrieves literature, and generates predicted activation patterns, thereby unifying text, brain representations, and large-scale scientific knowledge within a single architecture.

Methods

We trained NeuroVlm on a novel dataset of 30,000 fMRI-based text-brain pairs extracted from the literature, alongside 200,000 published papers without coordinates (meaning text-only).

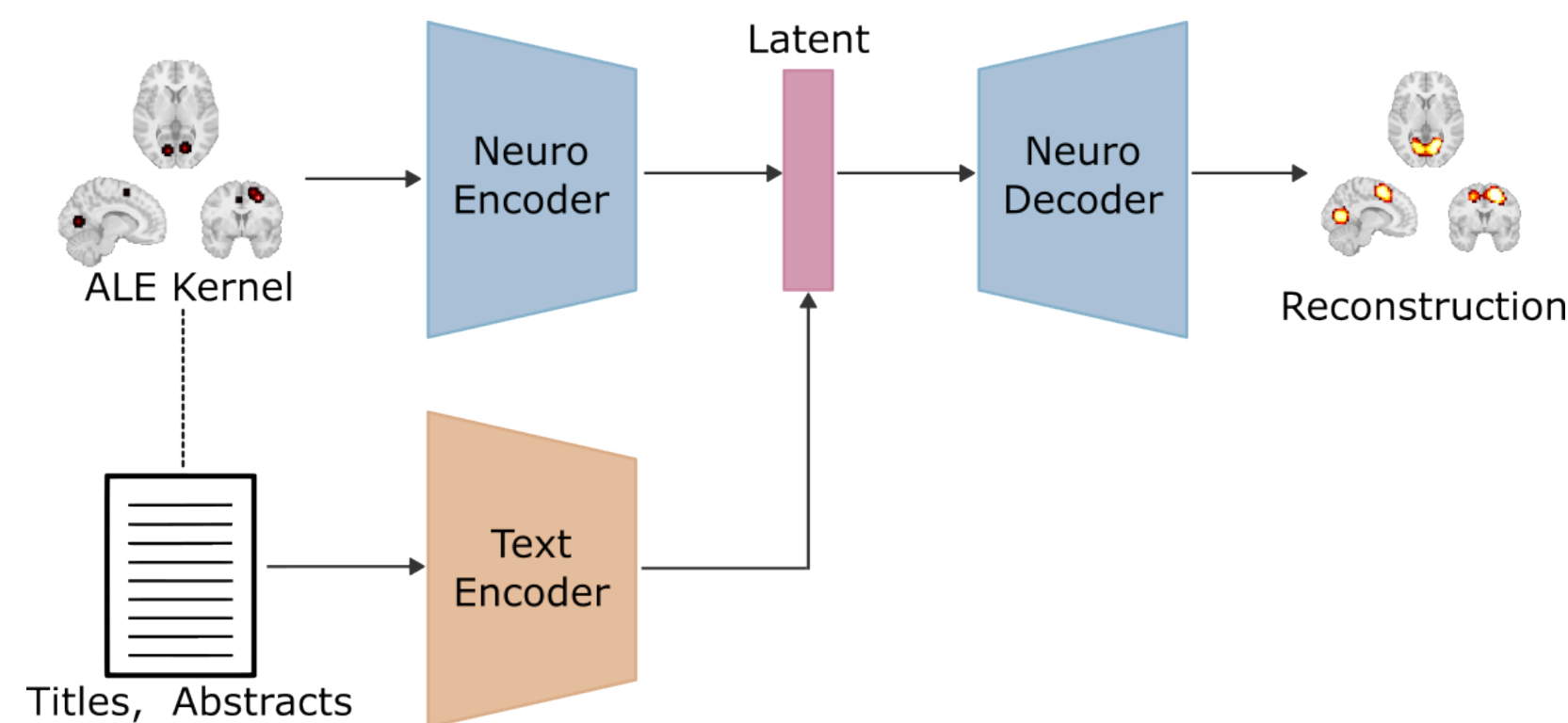


Figure 1. NeuroVlm Architecture

Neuro Autocoder: We trained a sequential autoencoder with three layers using images only. Latent space was set to be 768-dimensional.

Text Encoder: We finetuned SPECTER2 with 200k neuroscience articles to teach it domain-specific semantics.

Projection head: We trained a projection head to align latent text and brain embeddings using mean-squared error and InfoNCE loss.

Encoding and reconstructing canonical fMRI networks

We evaluated NeuroVlm's ability to encode and reconstruct canonical fMRI networks derived from ten widely used functional atlases. Although NeuroVlm was trained exclusively on task-evoked activation maps rather than atlas templates, its reconstructions achieved higher structural similarity and Dice scores, and lower mean squared error, compared to the Dictionary of Functional Modes (DiFuMo) reference baseline.

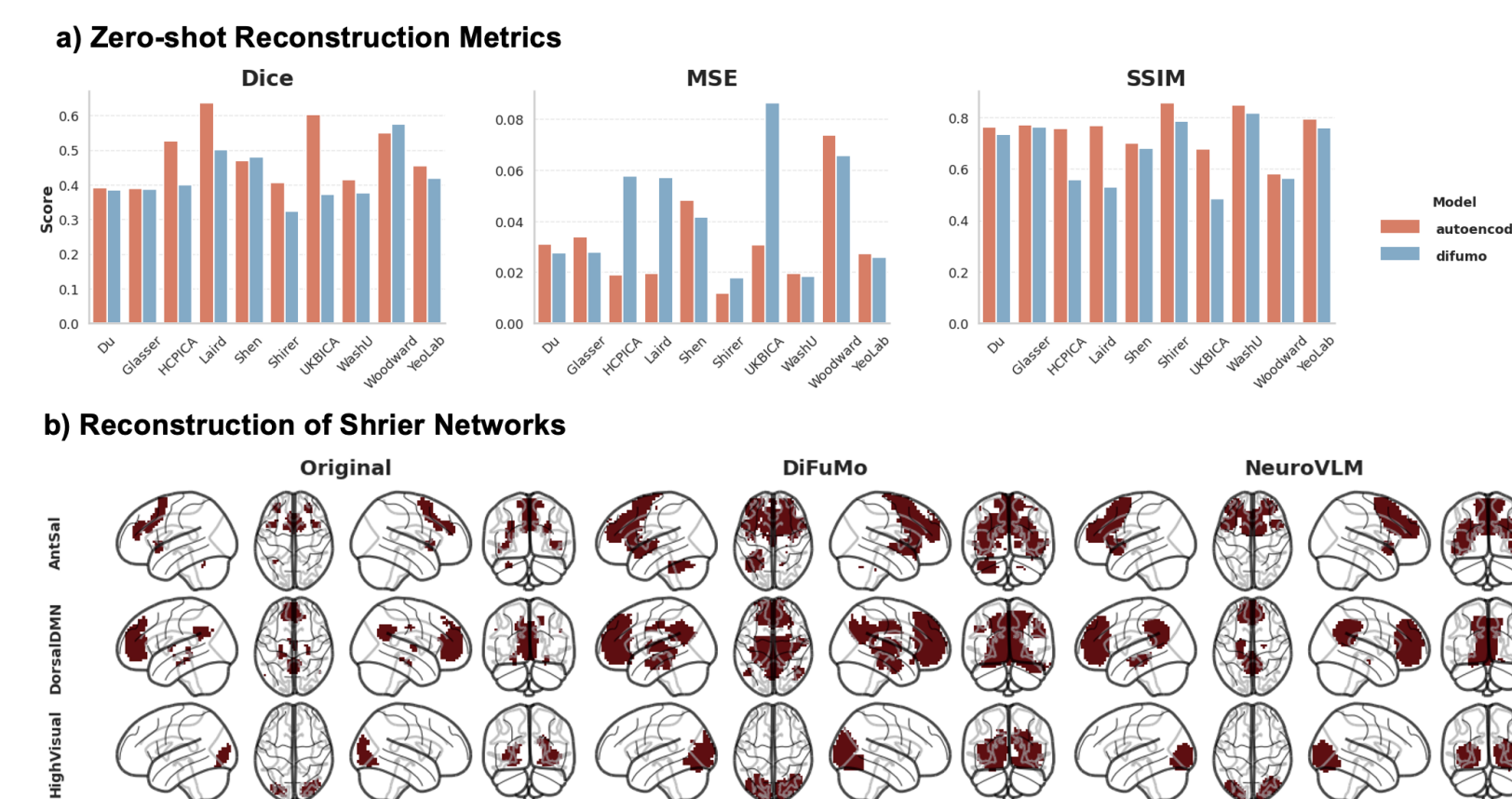


Figure 2. a) Reconstruction metrics when encoding and reconstructing fMRI networks from diverse atlas. b) Visual examples of the original binarized Shrier networks alongside the reconstruction using the DiFuMo basis and our autoencoder.

Ranking and retrieval capacity compared to larger models

Ranking and retrieval assess how well the model aligns brain maps and text. It measures whether the correct match appears among the top-ranked results, with higher recall reflecting stronger cross-modal alignment.

Table 1. Recall Performance

Metric	NeuroVlm		NeuroConText	
	Mean	Std	Mean	Std
Recall@20	0.2071	0.0106	0.2172	0.0093
Recall@200	0.5756	0.0092	0.5829	0.0140
Mix-Match	0.8418	0.0034	0.8414	0.0080

NeuroVlm matches NeuroConText in ranking and retrieval performance while using a 100M-parameter fine-tuned SPECTER2 backbone, compared to NeuroConText's 7B-parameter language model [6].

Text → brain

Despite being trained on full title–abstract pairs, NeuroVlm effectively decodes short-form text queries into meaningful neuroactivation patterns.

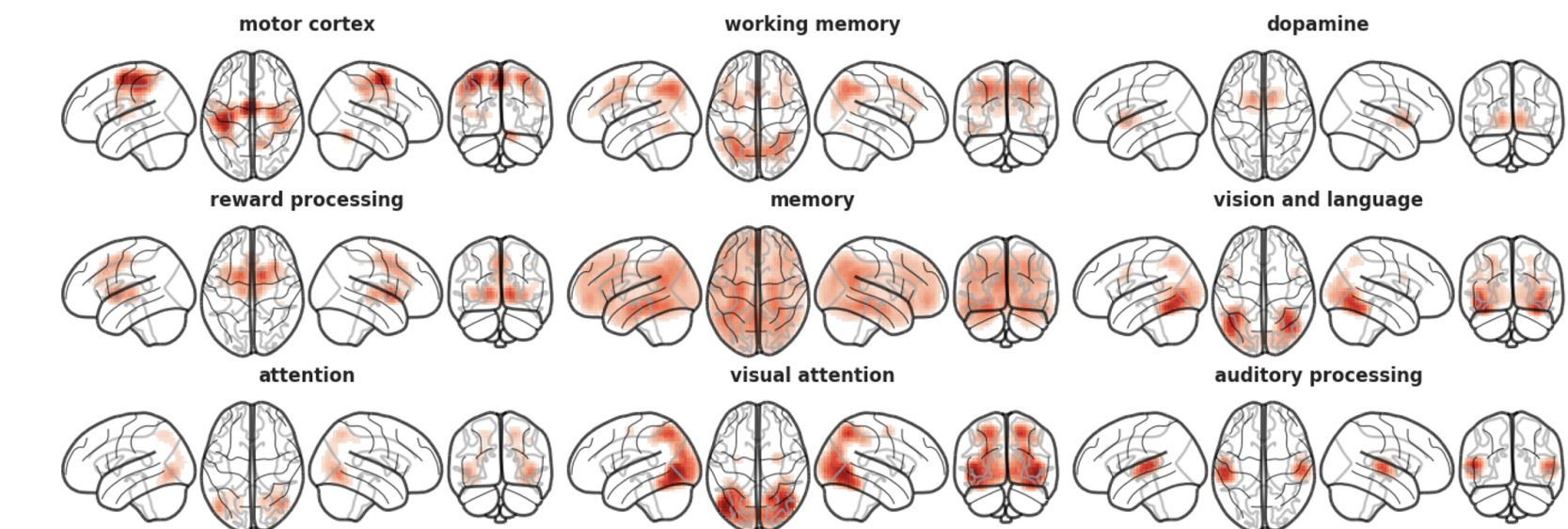


Figure 3. Qualitative Decoding Examples

When comparing the decoded activation maps with NeuroQuery—a coordinate-based meta-analytic model that predicts brain activations from text—we observe that NeuroVlm's reconstructions show higher spatial alignment and similarity to expected activation patterns.

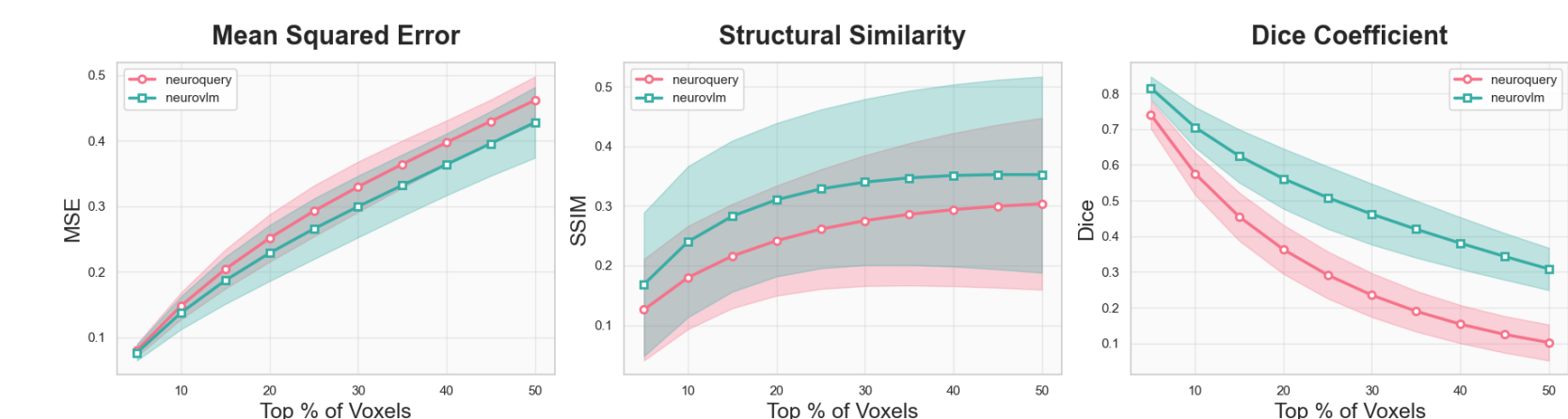


Figure 4. NeuroVlm and NeuroQuery Decoding Performance

Current and future work

- Explore *brain* → *text*: automatic labeling of unlabeled images and interpretation of brain maps.
- Extend *text* → *brain* decoding to temporal domains, investigating the feasibility of zero-shot *text* → *neurovideo* generation.
- and more!

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Disrupted aperiodic neural activity signatures in Rett Syndrome across human EEG and Mecp2-/+ mouse model electrophysiology

