# Beyond ERPs: 1/f Activity Carries Unique Neural Info

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Honors Thesis

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## Abstract

Since the invention of the EEG, scientists have attempted to decipher the role of different kinds of electrical neural activity. Using the Fourier transform, neuroscientists can convert neural time-series data into the power spectrum. However, it has not been clear to researchers which spectral phenomena in the power spectrum are most important. Researchers once believed that aperiodic (1/f) activity represented only background noise and that it provided no value. We now know that it is related to the E/I balance in neurons, where a higher aperiodic exponent corresponds to greater inhibition, and a lower one corresponds to greater excitation. Further research is needed to establish the significance of spectral phenomena in predicting post-stimulus power, independent of other spectral features. Notably, Gyurkovics et al. 2021 demonstrated that stimuli, specifically the visual oddball task, elicit changes in 1/f spectra that are separable from event-related potentials (ERPs). In this study, we replicate the findings from Gyurkovics et al. 2021. Our results demonstrate that these effects hold in a different dataset: the aperiodic exponent in the power spectrum shifts from pre- to post-stimulus, even when ERPs are removed, and serves as a significant predictor of post-stimulus changes in the frequency domain. Thus, we contribute to the growing body of literature demonstrating that aperiodic activity is a genuine and essential spectral phenomenon. Our verification of Gyurkovics's results using different data and ERPs underscores the reliability of this effect. Verifying the relevance of aperiodic activity relates to a more general issue: we must ensure that the features we measure in our data are significant and relevant. This issue is meaningful across scientific disciplines.

## 1 Introdcution

It was long believed that anything outside classic oscillatory peaks was "just noise." The non-oscillatory portion of electrophysiological recordings was largely ignored, with researchers focusing instead on narrowband rhythms (e.g., alpha, beta) (He, B.J., 2014). Only recently has the 1/f component begun to receive serious attention. Voytek et al. (2015) were among the first to challenge this assumption. Their study showed that the aperiodic exponent varies with age: older adults exhibit a flatter exponent compared to the steeper one in younger adults. By demonstrating that the aperiodic exponent changes across lifespan, this work opened the door to the idea that aperiodic activity represents meaningful spectral phenomena. Gao et al. (2017) then linked aperiodic activity to the balance between excitatory and inhibitory neuronal activity. Excitation makes neurons more likely to fire action potentials, while inhibition makes them less likely to fire. This provided a biological interpretation: the aperiodic slope could reflect this E/I balance, with a steeper slope indicating more inhibition and a flatter slope indicating more excitation. This also coincided with the notion that periodic and aperiodic components of neural time-series data should be separated. In 2020, Donoghue

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et al. introduced the FOOOF algorithm, which enables researchers to decompose the EEG power spectrum into periodic and aperiodic components and efficiently compute the aperiodic slope.

Until recently, however, aperiodic activity was assumed to be static. Even Donoghue et al. noted that FOOOF was designed under the assumption that the aperiodic component is stationary. Gyurkovics et al. 2021 was one study that challenged this assumption by demonstrating that the aperiodic slope changes in response to stimuli. Gyrukovvics, in his experiment used a visual oddball paradigm. In our study, we replicated Gyurkovics et al.'s findings using a different visual oddball dataset. Our goal was to test the robustness of their conclusion that the aperiodic slope genuinely changes in response to a stimulus.

We replicated their methods in Python, applying the same approach: calculating the ERP across trials, converting the ERP to the frequency domain, and subtracting its power spectrum from the averaged post-event trial windows. This allowed us to compare the post-stimulus slope (after ERP subtraction) to the pre-stimulus slope. In doing so, we showed—as Gyurkovics et al. did—that the aperiodic slope changes following stimulus presentation, independent of the ERP, highlighting that it is more than just background noise. Modeling further supported this finding. Gyurkovics et al. introduced three models to predict post-stimulus power spectra, each incorporating different spectral features. Model 3, which included the aperiodic component, was the most accurate. In our replication, Model 3 again most accurately predicted post-stimulus power across frequencies, likely because it incorporated the most complete spectral information.

In conclusion, we confirmed that the EEG power spectrum steepens following stimulus onset, even after removing the ERP component. Moreover, we found that using only the ERP and pre-stimulus power to predict post-stimulus spectra is insufficient; the aperiodic slope must be included. Our results support the robustness of Gyurkovics et al.'s findings and further validate the importance of considering aperiodic activity as a meaningful component of EEG analysis.

