Research Article

The Impact of Music-Induced Emotions on EEG Alpha Power and Aperiodic Exponent Across Age Groups

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ABSTRACT

Many studies have been conducted on the impact of music on periodic brain activity. However, there is a lack of research into how music influences background non-oscillatory brain activity, as measured by the aperiodic exponent. Additionally, music has the power to influence emotions which may cause novel neural activity. In the current study, we analyzed alpha power (8-13 Hz) and aperiodic exponent among different age participants during active music listening in order to discover whether age or contrasting music-induced emotions could evoke different neural activity. We conducted a secondary analysis on data obtained from OpenNeuro utilizing measures of alpha power and aperiodic exponent from electroencephalography (EEG) data. The following libraries in Python were used: Fitting Oscillations & One Over F (FOOOF) and Magnetic and Electric Neuroimaging (MNE). The analysis revealed no correlation between the emotional content of music and our EEG measures. However, there were significant increases in aperiodic exponent between younger and older participants, highlighting a change in brain activity across different age groups. This reveals the possible effects of age as a cause of change in neural activity. Future research on the differences in aperiodic activity among different-age adults during other creative tasks could improve our understanding of the effects on brain activity caused by aging.

Keywords: Alpha Power; Aperiodic Exponent; Music; Emotion; Power Spectra; Electroencephalogram; Age

INTRODUCTION

We often describe music as the universal language. Despite language barriers, people from across the world can enjoy the same music and connect with each other through this medium. Music is a combination of sounds and rhythms that come together in order to establish a message, often arousing multiple emotions. The effects of music on periodic brain activity have been researched previously, however, music's effect on aperiodic exponent hasn't yet been analyzed.

The brain's power spectral density can be broken down into two parts, periodic, and aperiodic. Oftentimes, people tend to focus on the periodic portion of the data considering there is a lot of evidence indicating its correlations with countless cognitive states. The current study focuses on Alpha power measurements. Alpha power refers to the frequency and amplitude of alpha

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waves in EEG data within the 8-13 Hz frequency band. The higher the amplitude, the greater its representation in the neural signal, as quantified by greater alpha power. Additionally, the aperiodic exponent is another key part of EEG data. In a log-log power vs frequency graph (Figure 1), the background "noise-like" aperiodic component can be seen as a smooth line across the graph.

This line follows a $1/f^x$ relationship with f representing frequency and x representing the aperiodic exponent. The aperiodic exponent represents the slope in this equation with higher values indicating a steeper line. As the aperiodic exponent increases, the power spectrum tends to flatten out, indicating greater noise in the brain.

Prior research on neural activity and creative tasks has heavily focused on the periodic data from EEG. For example, analysis of alpha power during creative tasks in EEG data shows a positive correlation between the two (1). Gamma and beta power have also been shown to correlate with musical enjoyment (2). Additionally, Music has been shown to be a possible therapy for mental disorders or diseases. EEG-Neurofeedback is a form of music therapy where music is used to evoke a certain brain state in a patient (3). This indicates the possible utilization of music as a form of therapy for certain brain disorders. However, the aperiodic part of the frequency domain could also present many interesting indicators of neural activity. For instance, smaller values in the aperiodic exponent have been shown to correlate with Attention deficit hyperactivity disorder (ADHD) symptoms (4). Age has also been shown to correlate with changes in cognitive functions. Studies show that as humans grow older, the functions of the brain usually deteriorate (5). Aperiodic exponent is also shown to be connected with age-related cognitive decline (6).

Although there has been much research into the periodic aspect of EEG data during active music listening, there is a lack of research regarding the aperiodic aspect. As aperiodic activity has been shown to indicate many interesting neural activities, our study wants to push our understanding of this even more by analyzing whether aperiodic exponent could be an indicator of difference in music-induced emotion. Our study intends to identify any correlations between emotionally different music that has different effects on alpha power and aperiodic exponent

In my investigation, I aimed to analyze the EEG data from a prior study of 31 healthy adults during active music listening to happy/sad songs. I measured the alpha power as well as the aperiodic exponent of the adults during the listening runs as well as the resting states. I separated the adults into different age groups spanning young [18-30], middle [30-40], and old [40+]. Afterward, I compared the data between adults in the same group listening to music that had rated as happy and music rated as sad. This gave the result that emotionally different music seemed to have no statistically significant difference in alpha power and aperiodic exponent. I also uncovered that there were significant differences in neural activity between young and old age groups.