VOYTEKlab

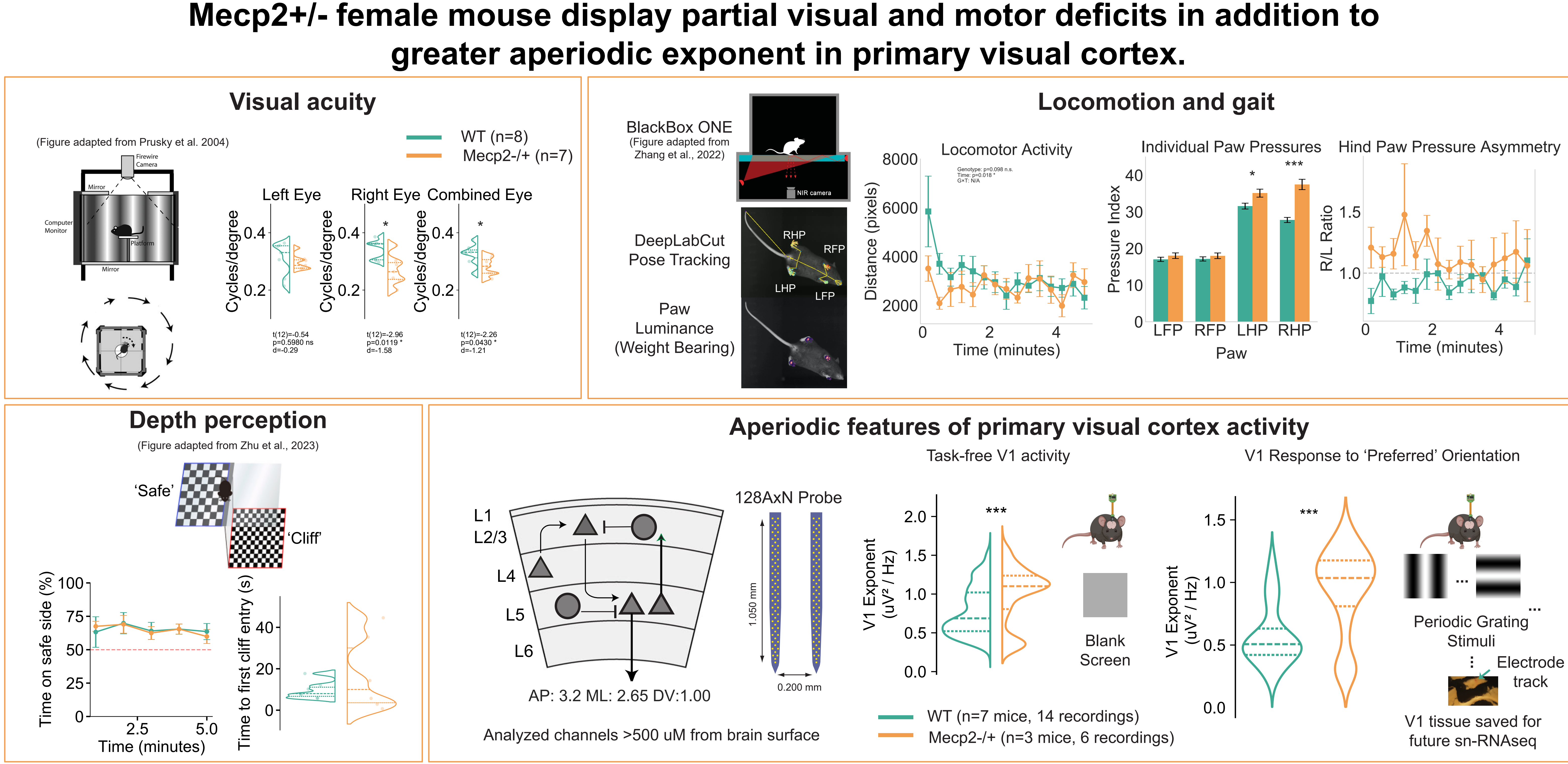
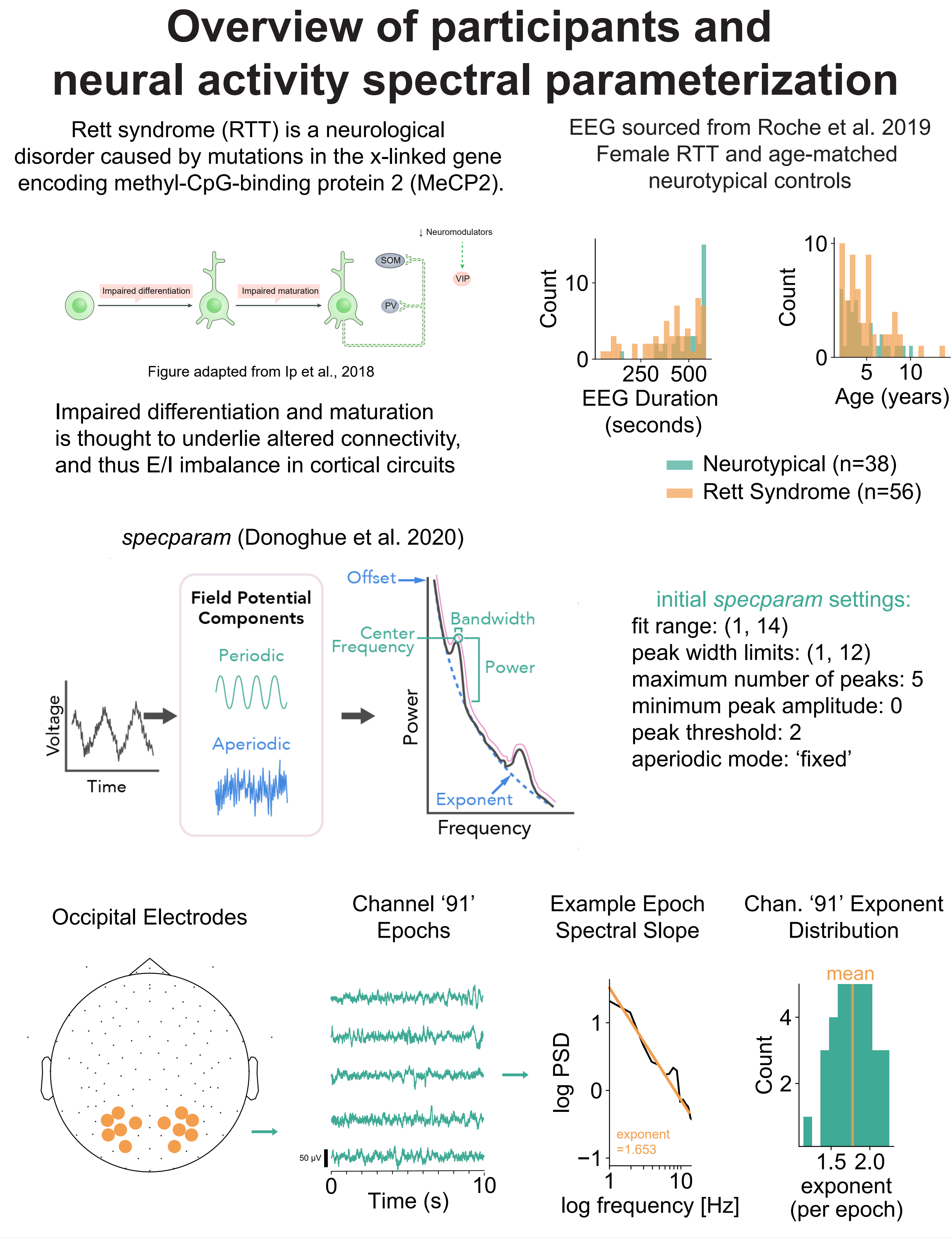
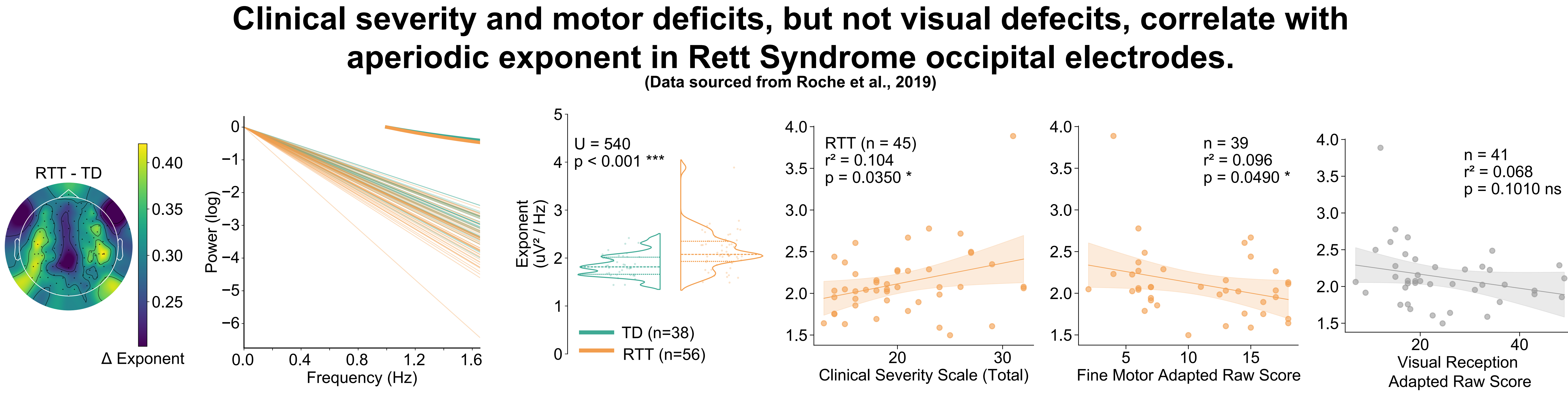
C. Cazares¹, S. Metanat¹, K. Lyon², N. Gandy¹, D. Kranz^{3,4}, A.R. Levin³, M. Faiolini^{3,4}, C.A. Nelson^{3,4}, B. Voytek^{1,5}

EEG signals consist of mixed periodic and aperiodic components that have been shown to reflect synchronized firing in cortical networks, and may serve as putative indices of cortical excitation-inhibition (E:I) balance in healthy and disrupted neurodevelopment.

Electrophysiological brain activity in children is linked to Rett Syndrome (RTT) risk and correlates with visual and behavioral deficits.

Mecp2-/+ female mouse model shows cortical E:I imbalance and can better recapitulate RTT.

Here we examined whether aperiodic electrophysiological signal features are correlated to symptomatic changes in RTT girls and the Mecp2-/+ female mouse model.



Spectral parameterization reveals that aperiodic electrophysiological features may serve as a cross-scale biomarker for symptomatic changes in Rett Syndrome that may link cellular-level imbalances in cortical excitation-inhibition to clinically observable visual and motor dysfunction.

Timescale changes across typical neurodevelopment and ADHD

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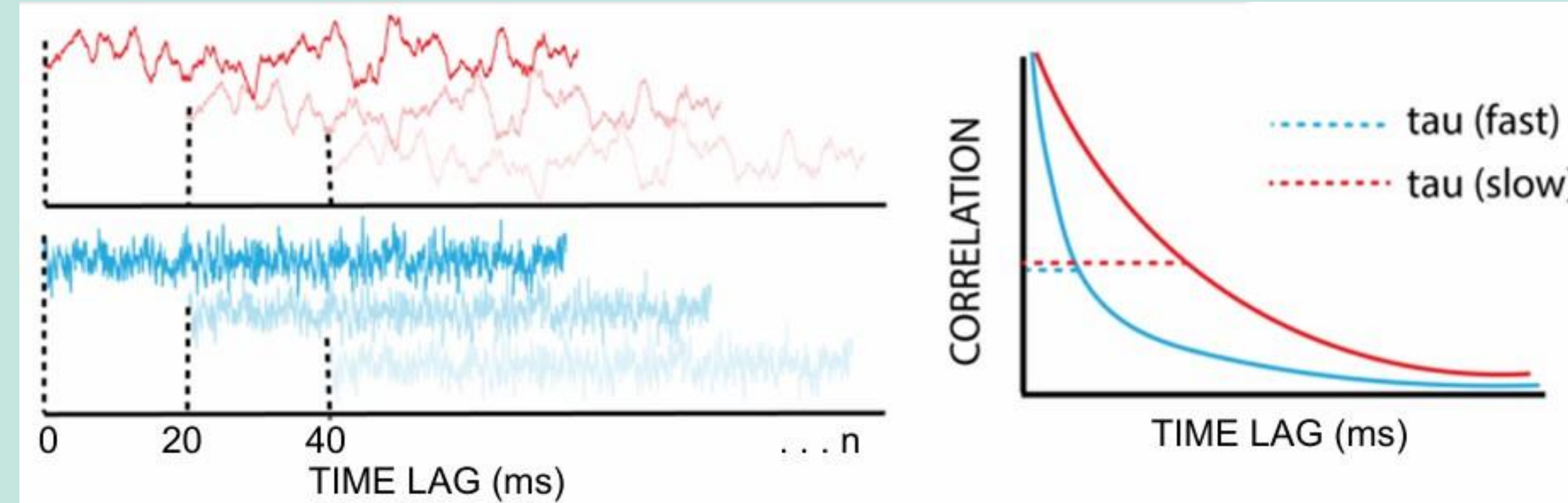
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Introduction

- Neural timescales capture the stochasticity or relative instability of a neural signal over time and are thought to reflect the brain's integration of external and internal stimuli¹⁻²

- Timescales can be measured using the autocorrelation function, which provides an estimate of how long it takes for a signal to lose correlation with itself¹⁼²

- Signals with a faster timescale have a steeper decay rate in the autocorrelation function



- Previous literature suggests that as age increases across typical development, power shifts from predominantly slower to relatively faster frequencies regarding both oscillatory and aperiodic activity³⁻⁹

- Given established research on typical neurodevelopmental changes in the periodic and aperiodic components of the power spectrum, we can make strong predictions regarding changes in the ACF that have yet to be tested

- Establishing typical neurological patterns of development allows exploratory investigation into neurodevelopmental disorders like ADHD, wherein these patterns may be altered

More on ADHD

- ADHD is a common and highly heterogenous neurodevelopmental disorder that usually presents with impaired levels of inattention, disorganization, or hyperactivity/impulsivity¹⁰

- Previous literature indicates that across development ADHD shows elevated low frequency power compared to typically developing peers, especially in frontal channels¹¹⁻¹⁴

- Further research suggests that the ADHD-Combined vs ADHD-Inattentive subtypes are distinct behavioral disorders, pointing to possible distinct developmental trajectories¹⁵⁻¹⁶

- Timescales, as metrics that combine periodic and aperiodic information and that are reflective of neural integration and segmentation, offer utility as a potential biomarker for demarcating these differing trajectories

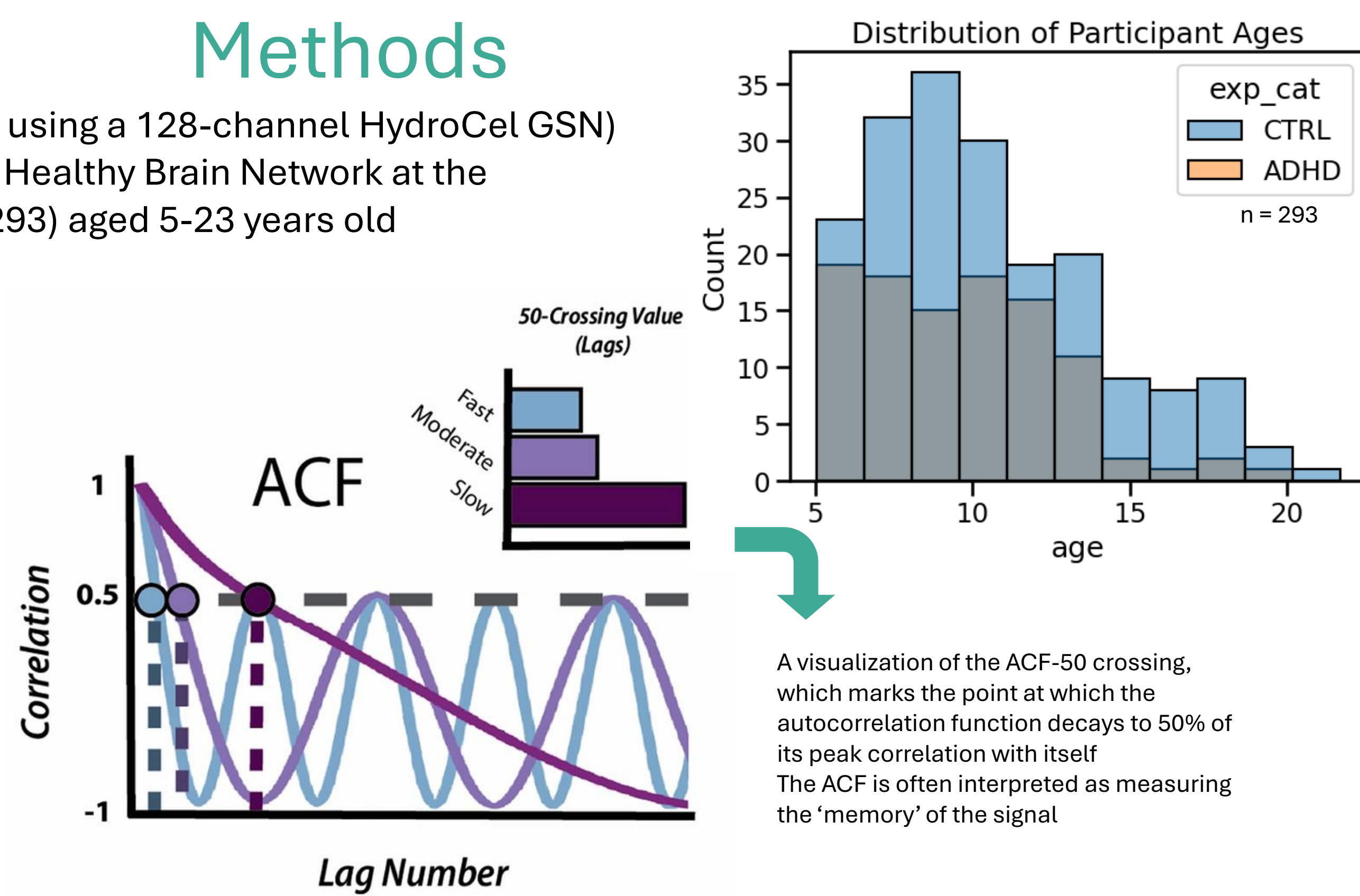
Methods

- EEG cross-sectional dataset (recorded using a 128-channel HydroCel GSN) of eyes-open/eyes-closed data from the Healthy Brain Network at the Child Mind Institute for participants (n=293) aged 5-23 years old

- Utilized an automatic preprocessing scheme involving automated channel rejection pipeline consisting of voltage thresholding, PSD thresholding, and established automated preprocessing pipeline PREP¹⁷

- Extracted and analyzed the PSDs and ACFs from the data

- TD and ADHD participants were age-matched using a nearest-neighbor based procedure