# 2 Methods

### 2.0.1 Open Data Sources

Data was gathered from OSF, a website featuring open EEG datasets for researchers. Specifically, the data from a project titled ERP CORE (Kappenman et al. 2020). A paper that created optimized paradigms for different ERPs so that there could be more standardization and reproducibility in the space of EEG data analysis. Specifically, the P3 ERP, visual oddball paradigm experimental setup was used. The total number of participants who provided informed consent was n = 40 (average age, 21.5 years; 25 female, 15 male) from the University of California, Davis. Participants were neurotypical (normal color perception and vision), which was necessary for the task, recorded using a standard 10-20 montage with 21 electrode positions, including 19 active scalp sites (Kappenman et al. 2020). The FDT and SET files that were used were already fully preprocessed by the researchers. Preprocessing steps included downsampling, high-pass filtering, and epoching the continuous experimental recording. The number of participants included in the analysis (n = 20) was used to account for script running times.

## 2.1 Task Description

Kappenman et al. (2020) adapted a visual oddball task from Luck et al. (2009), which is designed to elicit the P300 ERP, a response to novel stimuli, and referred to as the "Active Visual Oddball P3". Letters (A, B, C, D, E) are flashed on a screen (p = .2 for each letter). In each testing window, one letter is chosen as the target letter and flashed; participants then press a button in response to that letter. Letters flashed on the screen for 200 ms with intervals of 1200ms-1400ms in which a white fixation dot was shown. There was a total of 200 oddball trials per participant recorded at a 256Hz sampling frequency, divided into four 50-trial blocks in which the target letter changed.

## 2.2 Data Analysis

### 2.2.1 EEG Preprocessing and Spectral/ Aperiodic Analysis Pipeline

To replicate the results from Gyurkovics et al. (2021), we extracted aperiodic and offset values marked by whether they were target or non-target letters (frequent-rare, rare-frequent, frequent-frequent) for each participant and electrode. This allowed us to recreate figures 2B and 2C, which suggest that stimuli induce changes in 1/f. First, we preprocessed the set files by matching IDs to target and non-target letters (100 being frequent-rare, 200 being rare-frequent, and 300 being frequent-frequent), allowing us to later filter by target type.

Now that epochs were classified by pip type, we looped through epochs that matched the pip type and processed each participant's electrode, slicing its epochs to 600ms to +600ms around the epoch. This was necessary due to the constraints of the ERP CORE data set, where the epoch length of -1024 ms to +1024 ms from Gyurkovics would not work. Then, after slicing the epochs, we computed the Fast Fourier Transform (FFT) on the pre- and post-time windows, as well as the FFT frequencies. Averages were calculated across electrodes for the pre- and post-spectra, as well as the post-time windows to compute the averaged post-time windows (ERP). The ERP was then subtracted from the post-averaged spectra across electrodes to calculate the post-minus-ERP spectra. Lastly, FOOOF was used to calculate exponent and offset values across averaged pre-, post-, and post-minus-ERP spectra, and power indexed by pip type was saved out individually. This process was repeated for every electrode, every participant, and every condition.

#### 2.2.2 Permutation Testing

Permutation testing showed that the aperiodic shifts in the post-minus-ERP spectra were significant. From recording all the post-minus-ERP exponent values obtained by performing FOOOF, we conducted a two-tailed hypothesis test by flipping half the values(changing them from positive to negative) and then averaging them; this was done 10,000 times to obtain a null distribution centered around 0. If the null distribution were true, it would mean our observed mean for post-minus-pre would be somewhere close to that distribution. However, if our observed value fell outside the 2.5% (-0.11) and 97.5% (0.11) confidence intervals, then we could consider it significant. The process of permuting the signs 10,000 times and comparing the null distribution to our observed value was repeated individually for each pip type. The averaged values for all pip types were very significant: 1.51 for frequent-rare, 1.5 for rare-frequent, and 1.49 for frequent-frequent. This means there was a significant aperiodic shift in the post-spectra, even after the ERP was subtracted.