METHODS AND MATERIALS

I utilized the dataset "Brain-Computer Music Interface for Monitoring and Inducing Affective States (BCMI-MIdAS)" from OpenNeuro (7). This dataset measured

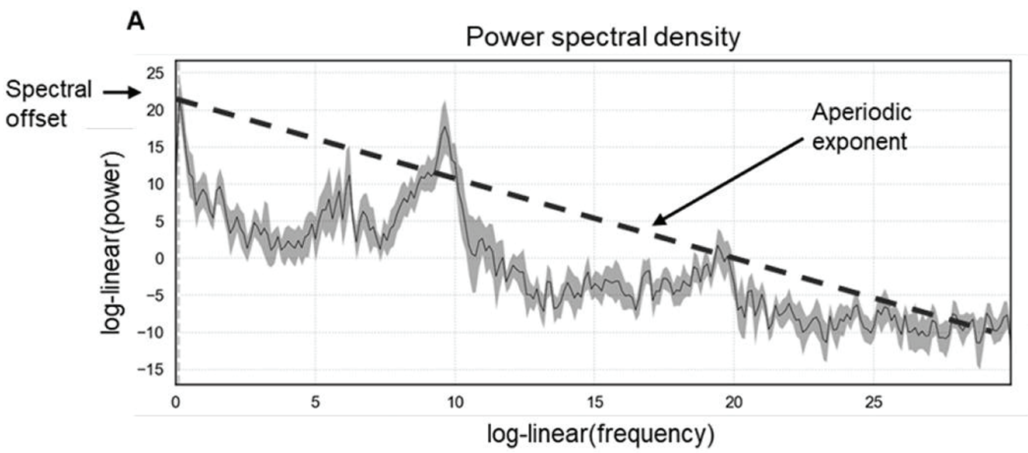

Figure 1. Power Spectrum Density Graph and Aperiodic Exponent Example Graph - an example of a possible power spectral density along with the aperiodic exponent graph.

EEG data from 31 healthy adult participants ranging from ages eighteen to sixty-six. Each adult had 6 runs with the first and last run being resting state runs where participants were asked to sit still, keep their eyes closed, and not move their eyes around. Runs two through five were active music listening trials where participants listened to 10 music clips, each 12 seconds in duration. The music clips were selected from a wide array of film scores from movies that are less well-known. This was to avoid recognition of music by the participants. At the end of the trial, participants were asked to rate the music clips on their emotions. This study only focuses on music clips the participants rated as happy or sad.

The study relied on Python to analyze and calculate the aperiodic exponent as well as alpha power in the dataset. I used Magnetic and Electric Neuroimaging (MNE) and fitting oscillations & one over f (FOOOF) packages in order to calculate these data points from the EEG data (8, 9). For our FOOOF settings, the peak width limits were between four to eight, the max number of peaks was set to three, the minimum peak height was set to 0.1, the peak threshold was set to 2, and the aperiodic mode was set to fixed. I calculated alpha power by subtracting the aperiodic fit of the neural power spectrum from peak power within the 8-13 Hz frequency band. After analyzing the data, I stored the values in a Google Drive folder.

In the code, I first set the analysis to only run two through five because those were the active music-listening runs. Each participant records how the music made them feel for 8 different emotions on a 1-9 point scale with a higher number representing a higher presence of that emotion. In our study, I only focused on the ratings for happy/sad emotions. I filtered out all trials where the participant did not feel happiness or sadness (score less than 5). I then found the time when participants rated the music clips on how happy or sad it made them feel. The code only recorded EEG signals 1.5 seconds before and after a response was made by the participant. Next, I filtered the data using a notch filter with an IIR filter with the notch frequency set to 50 Hz. I then calculated the power spectrum density with these parameters: method=”welch”, fmin=1, fmax=40, tmin=0, tmax=None, n_overlap=250, n_fft=1000. I then calculated the alpha power and aperiodic exponent values from the data and stored it in an array.

During our analysis, we utilized a two-way repeated ANOVA in order to determine correlation. Prior to conducting the repeated measures ANOVA, certain statistical assumptions were addressed. Each subject’s data was assessed for normality using visual inspection of Q-Q plots as well as the Kolmogorov-Smirnov Test (KS Test) for each participant’s alpha power and aperiodic exponent values. The majority of subjects had a p-value greater than 0.05 in the KS Test and displayed a straight diagonal line on the Q-Q plot. A few subjects did not pass the test. We treated these subjects as random errors and did not include them in our analysis. Homogeneity of variance was also evaluated using Levene’s Test on all subject data. There appeared to be no issues as all p-values were greater than 0.05. In presenting our results, I only used data from the frontal nodes(FP1, FP2, F7, F3, Fz, F4, F8). I separated each data point based on the run that it was a part of and plotted them using a bar graph. I also separated the data into Young [18-30], middle [30-40], and old [40+] age groups in a separate graph in order to look at possible differences in reactions across age groups.