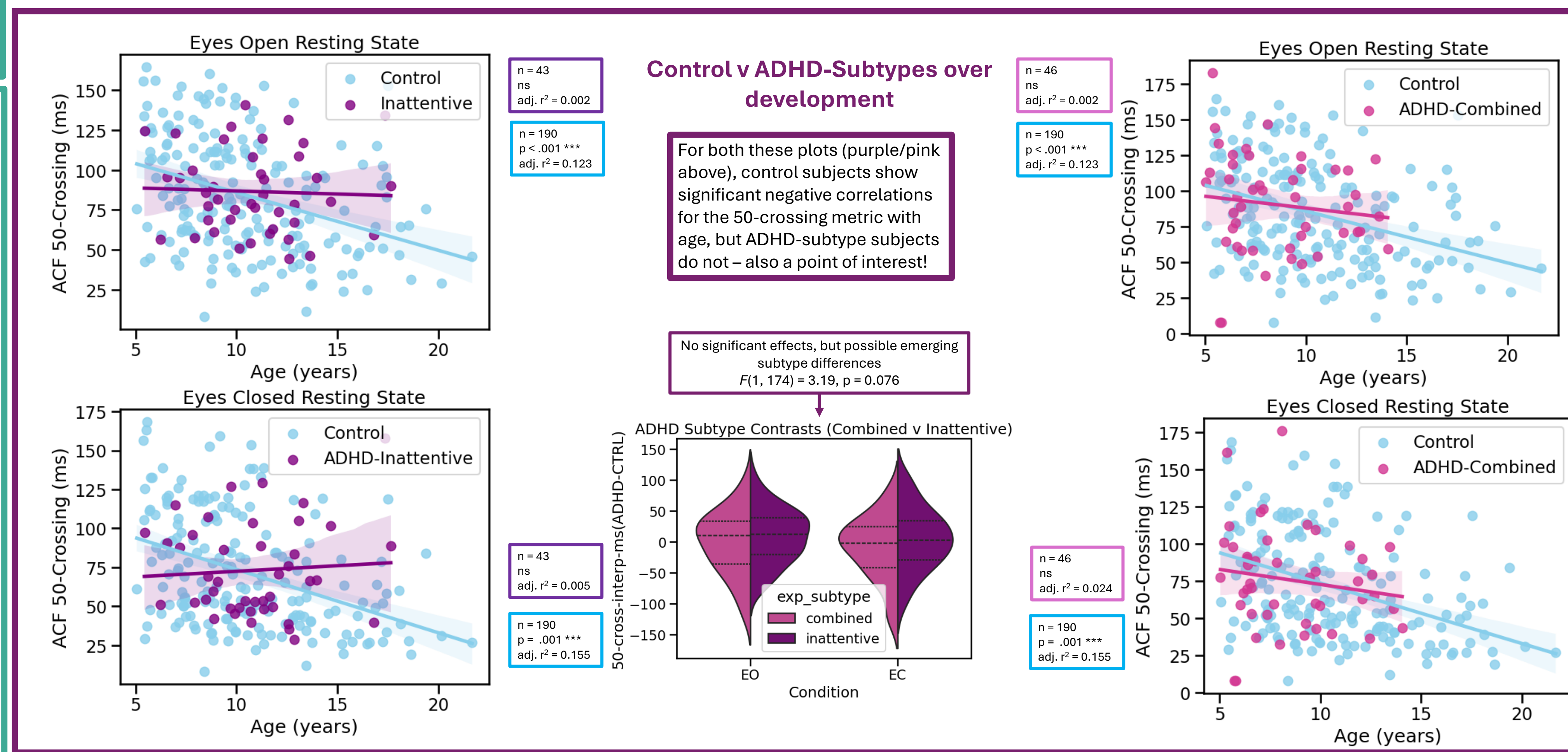
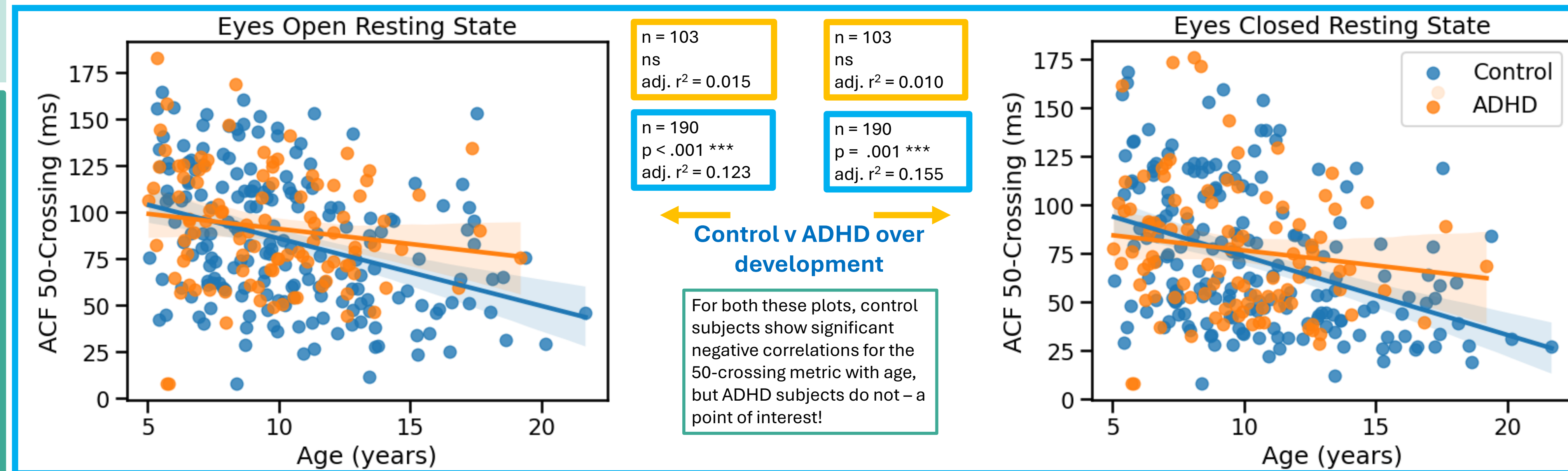
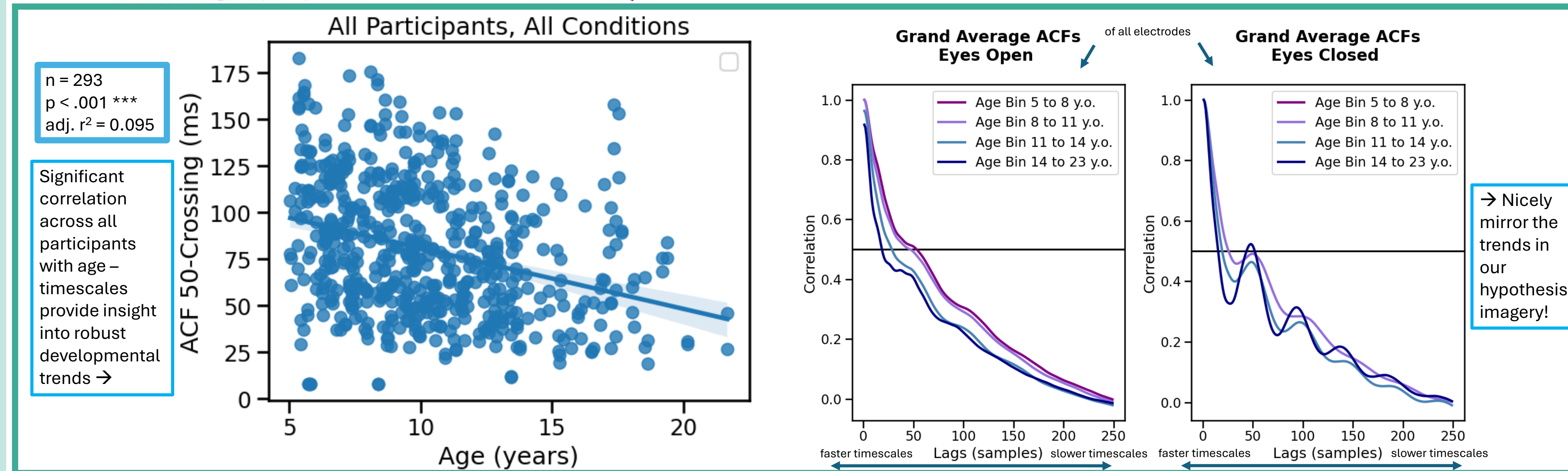
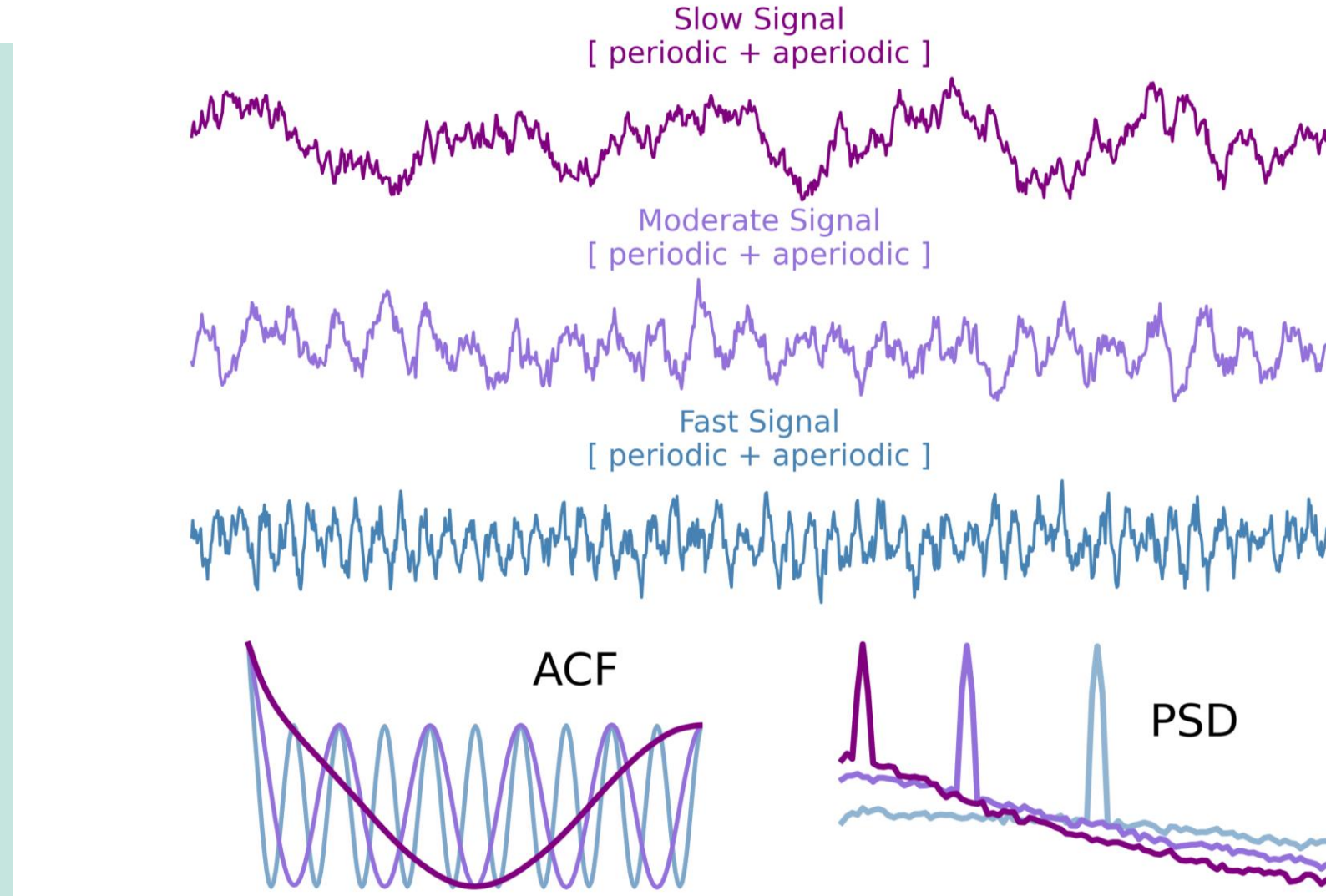


A visualization of the ACF-50 crossing, which marks the point at which the autocorrelation function decays to 50% of its peak correlation with itself. The ACF is often interpreted as measuring the 'memory' of the signal.

Hypotheses

- As age increases, the autocorrelation will have a steeper decay rate, indicating increased power in higher frequencies. The steeper decay rates are indicated by lower ACF 50-crossing values

- Due to incredibly mixed prior findings, we did not have concrete hypotheses regarding ADHD timescales and therefore conducted an exploratory analysis



Results

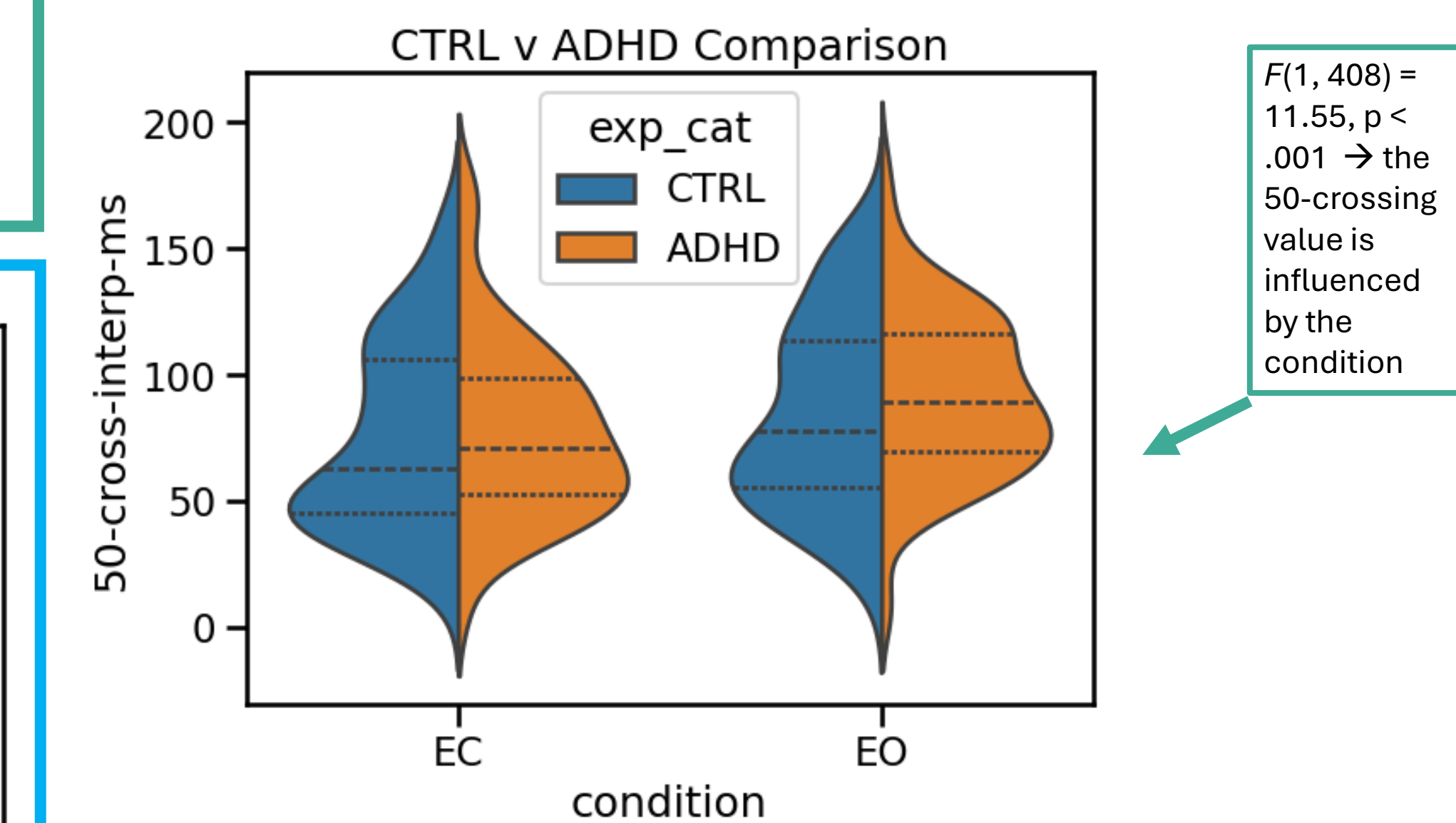
- Power spectrum findings regarding developmental trajectories within the aperiodic exponent replicated

- All participants show a negative correlation between age and 50-crossing values

- Linear regression of with age of the ACF-50 crossing regarding typical development shows a significant negative correlation, indicating faster timescales according to our hypotheses

- For ADHD participants however, the 50-crossing did not show a significant correlation with age. Additionally, there were no significant results between subtypes

- 50-crossing values are significantly influenced by EO/EC condition



Conclusions

- Various theories of ADHD:
-Dynamic developmental behavioral theory¹⁸
-Executive dysfunction theory¹⁹⁻²⁰
-State regulation theory
-Maturational delay theory: ADHD reflects the delay of, rather than a deviation from typical cortical development²¹⁻²²

-ADHD participants, including both subtypes, seem to show weaker age-related declines in 50-crossing values

-As timescales are shaped by cortical microarchitecture, a lack of significant correlation of the 50-crossing with age in ADHD participants could lend support to maturational delay theory⁴

-Can further investigate support for other theories by exploring possible links between timescales findings and behavioral correlates

-Digit span, WAIS excerpt
- ACE: mobile cognitive control assessment battery (attention, working memory, goal management)
-Temporal discounting task

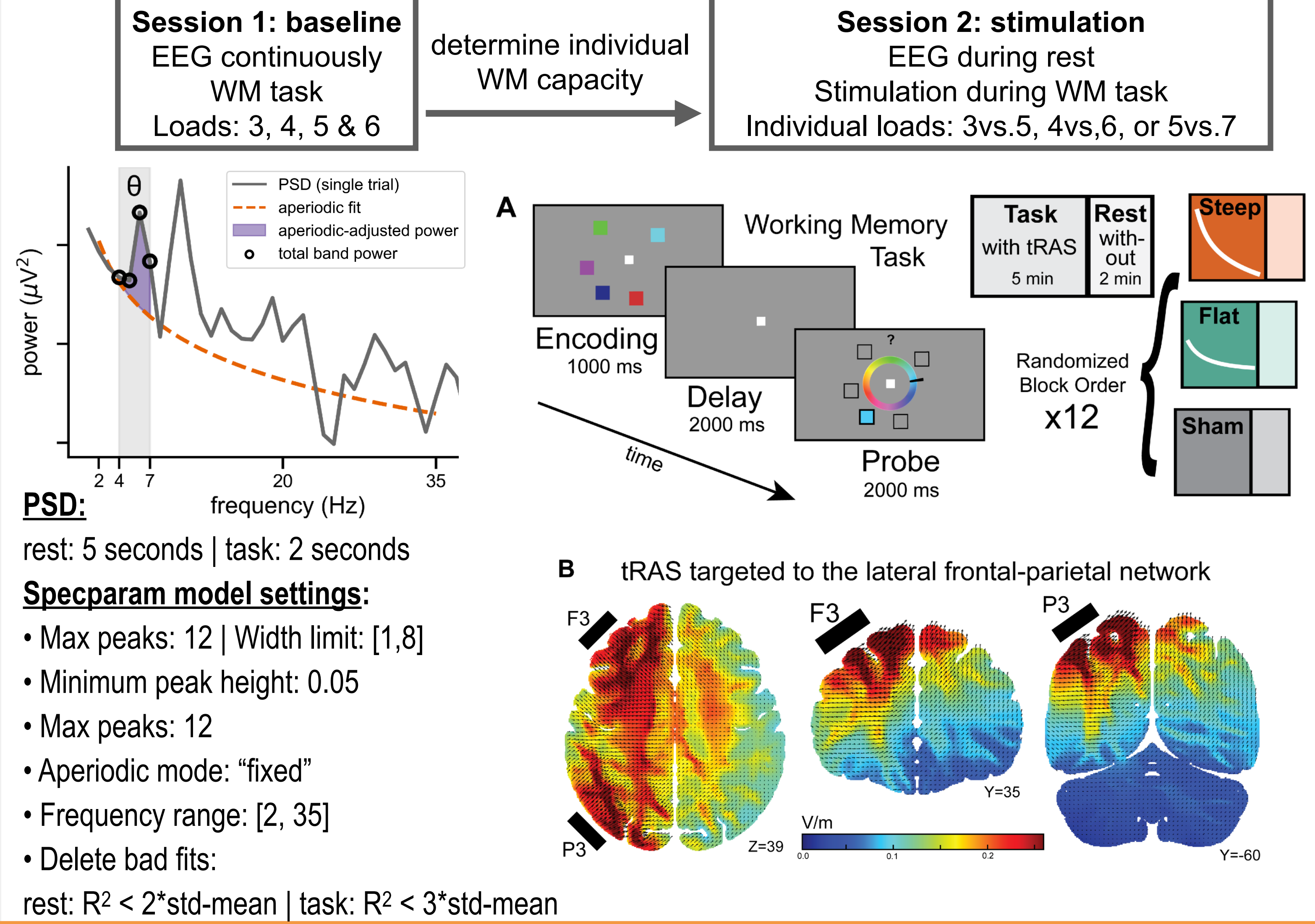
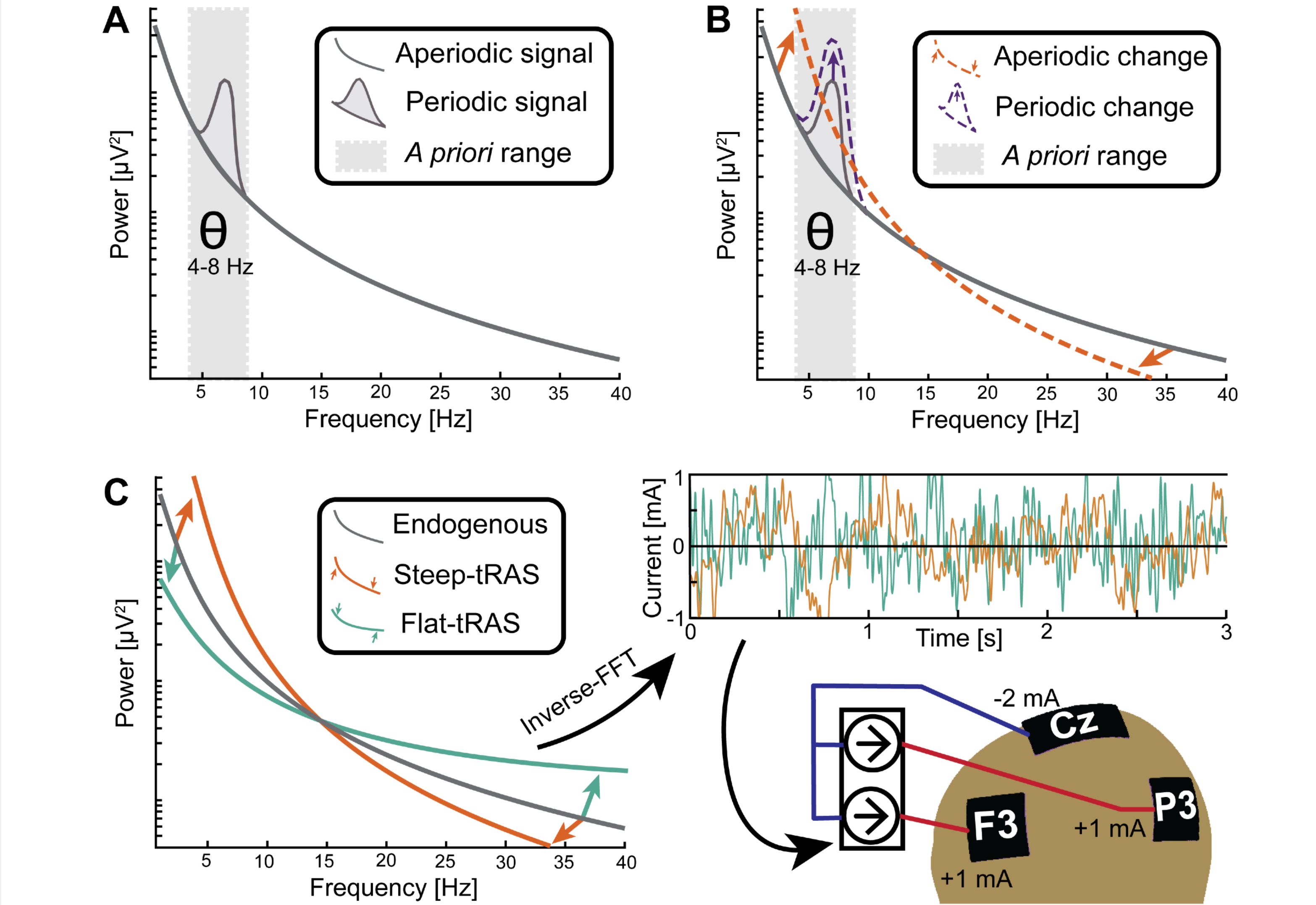
Causal steep-tRAS increases working memory precision