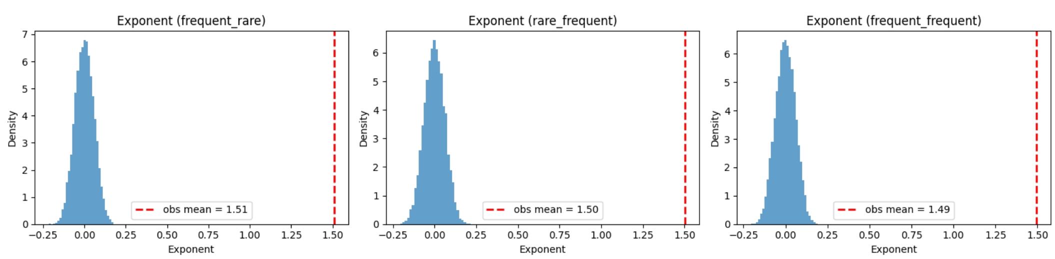


Figure 1: Null Distribution of Exponent Values With Observed Means Shows Significance.

#### 2.2.3 Violin Plot

A part of the procedure used to visualize the steepening of the aperiodic component after the stimulus was presented. Since we had values separated by condition type, three separate but identical plots were made. Mean values calculated from before (1.51 for frequent-rare, 1.5 for rare-frequent, and 1.49 for frequent-frequent) were combined with a strip plot showing the distribution of the exponent values. The pre-spectra values of 1.1 indicate a significant steepening post-stimulus.

#### 2.2.4 Model Creation

The goal of this section was to reconstruct the post-event EEG spectrum using the three different models proposed by Gyurkoics et al. (2020). Model 1, the simplest, only incorporates the pre-event spectrum as a predictor of the post-event spectrum; therefore, it was predicted that Model 1 would be the worst-performing. Model 2 incorporated the ERP component into the reconstruction. With the post spectra averaged, this component was added to the pre-event spectra to recreate Model 2. It was predicted that this model would be the second-best performer, as it incorporates more spectral information than Model 1. Lastly, Model 3 reconstructed post-power by modeling the sum of the three parts: pre, ERP, and simulated 1/f spectrum (Donoghue et al., 2020). The simulated $1/f$ spectrum was created using pre- and post-event delta offset and exponent values. Delta values are calculated by subtracting the pre-event value from the post-event value. Once these values were calculated for exponent and offset, they were added to their corresponding pre-event values and saved as a tuple. This tuple was then used to generate the power spectrum using the gen_power_spec FOOOF function. Lastly, the same steps were used as before, where we added pre-event, ERP, and simulated power together.

$$\begin{aligned}
\text{Model 1:} \quad & \hat{S}_{\text{post}} = S_{\text{pre}} \\
\text{Model 2:} \quad & \hat{S}_{\text{post}} = S_{\text{pre}} + S_{\text{ERP}} \\
\text{Model 3:} \quad & \hat{S}_{\text{post}} = S_{\text{pre}} + S_{\text{ERP}} + S_{1/f,\,\Delta}
\end{aligned}$$

Figure 2: Reconstruction of the post-stimulus power spectrum.

## 3 Results

### 3.1 Violin Plot

These violin plots show aperiodic exponent changes, pre and post-stimulus (as well as post-stimulus with the ERP component subtracted). There is a pronounced exponent shift after stimuli are presented. Across pip types, the mean exponent values become increasingly hostile, corresponding to a steepening of the power spectrum. The pre-exponential value of 1.35 decreases to 1.6 post stimulus, and stays at 1.5 with the ERP component subtracted. Thus, ERP removal does not affect the exponent value post-stimulus too significantly, as it is still more negative than the pre-stimulus exponent by 0.4 points. This negative change post-stimulus is observed across all pip types, although it is unclear whether it is more pronounced in the frequent-rare pip compared to the rare-frequent and frequent-frequent types. A more pronounced negative change in the frequency-rare exponent post-stimulus was the result observed by Gyurkovics. Thus, the main observable result from these violin plots is that the post-minus-ERP distribution remains significantly lower, showing that the exponent change is not solely an ERP artifact.

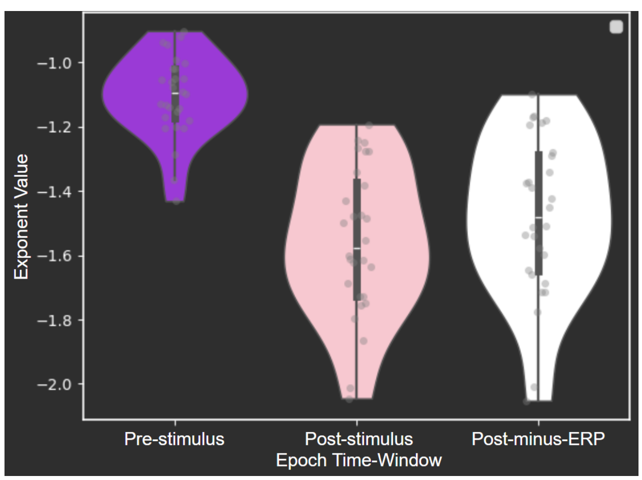


Figure 3: Exponent Values Remain Negative Even With ERP Removal.