RESULTS

Across the four runs, alpha power remained relatively unchanged between the different music-induced emotions (two-way Repeated Measures Analysis of Variance (ANOVA), no effect of Run or Emotion, $p>0.05$). The median value for alpha power remained in the 0.4 to 0.6 range across all runs (Figure 2). Additionally, the data for aperiodic exponent indicated no correlation between different music-induced emotions (two-way Repeated Measures ANOVA, no effect of Run or Emotion, $p>0.05$). Median aperiodic exponent values stayed within a general range of 1.5 - 2.0 across all 4 runs(Figure 2). Despite the correlation that has been found between artistic expression and alpha power, there seems to be no indication that different music-induced emotions have different influences on alpha power and aperiodic exponent.

When examining each run independently, there were no significant effects of emotion, age range, or interaction (all $p > 0.05$). However, the comprehensive model across all runs demonstrated significant relationships between age and aperiodic exponent. Specifically, during runs 3, 4, and 5 middle and old age groups presented significantly higher aperiodic exponent values ($p < 0.05$). This suggests that Age may have a significant run-dependent effect on aperiodic exponent .

DISCUSSION

Music has a major influence on our emotions and brains. Previous research on the effects of music on the brain primarily focuses on the influence of music on the periodic data from an EEG. The goal of the current study

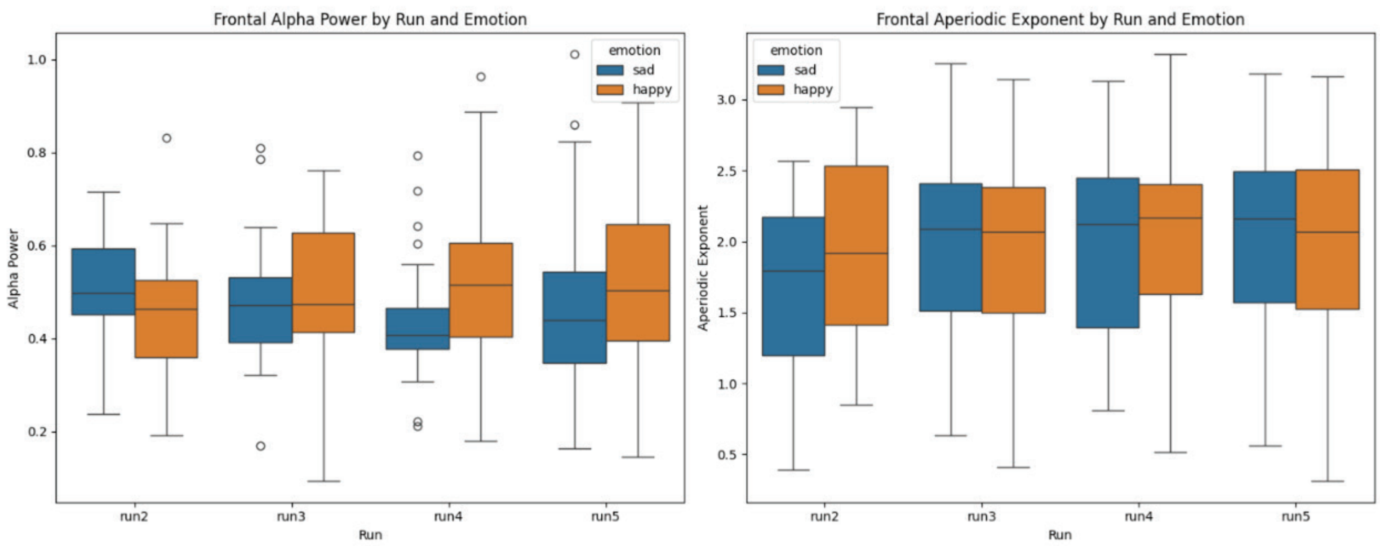

Figure 2. General Overview of Emotion-Power Spectra Interaction - Values of alpha power displayed no significant difference between emotions across all 4 runs. Median alpha power stayed between 0.4 and 0.6 across all runs. Aperiodic exponent also displayed similar values across runs with the median value staying between 1.5 and 2.0.

was to expand upon this research by analyzing music with different emotions, and its effect on brain activity. Additionally, our study attempted to analyze the possible influences music had on aperiodic data.