Quirine van Engen^{1,7}, Justin Riddle^{2,3,8}, Bradley Voytek^{1,4-7}

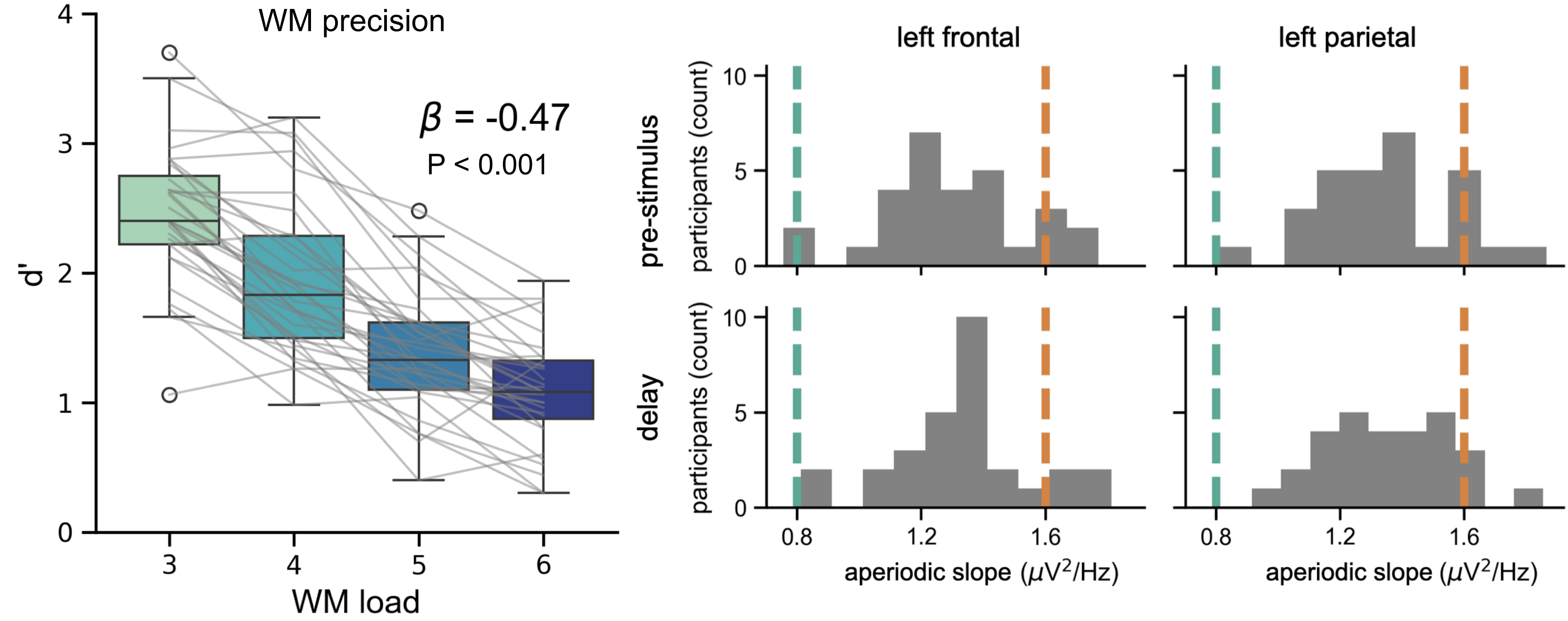
¹Dept. of Cognitive Sci., ²Dept. of Psychology, ³Program of Neuroscience, ⁴Hacıoğlu Data Sci. Inst., ⁵Neurosciences Grad. Program, ⁶Kavli Inst. for Brain and Mind, ⁷University of California San Diego, La Jolla, CA, ⁸Florida State University, Tallahassee, FL

Working Memory & Aperiodic Activity

- Working Memory (WM)** is our ability to briefly maintain information in mind (Baddeley, 1992)
- WM has been extensively studied in relation to oscillatory brain dynamics
 - Theta (4-8Hz) (Adam et al., 2018)
 - Higher theta power ~ better WM capacity (Klimesch, 1999; Lara & Wallis, 2015)
 - Network coherence - frontal and parietal (Johnston et al., 2017; Wallis et al., 2015)
 - Theta tACS improves WM capacity (Polania et al., 2012; Wolinski et al., 2018)
- However; theta oscillations are surprisingly scarce (Mitchell et al., 2008; Wilson et al., 2022; Bailey et al., 2022)
- Besides oscillations, EEG activity also contains **aperiodic activity**:
 - Time-domain: "background" activity manifesting as arrhythmic, unstructured fluctuations (Donoghue, Haller, Peterson, et al., 2020)
 - Frequency-domain: 1/f like distribution with systematic higher power in lower frequencies and lower power in higher frequencies
 - Decreases with age, altered by disease, and brain state (Voytek et al., 2015; Colombo et al., 2019; Smith, Kosik, van Engen et al., 2023)
- Mixed results how aperiodic activity functionally supports WM (Virtue-Griffith et al., 2025; van Engen et al., under review; McKeon et al., 2025)
- Is aperiodic activity causally involved in WM capacity?
 - transcranial Random Aperiodic Stimulation (tRAS)

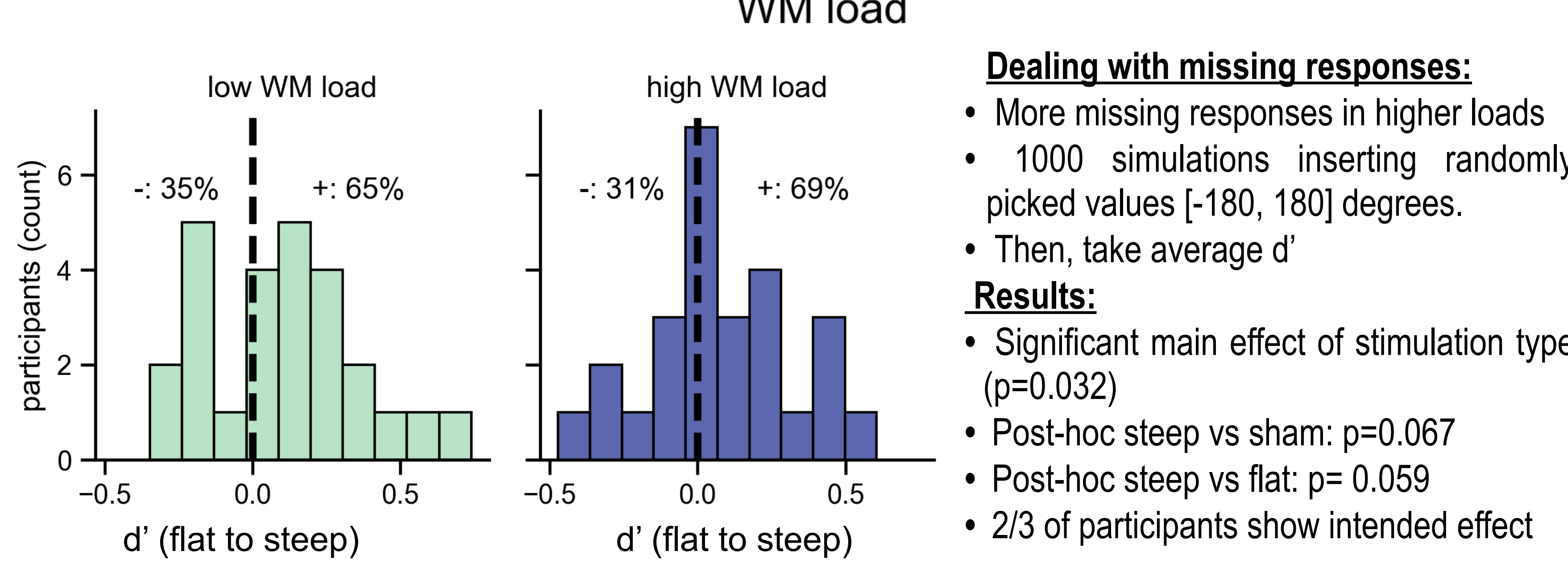
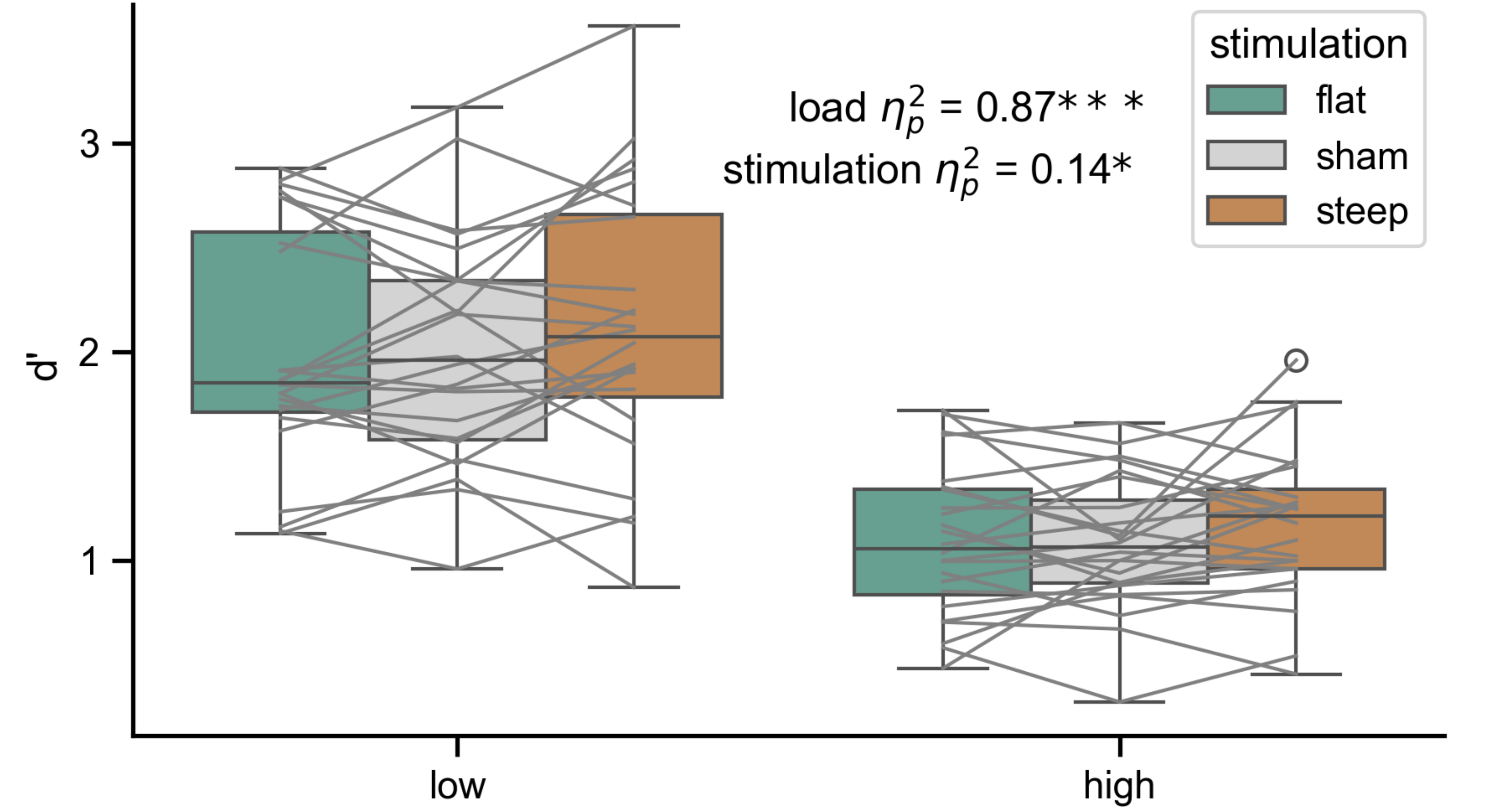


WM precision decreases with load



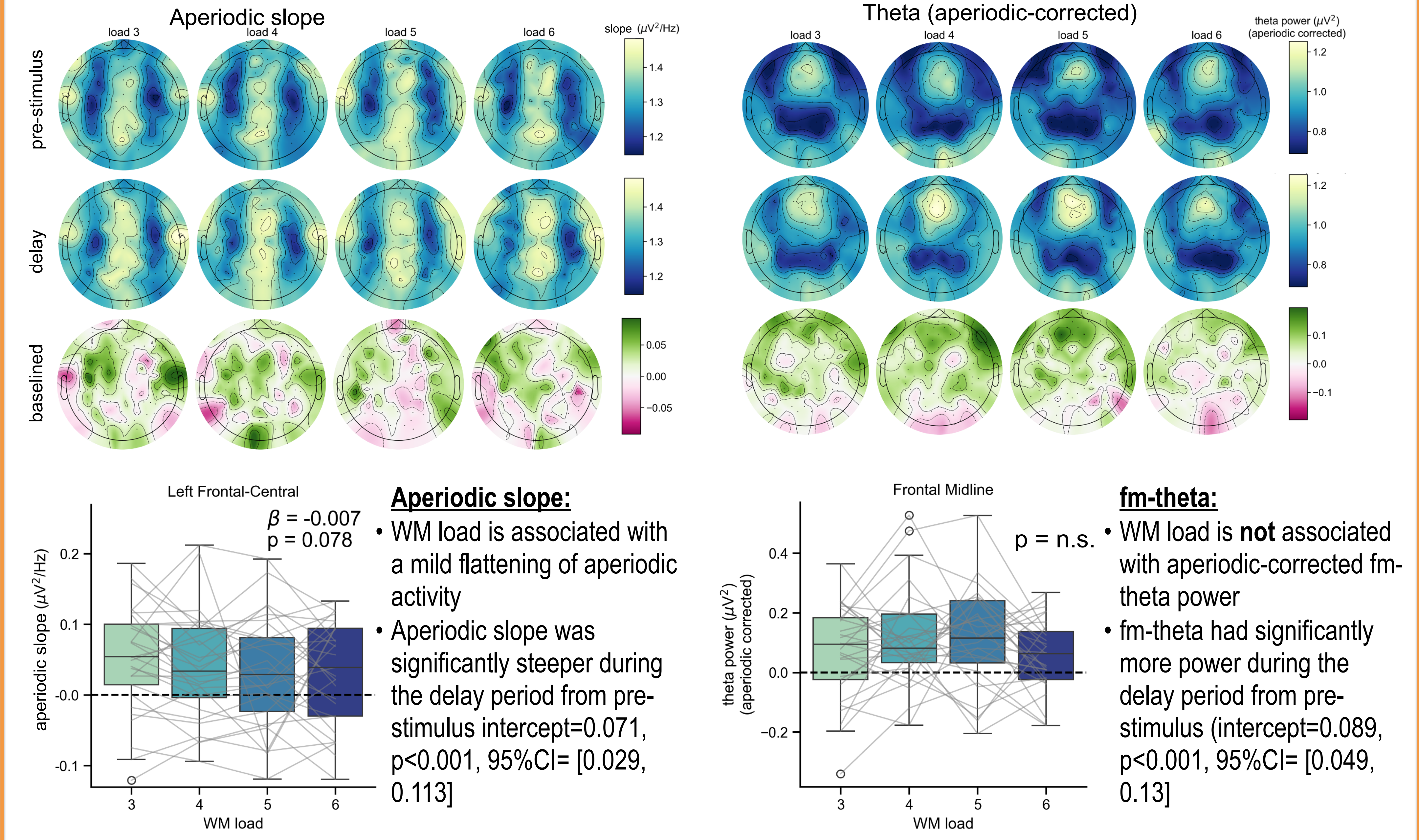
- Linear Mixed Model:
- Task shows a linear decrease of WM load on WM precision
- Checking stimulus parameters
- The measured aperiodic slope in Session 1 (baseline) is within the stimulation parameters for Session 2.