### 3.2 Residual Plot

This plot illustrates residuals across the three models outlined in Gyurkovics, which predicted post-simulus power. The purpose of these models was to gain a better understanding of what the spectral features contributed most to the post-stimulus change. We can observe that the residual values in the delta band ( 0.5-4 Hz) for model 3 are substantially smaller than those of models 1 and 2. Between 3-5 Hz model 3 residuals never go above 0.5, while model 2 is  1.25 and model 1 is  2. The trend appears to be that the more spectral features we add, the smaller the residuals, with model 3 (pre + ERP $\Delta 1/f$) being the best predictor of post-stimulus power, followed by model 2 (pre + ERP), which is the second best predictor. However, its residuals are significantly larger in the delta frequency range than those of model 3 (difference of more than 1). We fail to reject the null hypothesis that 1/f aperiodic activity is an ERP artifact.

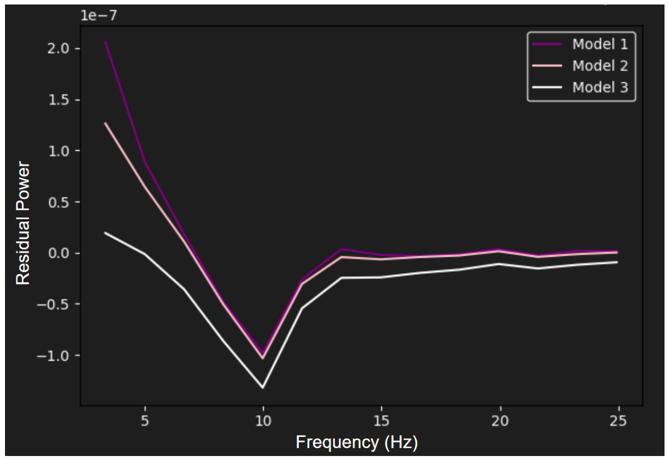


Figure 4: Model 3 Most Accurately Models Post-Stimulus Spectral Power.

## 4 Discussion

Exponent values reliably steepen post-stimulus (pre  1.35 $\rightarrow$ post  1.60), even after ERP removal ( 1.5), suggesting that 1/f spectral changes are not solely due to ERP artifacts. Rather, 1/f spectral activity can be thought of as its own phenomenon equally changed by stimuli. Not only was the stimulus-induced change in 1/f confirmed, but consistent negative exponent changes were visible across all pip types, replicating the results of Gyurkovics. Regarding the violin plots, we can infer that model 3 was the most effective, yielding the smallest residuals, particularly in the lower frequencies (Theta frequency range). Smaller residuals in model 3 were also visible in the entire window (3 Hz < 26 Hz) compared to models 1 and 2, implying that 1/f spectral activity contributes significantly to post-stimulus power. ERPs are not enough to simulate post-stimulus power.

We have added evidence to the importance of recognizing the aperiodic component in EEG spectral analysis; however, our experiment has some limitations. For example, we were unable to substantiate Gyurkovics' claim that the frequent-rare pip type produced the largest exponent shift post-stimulus, even after ERP subtraction. We need to conduct some statistical analysis to confirm which 1/f spectral values are the largest across pips. Confirming this finding from the paper is important because researchers are still uncertain whether stimulus-induced changes in 1/f noise are substantially different across experimental conditions, such as those involving novel stimuli. Gyurkovics was able to show that novel stimuli elicited a more negative exponential shift than other pip types. Moreover, while we replicated the Gyrukovics' experiment and findings, the discrepancy between the original data set and our data set (visual oddball P3) allows room for error. For example, we were forced to use a different epoch window (-600ms to 600ms) compared to Gyurkovics (-1024ms to +1024ms). Due to the jittering in our dataset between stimuli (when letters were flashed on the screen), we couldn't use an epoch length of -1024ms to 1024ms. Discrepancies in window sizes are potentially problematic because, to generate ERPs, you generally need larger epochs, and our total window size of 1200 ms is substantially smaller compared to the 2028 ms used originally. The consequences of our changes are that we were unable to generate frequencies of 0-3 Hz, which also leaves room for error in the generation of our event-related potentials (ERPs). The limitations of our data analysis leave some room for future research directions, such as experimenting with different ERPs to ensure that stimulus-induced changes in 1/f spectral activity are robust and reliable. Currently, we can only confirm these findings for a single ERP type: auditory oddball tasks, specifically when eliciting P3s.