Our results indicated that changes in emotion from music were not indicators of changes to alpha power and aperiodic exponent. Although changes in emotion from music did not influence neural activity, age seemed to show a significant influence on neural activity as the older age group participants experienced significantly higher aperiodic exponent values in later runs. This could be due to the deterioration of neural activity caused by aging as indicated in other studies (5, 6).

Some limitations of the study included the use of participants' subjective ratings, a lack of usable alpha power data points, and a small sample size. The dataset included a list of stimuli used, but no way to determine which clip was listened to during each EEG run. Because of the lack of specific stimuli, we instead relied on participants' own ratings of the emotionality of music. This could result in bias depending on participants' perceptibility to emotional music, possibly causing inaccurate representations of emotion in some data points. Future research should seek to mark specific musical stimuli and utilize a standard scale for emotional rating in order to avoid bias. Additionally, the data had a lack of usable data points for alpha power. Many of the data points were invalid, as there was no peak above background aperiodic activity, so these points were not used in our final results. This could've hidden certain results from our analysis. Future approaches should use non-linear statistics to account for these sorts of missing values. Our study utilized a small sample size of only 31 subjects, limiting the generalizability of our study. Future research should utilize larger sample sizes for a more robust analysis and generalizability.

Research on age as an influence on aperiodic exponent during creative tasks could help present a more robust analysis of the full impacts of age on neural activity. The effects of music in people diagnosed with mental disorders correlated with the aperiodic exponent, such as ADHD or Schizophrenia, may prove beneficial by presenting the feasibility of music therapy as a treatment for mental disorders. Neurofeedback is a way for doctors to track eeg-signals in the brain. Research on the effects of music in people diagnosed with mental disorders could indicate the possibility for neurofeedback to detect emotional changes in the brain and allow doctors to correct abnormal activity.

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DECLARATION OF CONFLICT OF INTERESTS

I declare that there are no conflicts of interest regarding the publication of this article.

REFERENCES

1. Fink A & Benedek M. Eeg Alpha Power and creative ideation. *Neuroscience & Biobehavioral Reviews*. 2014; 44: 111–123. https://doi.org/10.1016/j.neubiorev.2012.12.002
2. Ueno F & Shimada S. Neural mechanism of musical pleasure induced by prediction errors: An EEG study. *Brain Sciences*. 2024; 14 (11): 1130. https://doi.org/10.3390/brainsci14111130
3. Bhavsar P, Shah P, Sinha S & Kumar D. Musical neurofeedback advancements, feedback modalities, and applications: A systematic review. *Applied Psychophysiology and Biofeedback*. 2024; 49 (3): 347–363. https://doi.org/10.1007/s10484-024-09647-0
4. Ostlund BD, Alperin BR, Drew T & Karalunas SL. Behavioral and cognitive correlates of the aperiodic (1/F-like) exponent of the EEG power spectrum in adolescents with and without ADHD. *Developmental Cognitive Neuroscience*. 2021; 48: 100931. https://doi.org/10.1016/j.dcn.2021.100931
5. Lee J & Kim H-J. Normal aging induces changes in the brain and neurodegeneration progress: Review of the structural, biochemical, metabolic, cellular, and molecular changes. *Frontiers in Aging Neuroscience*. 2022; 14: 931536. https://doi.org/10.3389/fnagi.2022.931536
6. Finley AJ, Angus DJ, Knight EL, van Reekum CM, *et al*. Resting EEG periodic and aperiodic components predict cognitive decline over 10 years. *The Journal of Neuroscience*. 2024; 44 (13). https://doi.org/10.1523/jneurosci.1332-23.2024
7. Ian Daly and Nicoletta Nicolaou and Duncan Williams and Faustina Hwang and Alexis Kirke and Eduardo Miranda and Slawomir J. Nasuto (2024). An EEG dataset recorded during affective music listening. OpenNeuro. [Dataset) doi: doi:10.18112/openneuro.ds002721.v1.0.3
8. Donoghue T, Haller M, Peterson EJ, Varma P, *et al*. Parameterizing neural power spectra into periodic and aperiodic components. *Nature Neuroscience*. 2020; 23 (12): 1655–1665. https://doi.org/10.1038/s41593-020-00744-x
9. Gramfort A, Luessi M, Larson E, Engemann DA, *et al*. (2013). MEG and EEG data analysis with MNE-Python. *Frontiers in neuroscience*. 2013; 7: 267. https://doi.org/10.3389/fnins.2013.00267