Steep-tRAS improves WM precision

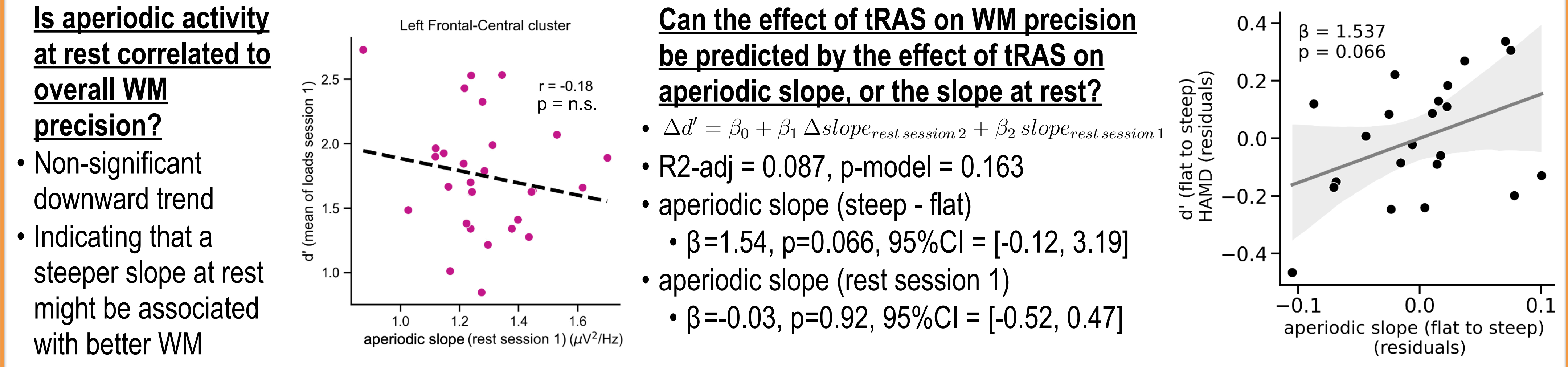


- Results:
- Significant main effect of stimulation type (p=0.032)
 - Post-hoc steep vs sham: p=0.067
 - Post-hoc steep vs flat: p=0.059
 - 2/3 of participants show intended effect

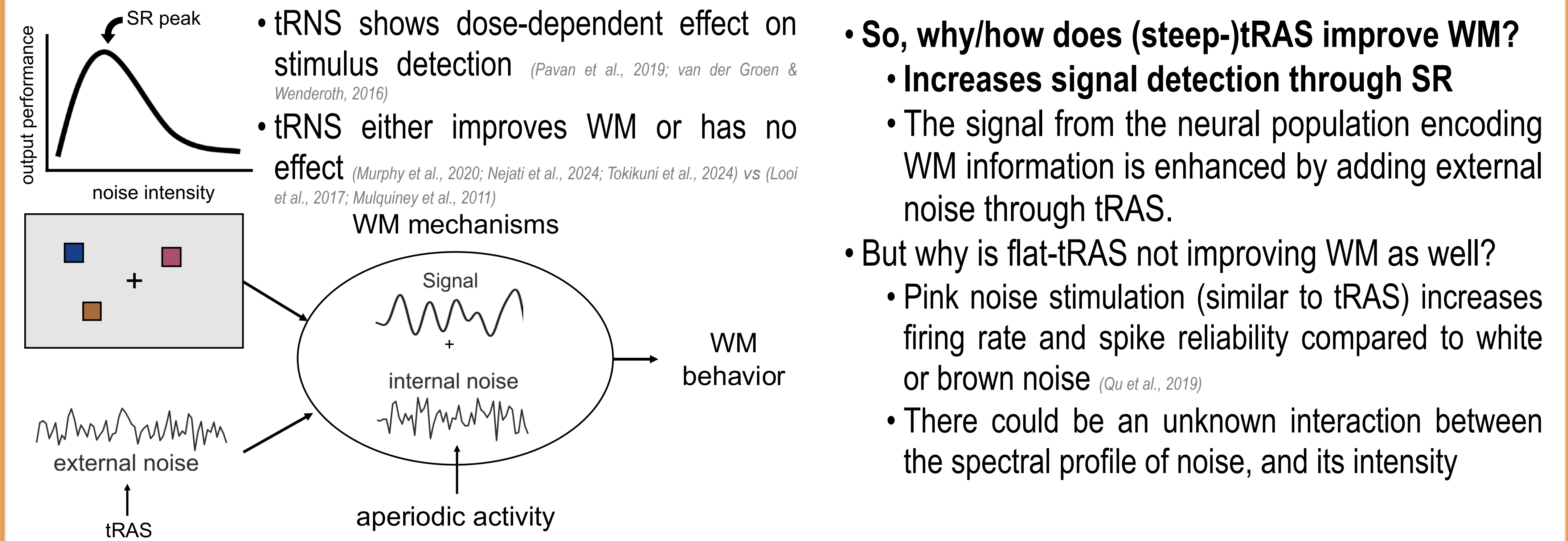
Session 1: aperiodic activity & fm-theta



Does aperiodic activity correlate with WM?



Stochastic Resonance (SR) as mechanistic explanation



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Developmental Trajectory of Rhythmic and Non-Rhythmic Spiking in hiPSC-derived Cortical Tissue

Austin Hutton¹, Deborah Pré², Alexander T. Wooten², Anne G. Bang², Bradley Voytek¹, Christian Cazares¹

Motivation

Electrical neural signals consist of mixed **periodic (rhythmic)** and **aperiodic (non-rhythmic)** spectral components that have been shown to reflect synchronized firing in cortical networks, and may serve as putative indices of cortical excitation-inhibition (E:I) balance.

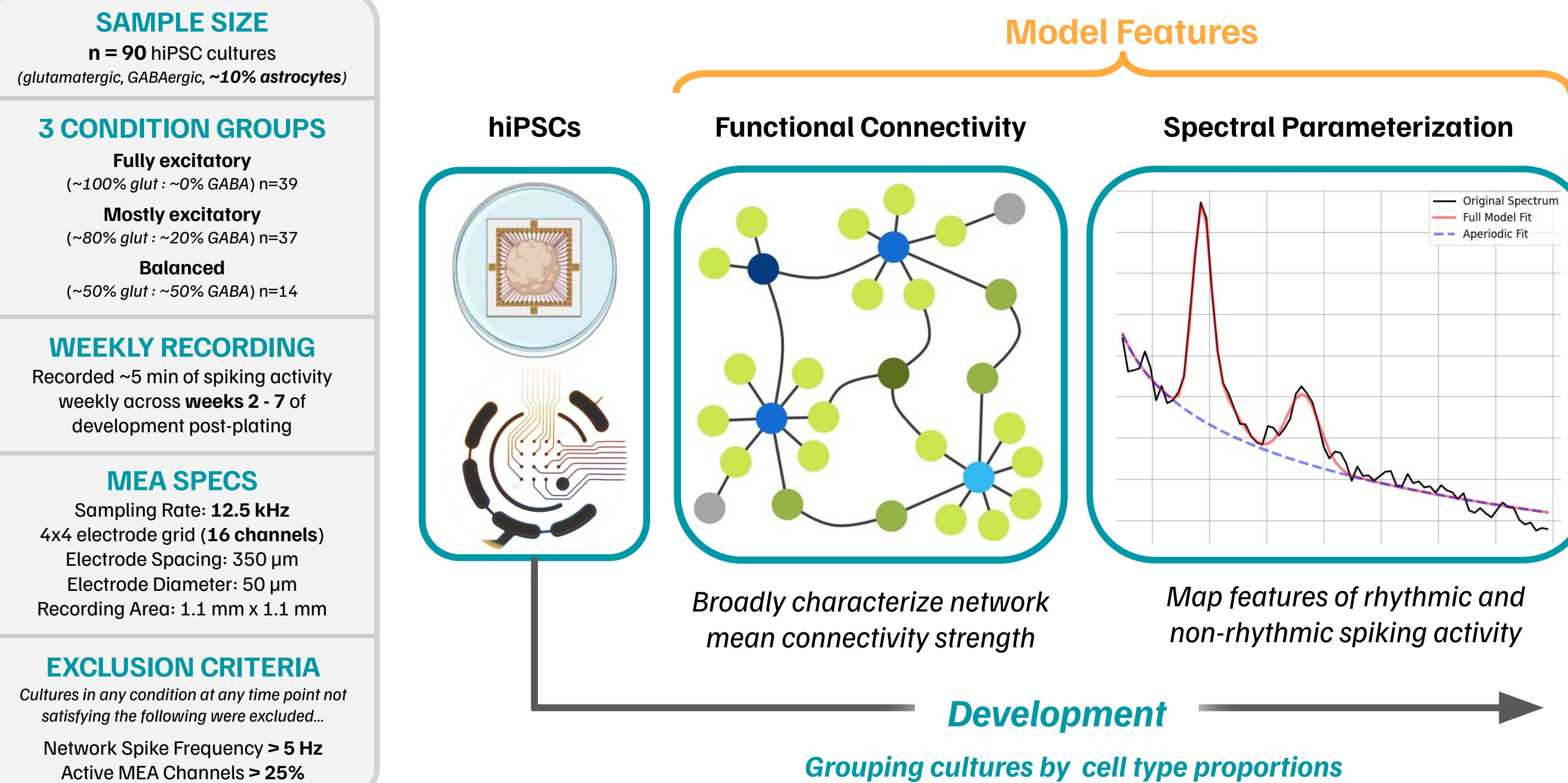
However, it's unclear **how spectral components emerge** at the earliest point of human development, **how they become structured** in space and time, and **how different underlying biological properties influence the development** of these neural activity features.

Human induced pluripotent stem cell (hiPSC)-derived cortical tissue cultures offer a promising platform (high throughput, experimentally controlled access to in vitro human neurodevelopment) for characterizing spectral component features at the earliest stages of human neurodevelopment.

RESEARCH OBJECTIVE

Quantify developmental changes in network connectivity and in periodic and aperiodic-like spiking activity across cortical tissue cultures engineered with distinct excitatory–inhibitory cell-type proportions

Overview of Design and Approach



E:I Balance-Specific Development



Computational Methods

Connectivity

Spike Time Tiling Coefficient (STTC)

(Cutts & Eglen, 2014)

The STTC is a non-directional, correlational **index of spike synchrony** between two spike trains robust to firing rate.

$$\text{STTC} = \frac{1}{2} \left(\frac{P_A - T_B}{1 - P_A T_B} + \frac{P_B - T_A}{1 - P_B T_A} \right)$$

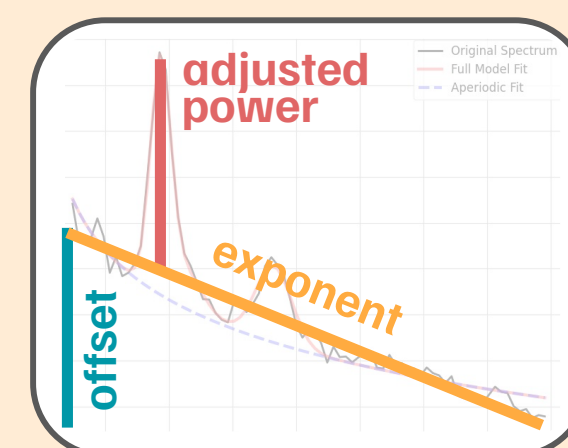
Computing the STTC requires defining a Δt such that (1) **T is the proportion of time** within $\pm \Delta t$ of all spikes in a spike train and (2) **P is the proportion of spikes** in one spike train occurring within $\pm \Delta t$ of spikes in another spike train. Coefficient values **range from -1 to 1** (-1 is anticorrelated, 0 is no correlation, 1 is highly correlated). We computed STTC with $\Delta t = 5$ ms.

Power Spectra

Spectral Parameterization

(Donoghue et al, 2020)

SpecParam decomposes features of the power spectrum to separate **periodic** (oscillatory) from **aperiodic** (1/f) background structure (offset and exponent)



Offset (vertical shift in power spectrum, overall background activity)
Exponent (steepness of 1/f decay, linked to a network's E:I balance)
Adjusted Oscillatory Power (Delta 1-4 Hz, theta 4-8 Hz, alpha 8-13 Hz)

Statistical Models

Linear Mixed Effects

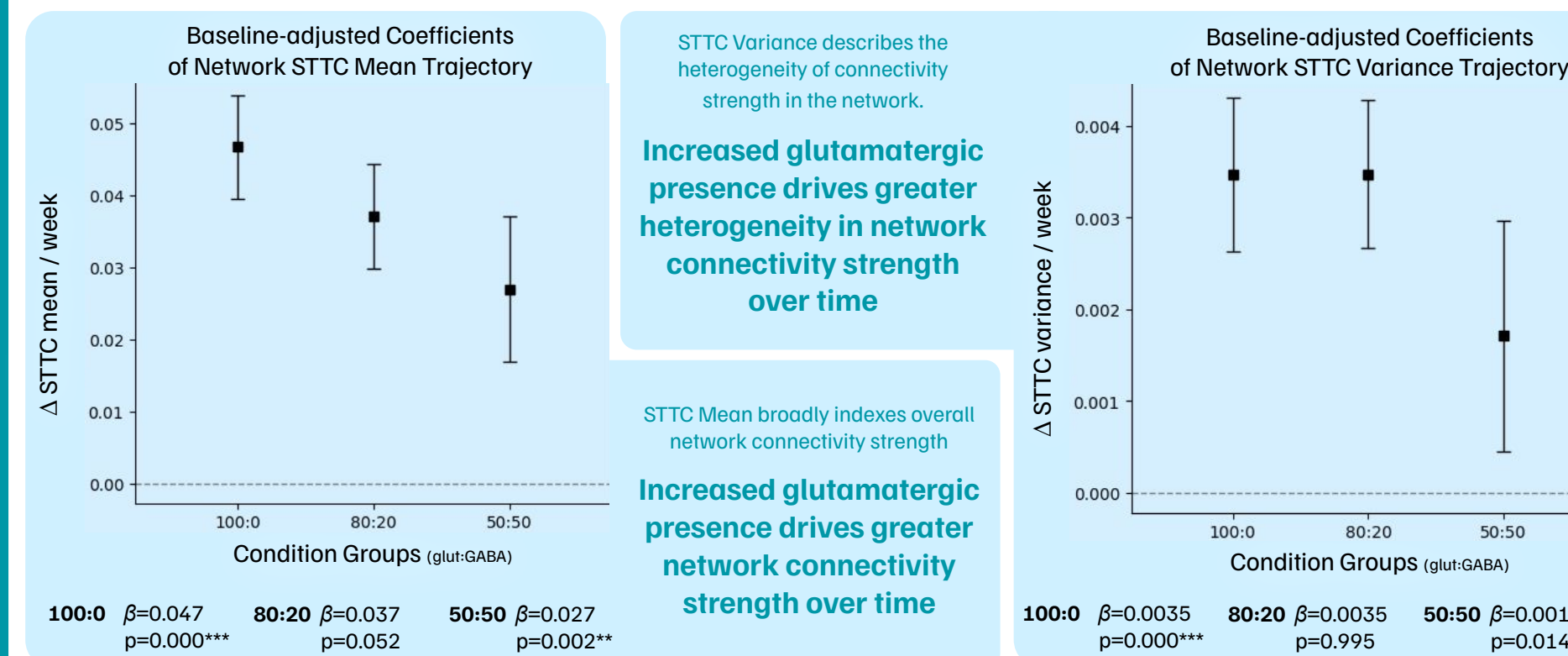
Model Formula

$$\text{Feature} = \beta_0 + \beta_1 \text{Time} + \beta_2 \text{Group}_1 + \beta_3 \text{Group}_2 + \beta_4 (\text{Time} \times \text{Group}_1) + \beta_5 (\text{Time} \times \text{Group}_2) + u_{\text{well}} + \epsilon$$

Note: For reported model coefficients (β), group developmental trajectories were reconstructed as follows...

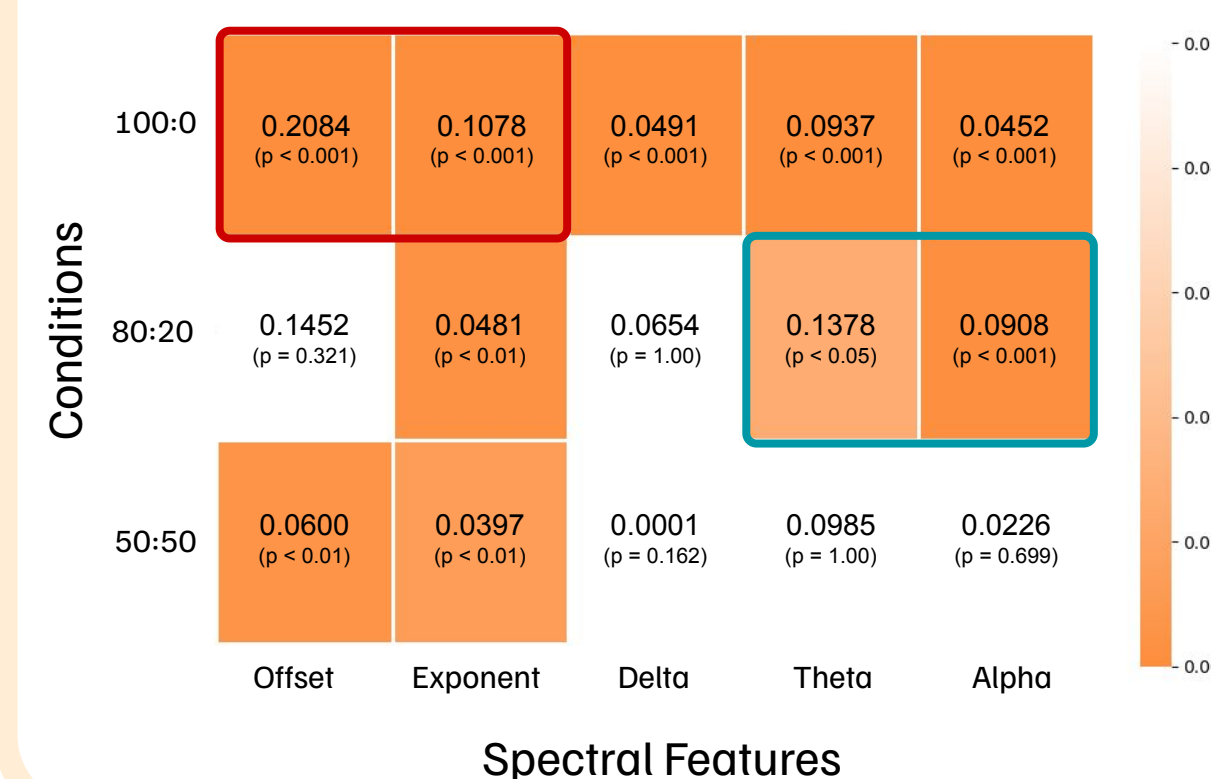
$$\begin{aligned} 100:0 &\rightarrow \beta = \beta_1 \\ 80:20 &\rightarrow \beta = \beta_1 + \beta_4 \\ 50:50 &\rightarrow \beta = \beta_1 + \beta_5 \end{aligned}$$

Modeling Divergent Network Dynamics



Developmental Trajectories of Spectral Features

(heatmap values show model coefficients, p-values are Bonferroni corrected)



Broad developmental increases in aperiodic features (offset and exponent), as well as aperiodic-adjusted oscillatory power occurred across all cell-type proportion groups