Next, these methods can be applied to other ERPs, such as the N170, an ERP elicited in oddball visual tasks for faces (Bentin et al.1996). The more modalities we use to investigate whether stimuli change 1/f exponents, the more robust the claim will be.

## 5 Conclusion

In summary, ERPs and aperiodic (non-oscillatory) exponents make similar contributions to post-stimulus power. Although the changes in post-spectra are alike, our research has demonstrated that they are distinct effects. Gyurkovics et al. showed that stimuli induced changes in the aperiodic exponent in an auditory oddball task, and we have expanded the findings to auditory oddball tasks as well. Replication was also done with an open data set (ERP CORE) and in a different programming language (Python). Specifically, we have replicated findings that the steepening of post-spectra is visible across all pip types (frequent or infrequent), and aperiodic slope changes are an essential component in modeling post-stimulus power at all frequencies (3 < 25 Hz); however, we have not yet quantified whether ERP or aperiodic components have more pronounced changes post stimuli as well as wether condition — frequent or infrequent — has greater effect on one or the other.

Our research contributes to the growing body of literature that proves the relevance of non-oscillatory components, such as aperiodic slope (Voytek et al. 2015). As scientists, we must be cautious that confounding variables do not influence the changes in the variables we claim to study. By subtracting the ERP from the post-stimulus windows, we observed that there was still a significant difference in the aperiodic exponent from pre to post. Only through this type of testing can we truly understand the effects of the variables we investigate. Another implication of this research is that replicability is not always prioritized in the EEG community. Researchers seldom prioritize replication verification, so by validating Gyurkovics' study, we set a precedent for future researchers to do the same. Replication of existing findings strengthens their reliability and our confidence that they can be applied to different datasets.

## References

[1] Bentin, S., Allison, T., Puce, A., Perez, E., & McCarthy, G. (1996). Electrophysiological studies of face perception in humans. *Journal of Cognitive Neuroscience, 8*(6), 551–565. `https://doi.org/10.1162/jocn.1996.8.6.551`

[2] Donoghue, T., Haller, M., Peterson, E. J., Varma, P., Sebastian, P., Gao, R., ... Voytek, B. (2020). Parameterizing neural power spectra into periodic and aperiodic components. *Nature Neuroscience, 23*(12), 1655–1665. `https://doi.org/10.1038/s41593-020-00744-x`

[3] Gao, R., Peterson, E. J., & Voytek, B. (2017). Inferring synaptic excitation/inhibition balance from field potentials. *NeuroImage, 158*, 70–78. `https://doi.org/10.1016/j.neuroimage.2017.06.078`

[4] Gyurkovics, M., Clements, G. M., Low, K. A., Fabiani, M., & Gratton, G. (2022). Stimulus-induced changes in 1/*f*-like background activity in EEG. *Journal of Neuroscience, 42*(37), 7144–7151. `https://doi.org/10.1523/JNEUROSCI.0414-22.2022`

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

[6] Kappenman, E. S., Farrens, J. L., Zhang, W., Stewart, A. X., & Luck, S. J. (2021). ERP CORE: An open resource for human event-related potential research. *NeuroImage, 225*, 117465. `https://doi.org/10.1016/j.neuroimage.2020.117465`

[7] Luck, S. J., Kappenman, E. S., Fuller, R. L., Robinson, B., Summerfelt, A., & Gold, J. M. (2009). Impaired response selection in schizophrenia: Evidence from the P3 wave and the lateralized readiness potential. *Psychophysiology, 46*(5), 776–786. `https://doi.org/10.1111/j.1469-8986.2009.00817.x`

[8] Voytek, B., Kramer, M. A., Case, J., Lepage, K. Q., Tempesta, Z. R., Knight, R. T., & Gazzaley, A. (2015). Age-related changes in 1/*f* neural electrophysiological noise. *Journal of Neuroscience, 35*(38), 13257–13265. `https://doi.org/10.1523/JNEUROSCI.2332-14.2015`