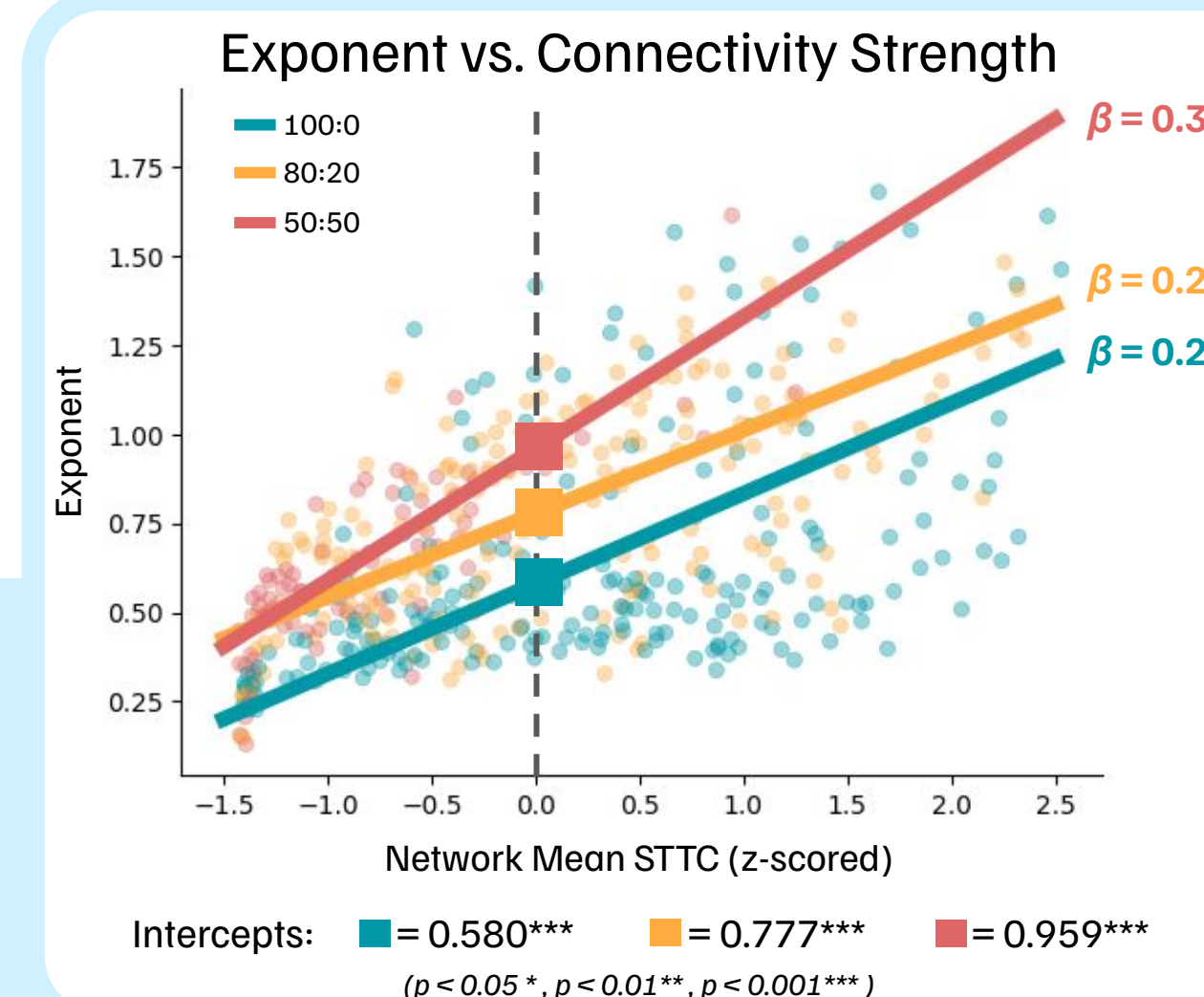
Cultures with increased glutamatergic presence showed steeper increases in aperiodic offset and exponent throughout development

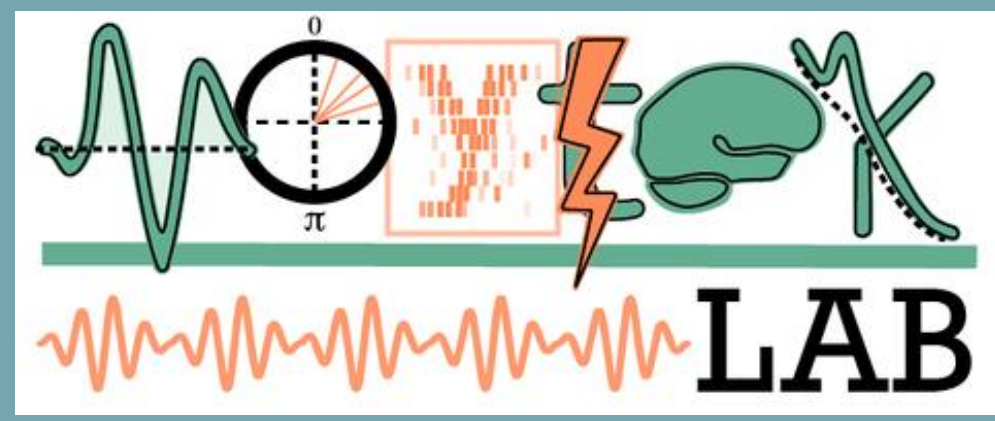
Cultures in the 80:20 (glut:GABA) condition, showed steeper increases in aperiodic-adjusted oscillatory power, specifically in Theta and Alpha frequency bands

Outcome & Impact

Cell-type composition profiles significantly impact developmental trajectories of spectral components and connectivity in hiPSC-derived cortical cultures

Aperiodic exponent covaries with network connectivity strength, but in diverging trajectories for different E:I cell-type proportions





Neural Signatures of Sleep Deprivation in Aperiodic EEG Activity

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Introduction

- EEG signals are composed of both periodic (oscillatory) and aperiodic (non-oscillatory) features. Aperiodic features have been shown to influence the excitatory-inhibitory (E-I) balance of neural processes (Weist et al, 2023).
- Sleep loss affects this E-I balance by increasing inhibition rate. Previous work describes aperiodic changes across sleep stages and after sleep deprivation, this change can result in neurological impacts such as worsened attention and memory.
- In the present investigation, we analyze an open resting-state EEG dataset with two sessions per subject: normal sleep (NS) vs. 24-h sleep deprivation (SD) - OpenNeuro ds004902 (Xiang, Fan, Bai, Lv, Lei; v1.0.8).
- Using a spectral parameterization model (SpecParam), we extract parameters, aperiodic offset and aperiodic exponent, per channel and compare NS vs SD within-subject.
- Results show a significant increase in aperiodic offset after SD in 5 different channels, with no significant change in aperiodic exponent. This is consistent with the expected disruption in E-I balance after SD.

Methods

- Resting-state EEG, N=71 (34 F, 37 M), ages 17–23 (20 ± 1.44); two sessions: normal sleep (NS) and sleep deprivation (SD) (24 h monitored wakefulness with not rigorous physical activity).
- Subject metadata also includes condition order and behavioral/mood metrics for future analysis.

Preprocessing

- DC offset adjustment, notch, and high/low pass filtering, muscle artifact removal, and ICA for blink removal.
- Power Spectral Density (PSD) plots were generated per channel to visually identify and remove channels outside standard spectral ranges.

Spectral Parameterization

- *SpecParam* was used to extract key aspects of aperiodic activity found in EEG signals. The two parameters include **aperiodic exponent**, which quantifies the 1/f-like background activity found in neural signals and **aperiodic offset**, which quantifies the vertical shift of the entire power spectrum across all frequencies.

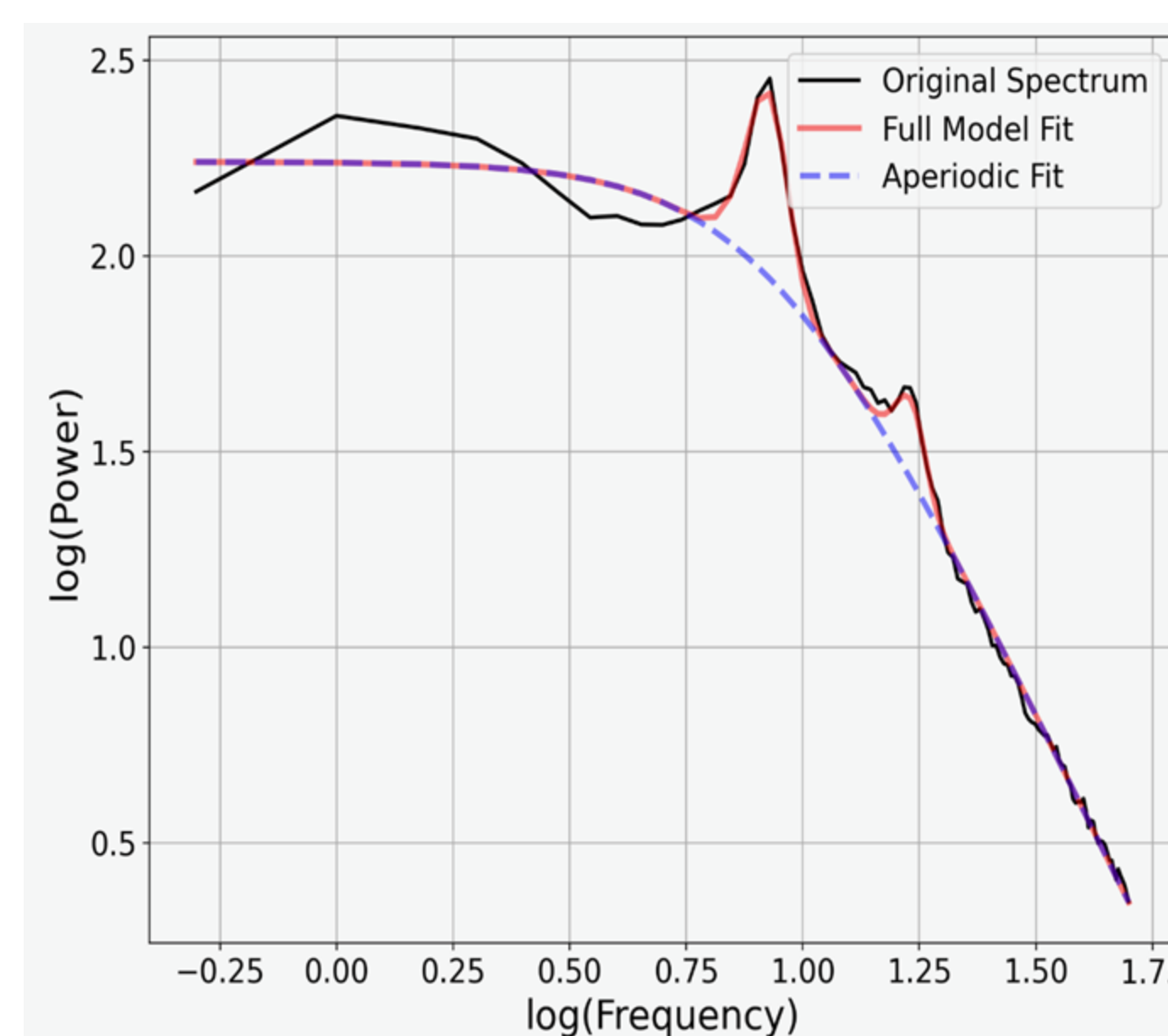


Figure 1. Example SpecParam aperiodic model fit

- Parameters were calculated for each channel across both conditions for all subjects.
- Paired t-tests were conducted on within-subject differences (SD - NS) for aperiodic exponent and offset parameters across all channels. Bonferroni correction was applied to account for testing two parameters per channel (corrected $\alpha = 0.025$).

Results

- Between sleep conditions, five channels showed significant aperiodic offset increases following sleep deprivation. These channels are clustered primarily in frontal and parietal regions.
- The offset shift reflects enhanced background neural activity across all frequencies, consistent with increased aperiodic activity following sleep loss.

SD Reveals Difference in Aperiodic Offset

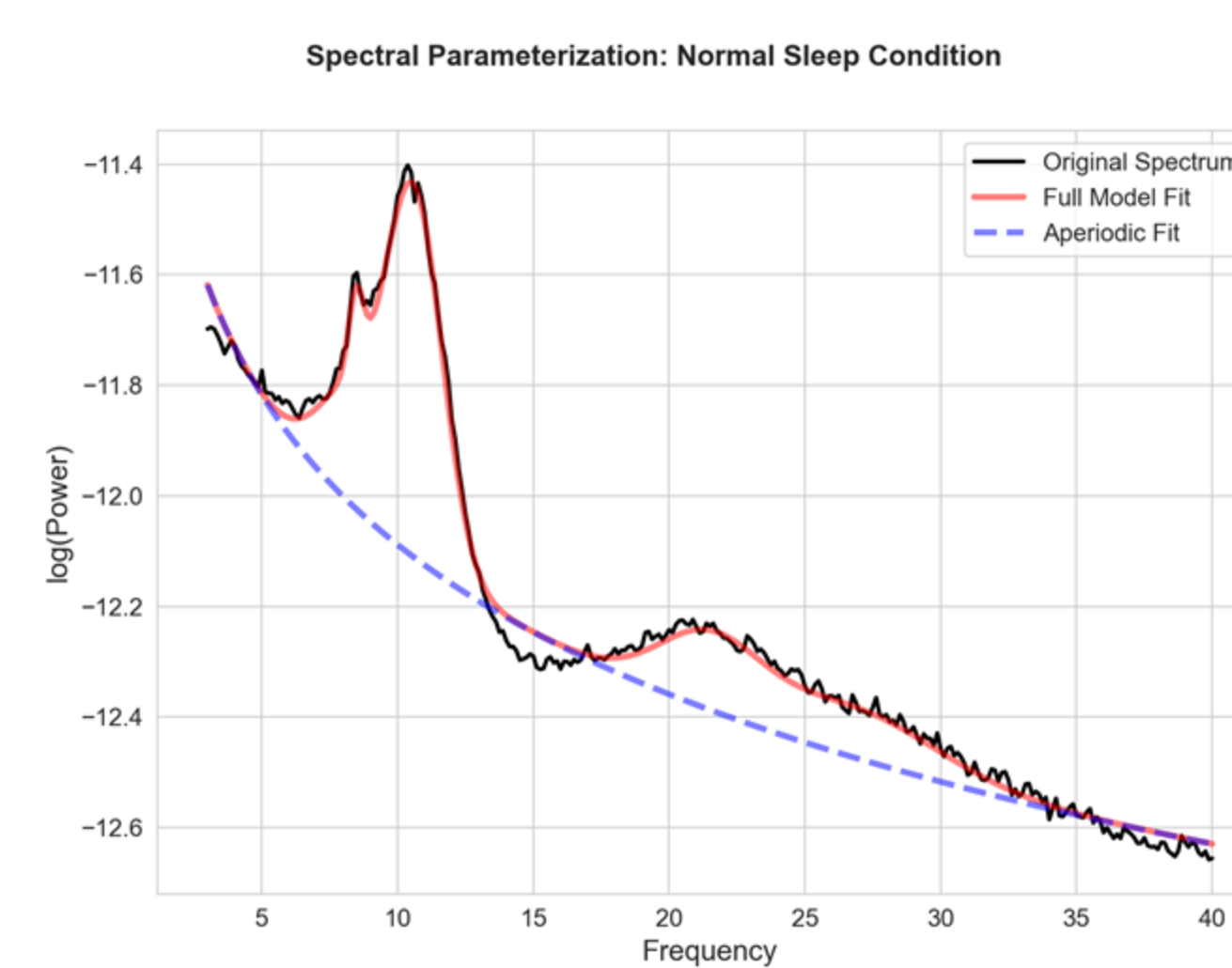


Figure 2. Spectral parameterization of mean Normal Sleep power spectrum across significant channels

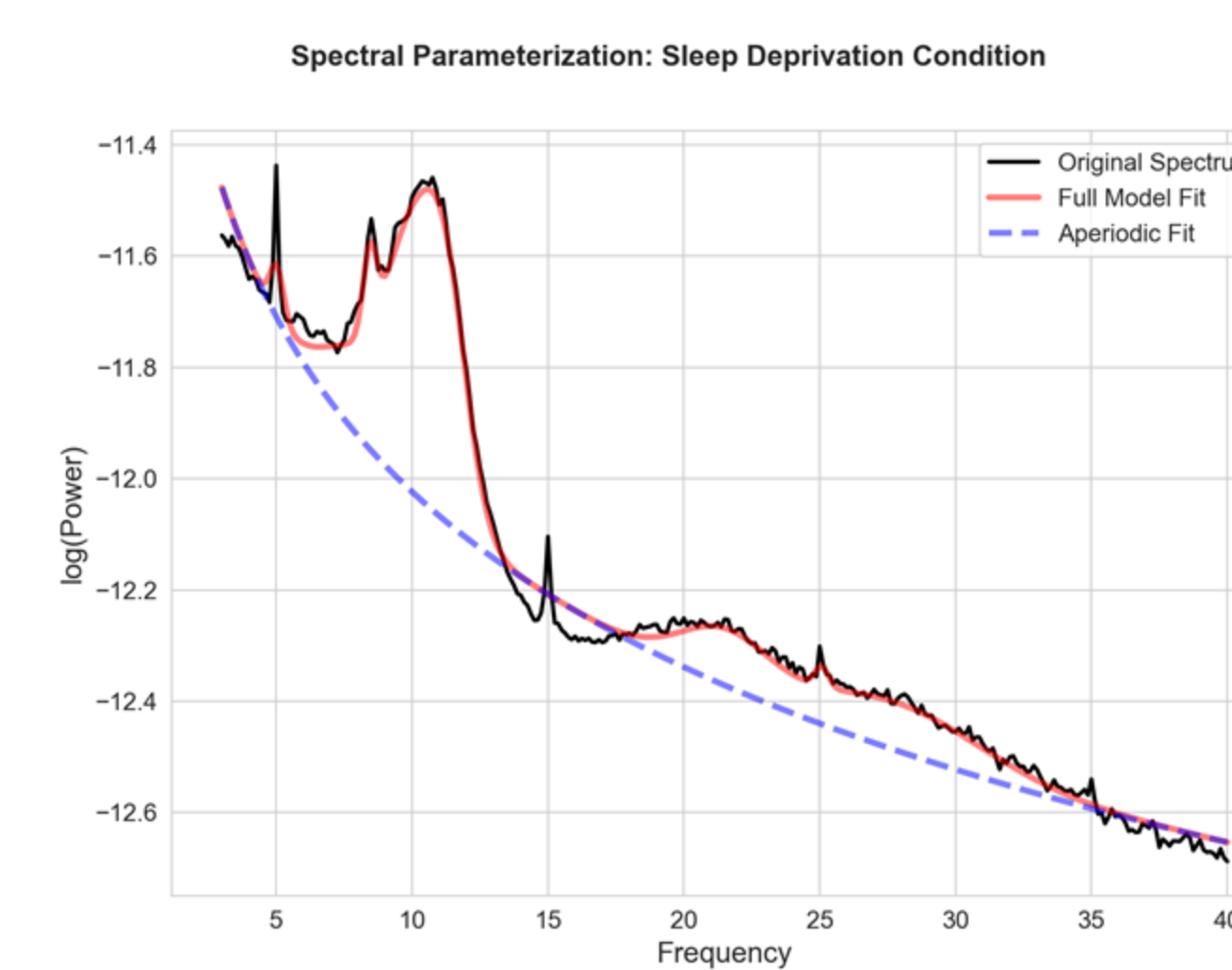


Figure 3. Spectral parameterization of mean Sleep Deprivation power spectrum across significant channels

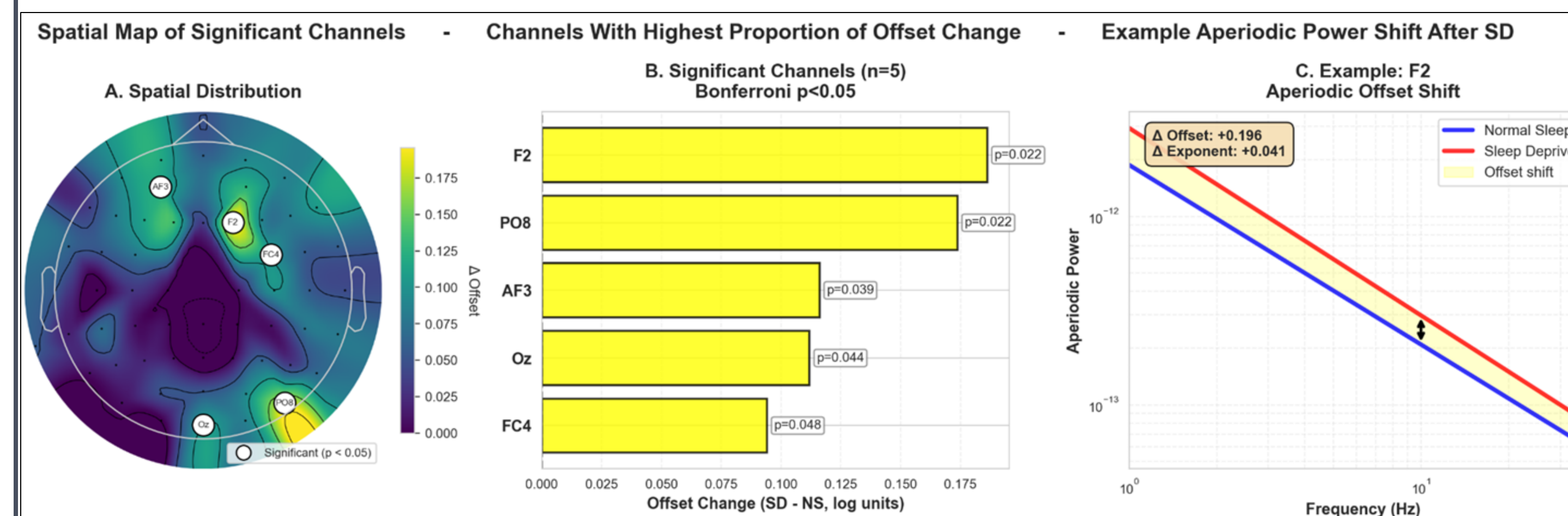


Figure 4A. Topo map of channels showing spatial distribution of significance

Figure 4B. Channels significance and it proportion of offset difference

Figure 4C. Example power shift of aperiodic component across conditions

Frequency Specific Aperiodic Shift

- Band-specific analysis reveals these offset changes differentially affect frequency bands.
- Due to offset and exponents strong collinearity, vertical offset shift or exponent steepness can both describe aperiodic power shifts in SD.

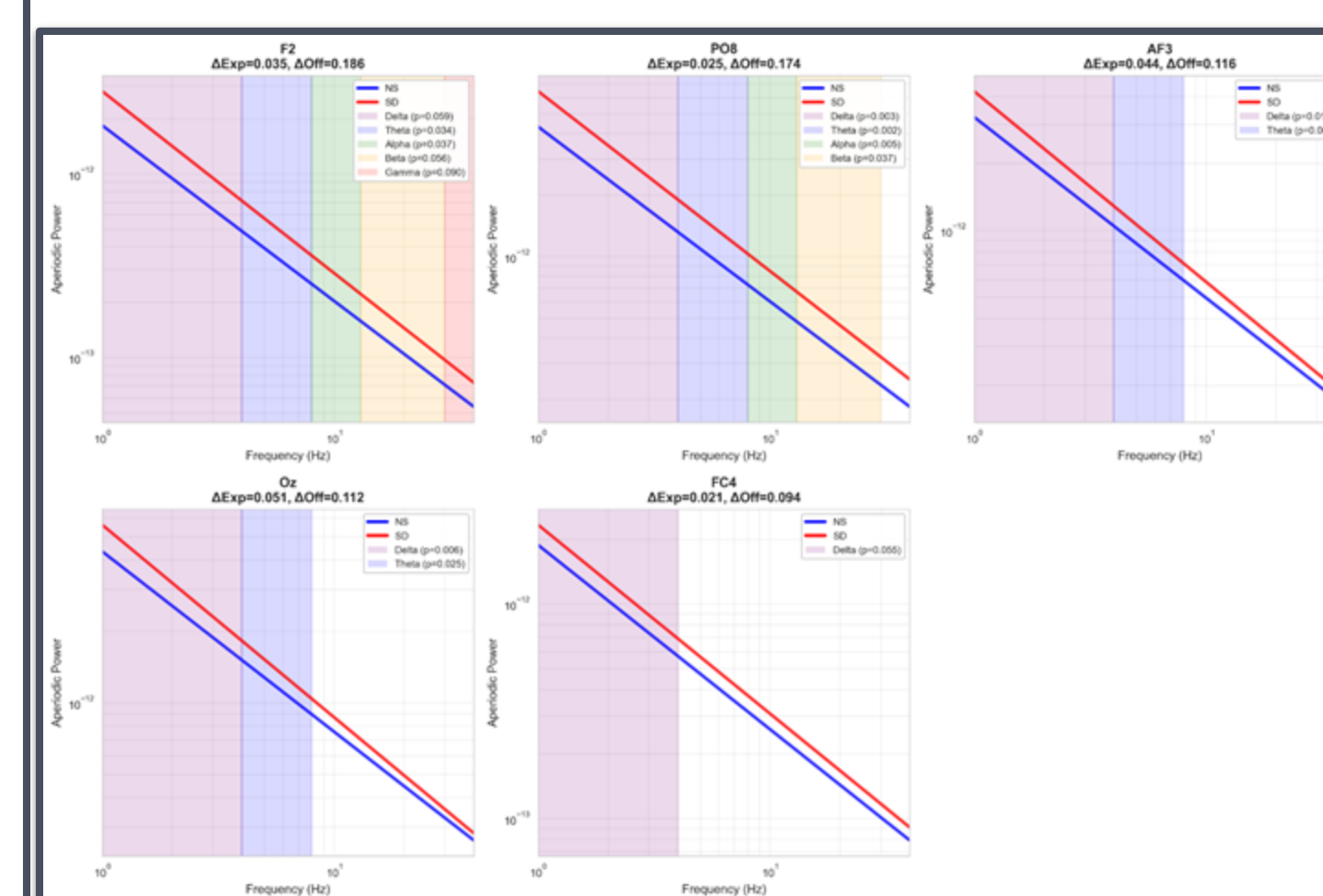


Figure 5. Significant channel aperiodic PSD and the frequency band they significantly shifted in

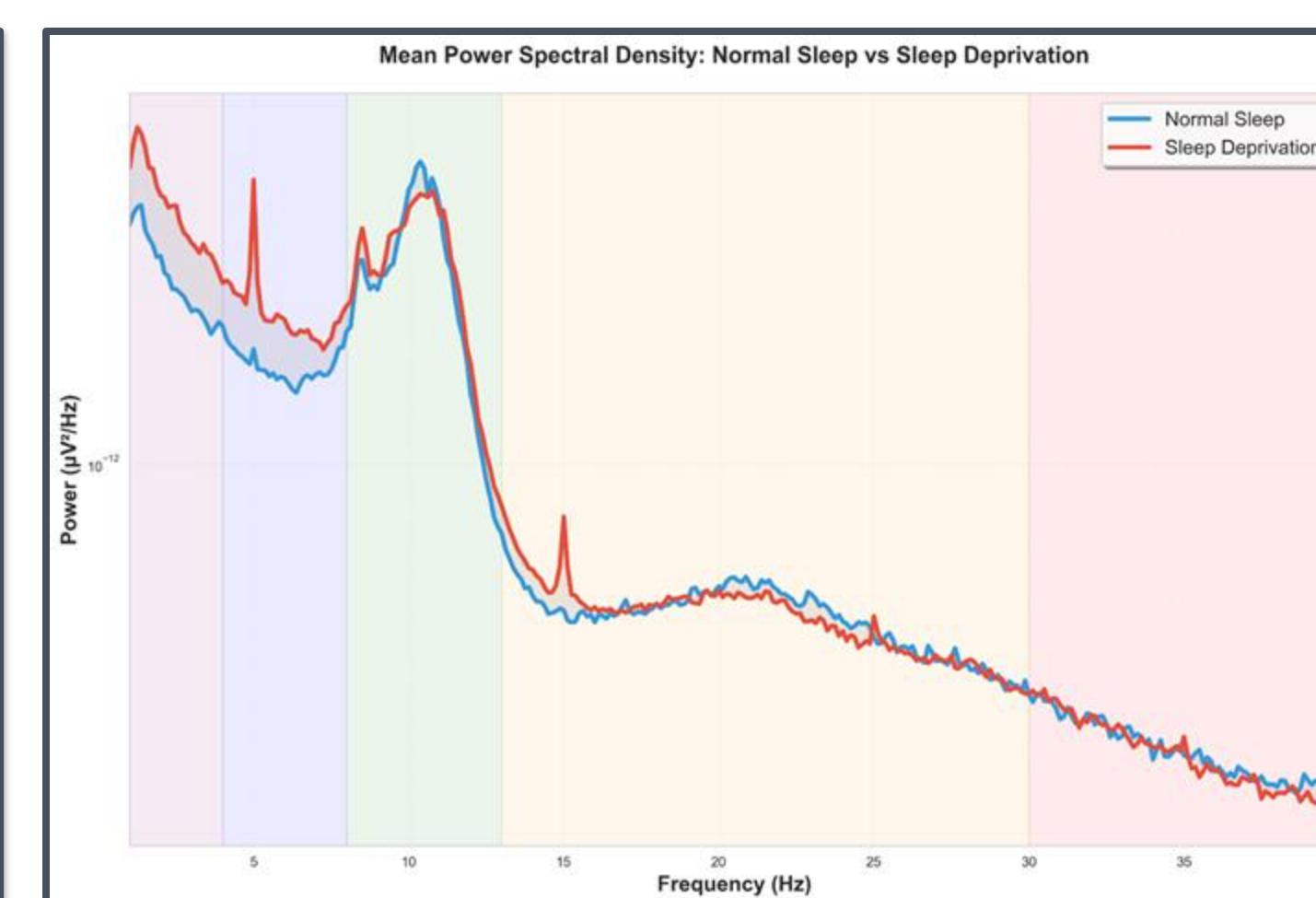


Figure 6. Average PSD of significant channels across conditions. Colors denote frequency band

Conclusion

- Our results are in agreement with work from “Impact of Sleep Deprivation On Aperiodic Activity: A Resting-State EEG Study” (Bai, Hu, Jülich, Le). Sleep deprivation produces significant increases in aperiodic EEG activity across frontal and parietal regions, predominantly affecting lower frequency bands (delta/theta).
- These changes reflect elevated background neural activity (1/f-like) consistent with reduced E-I balance as a result of SD. An increased aperiodic power increases inhibition rate in which can affect neural communication.
- Testing aperiodic components against spectral power across conditions allows for simple and clear effect size measuring that affirm similar findings.
- The spatial pattern of significantly affected channel aligns with previous work showing frontal sensitivity to sleep deprivation (Bai et al., 2024; Mu & Li, 2013).

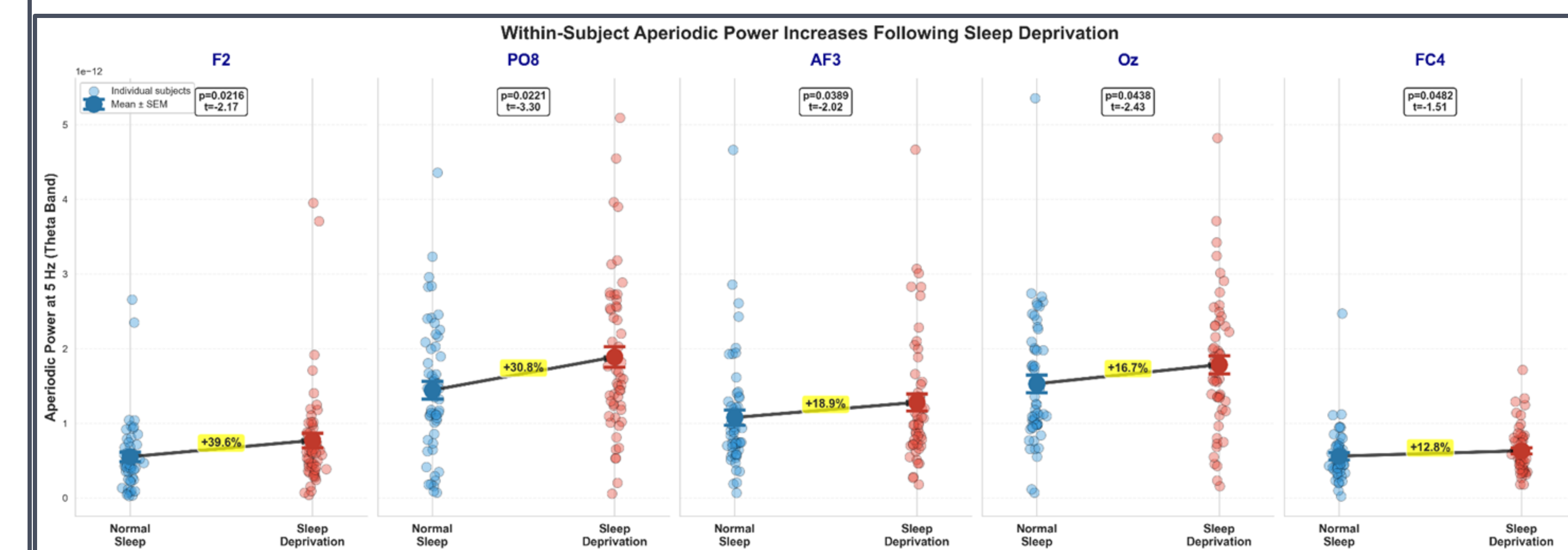


Figure 7. Within-subject differences between conditions and percentage of aperiodic power change, sampled at 5 Hz.

Future Directions

- Relate findings to studies that examine how quickly aperiodic patterns normalize with sleep recovery, and do individual differences that rate.
- Explore relationships between aperiodic activity and sleep-specific oscillations (K-complexes, sleep spindles) to understand mechanisms of memory consolidation.
- Explore whether aperiodic biomarkers can predict susceptibility to sleep-related cognitive disorders or be an early detection method.

Acknowledgements

- References:
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Aperiodic activity as an EEG biomarker for sertraline response: Applications and limitations

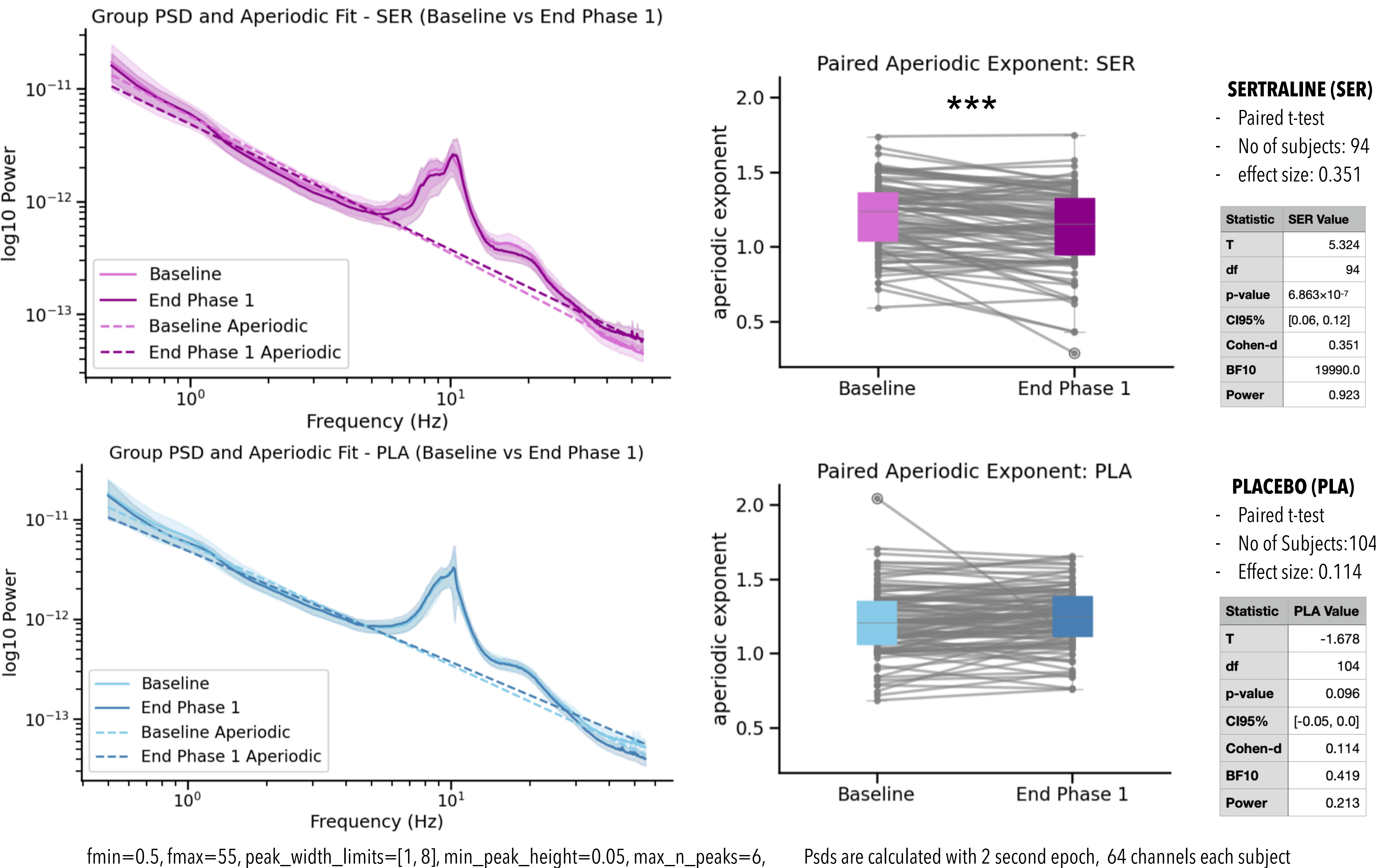
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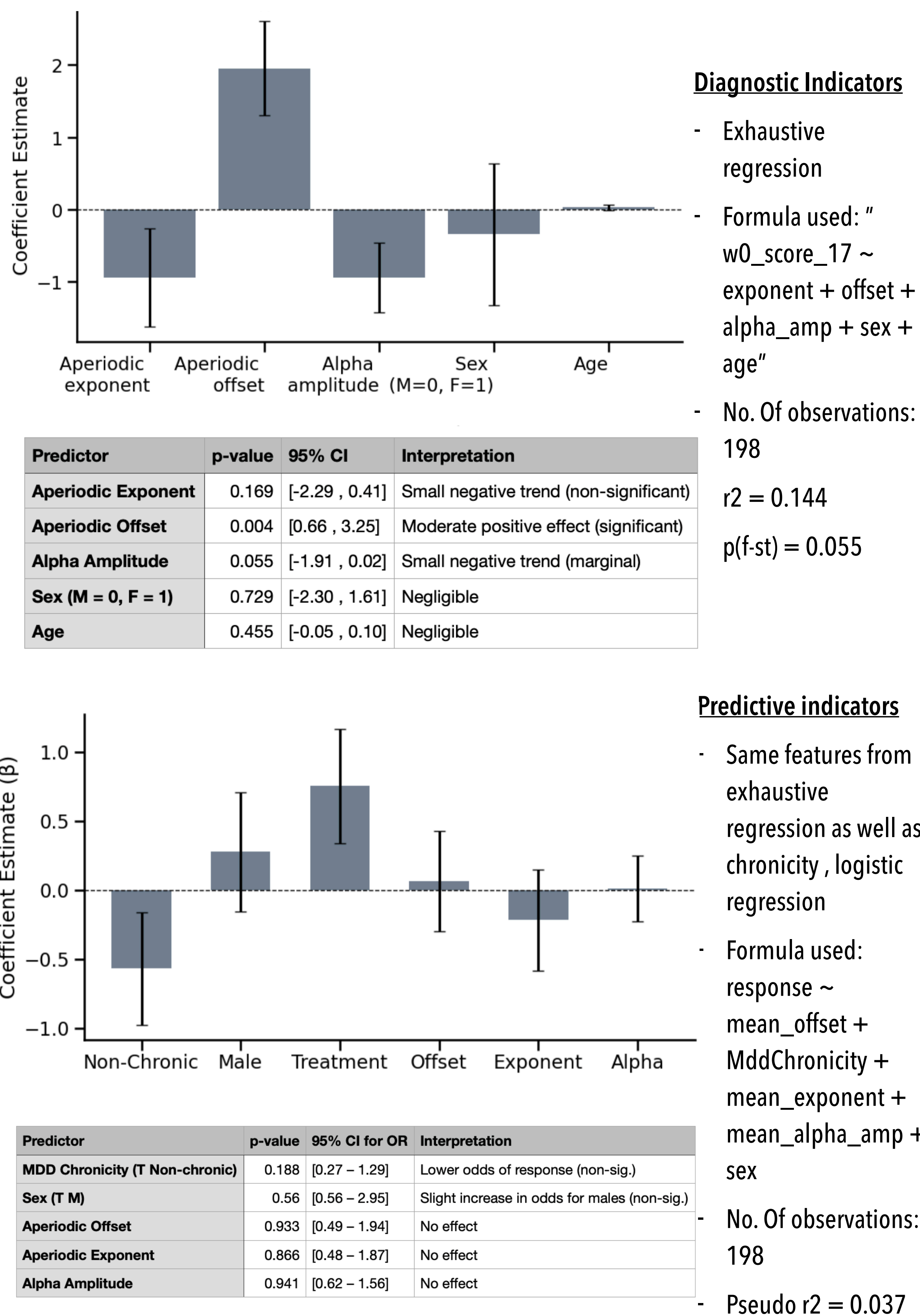
BACKGROUND

- Major Depressive Disorder (MDD) affects approx 1 in 12 people in the US**
 - Commonly treated with Selective Serotonin Re-uptake Inhibitors (SSRIs) like Sertraline
 - Response to SERT or other mediations is variable, which needs biological indicators to guide treatment. These indicators can vary with **severity, response to medication and mechanistic indicators**, possibly identifiable through EEG, though so far, has been inconclusive
- Aperiodic component (broadband 1/f)** overlooked by traditional metrics, and not been explored for antidepressant response to sertraline
- Data has 198 resting state EEG from patients in a clinical trial (EMBARC Establishing Moderators and Biosignatures of Antidepressant Response in Clinical Care) for sertraline over 8 weeks
 - 94 treated with **Sertraline**
 - 104 treated with **Placebo**
- We examined the utility of periodic and aperiodic components from the EEGs as:
 - Biological indicators** of MDD severity,
 - Predictive indicators** of sertraline treatment response, and
 - Mechanistic indicators** of neural changes due to sertraline
- While the outcome of biological and predictive indicators were inconclusive, we identified a highly significant reduction in aperiodic exponent in patients who received sertraline, a change not observed in patients who received placebo
- provides a foundation for broader application of aperiodic spectral measures for other depression treatments and clinical populations

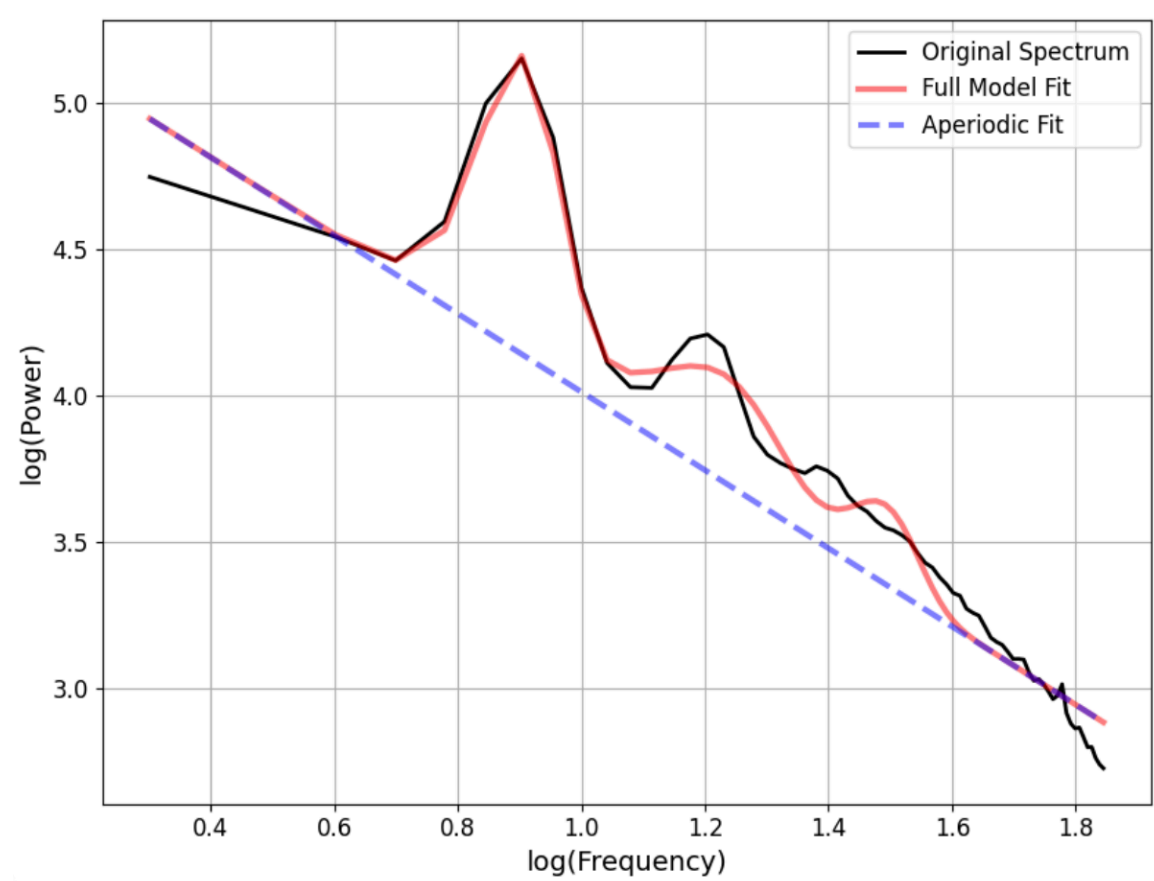
8 WEEKS OF SERTRALINE TREATMENT DECREASES APERIODIC EXPONENT



APERIODIC EXPONENT IS NEITHER EFFECTIVE AS A BIOLOGICAL NOR AS A PREDICTIVE INDICATOR



What is the Aperiodic component of EEG?



Spectral parameterization (specparam, formerly foof) is a fast, efficient, and physiologically-informed tool to parameterize neural power spectra.

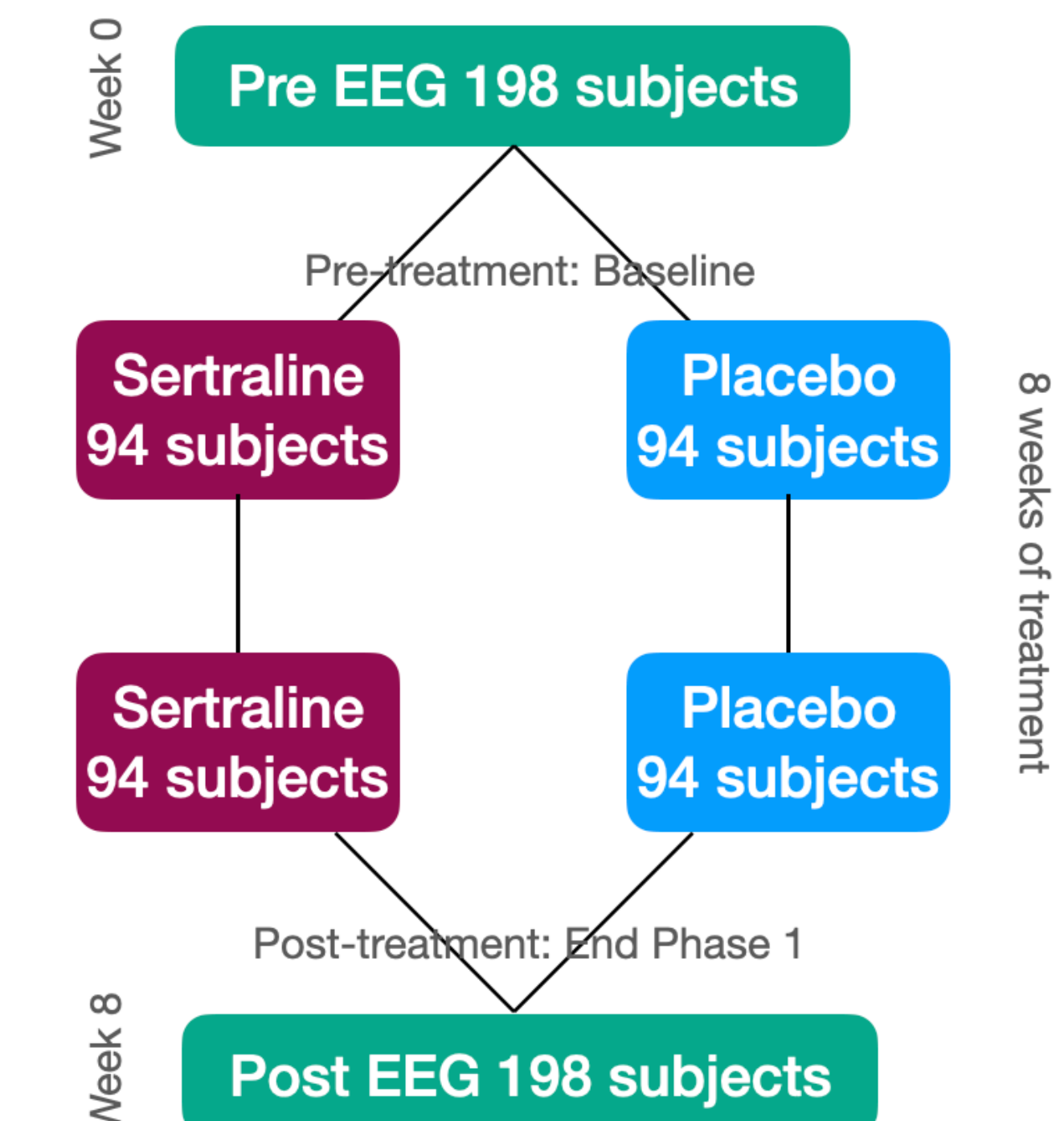


More on Specparam - Link to GitHub!

Donoghue, T., Haller, M., Peterson, E.J. et al. Parameterizing neural power spectra into periodic and aperiodic components. *Nat Neurosci* 23, 1655–1665 (2020). <https://doi.org/10.1038/s41593-020-00744-x>

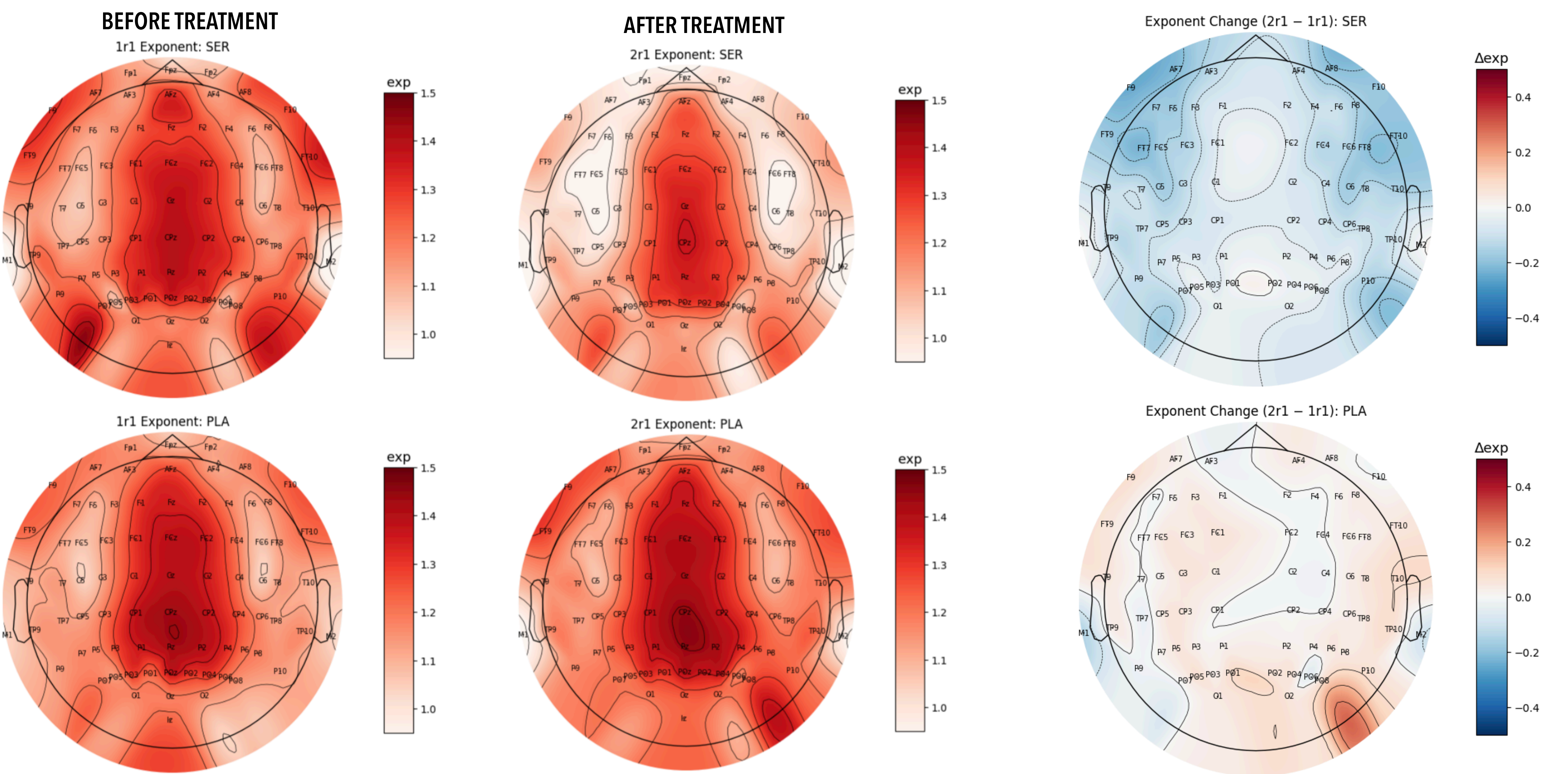
DATASET

Resting stage EEG data was collected from 198 patients diagnosed with MDD before and after a double blind treatment of either sertraline or placebo over 8 weeks



Variable	Descriptive Statistics	
N		198
Age (mean ± SD, years)	35.22 ± 12.35	
Gender (M/F)	38/78	
Race (top 3, %)	White: 64.7%; Black or African Am: 16.4%; Other: 12.1%	
Stage/TX (SER/PLA)	SER: 94; PLA: 94	
HDRS-17 Week0 (mean ± SD)	18.33 ± 4.44	
HDRS-17 Week8 (mean ± SD)	10.10 ± 6.93	
Responders (≥50% ↓ HDRS-17)	50 / 107, 46.728%	

WEEK 1 VS WEEK 8 TOPOMAPS DISPLAYING EXPONENTS



TOPOMAPS DISPLAYING EXPONENT CHANGES IN PATIENTS TREATED WITH SERTRALINE VS PLACEBO

DISCUSSION AND FUTURE DIRECTIONS

- Analyses relating the observed change in exponent to therapeutic outcome is ongoing.
 - By focusing on the aperiodic exponent, a parameter rarely emphasized in standard neurophysiological analyses, our findings explore its potential utility (or lack thereof) as a predictive biomarker and mechanistic indicator of treatment efficacy.
- Future Directions:
- This work provides a foundation for broader application of aperiodic spectral measures for other depression treatments and clinical populations.
 - Look at electrode clusters that change the most during sertraline treatment for either both as a diagnostic indicator or as a predictive indicator at baseline.
 - Using the cluster analysis to see what features at what part of the brain is useful to either diagnose or predict.