Analyzing Trends of Aperiodic EEG Activity in Neurotypical Versus Neuropsychiatric Patients Across Lifetime Using Power Spectral Density

Aayan Ali[1,4], Samarth Gupta[2,4], Michael Qu[3,4], Patrick F. Bloniasz[4], Eugene Pinsky[4]

Allen High School, 300 Rivercrest Blvd, Allen, TX 75002[1]; Irvington High School, 41800 Blacow Rd, Fremont, CA 94538[2]; Mission San José High School, 41717 Palm Ave, Fremont, CA 94539[3]; Boston University, Boston, MA 02215[4]

Introduction

Issue: Recent research suggests that aperiodic slopes in signals flatten as individuals get older and has been linked to cognitive decline.[1] However, most existing work is limited to neurotypical or single-disordered people and only in narrow age ranges.[2]

Our Work: Using the TDBRAIN database[3,4], we gathered various individuals (**N=337**) with neuropsychiatric disorders like **ADHD, OCD, and MDD**. We observed resting state, eyes-closed EEG data per subject. The data spanned **ages 6-78**.

Hypothesis: Aperiodic slope can serve as a standardized, age-sensitive biomarker for brain function and age across even neuropsychiatric conditions.

Terminology

EEG: a non-invasive method to record electrical brain activity from the scalp. It represents brain waves in study participants over a small period of time and is often noisy (messy)

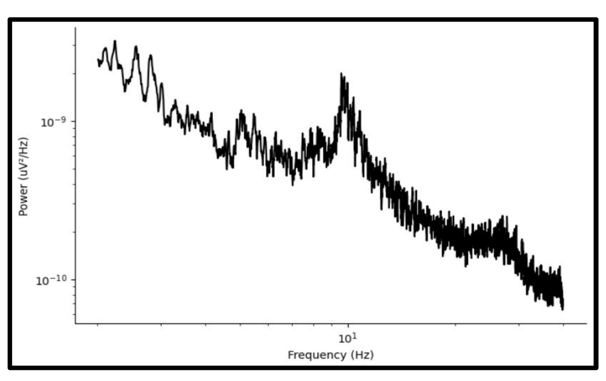

Figure 1. Example graph of possible Power Spectral Density

Power Spectral Density (PSD): Power spectra represent the decomposition of a signal's variance as a function of frequency (see Figure 1). This is typically computed by transforming the signal from the time domain to the frequency domain using the **Discrete Fourier Transform (DFT)**

$$P \propto 1/f^{\beta}$$

Figure 2. 1/f power law in neural signals (for biological purposes)

Aperiodic Slope: biological observation of inverse power-frequency relationship in background activity that tells about average firing rate, neural balance, etc. (based on power law in Figure 2)

Methods

EEG Preprocessing (MNE-Python):

- Bandpass filtered (2–24 Hz) to remove noise
- Subjects with >50% noisy channels (abnormally high micro voltage or muscle artifacts) were excluded
- Bad channels interpolated using nearby electrodes
- **ICA** used to remove eye and heart artifacts
- Data segmented into 2-second epochs

1. Pre-Process Steps

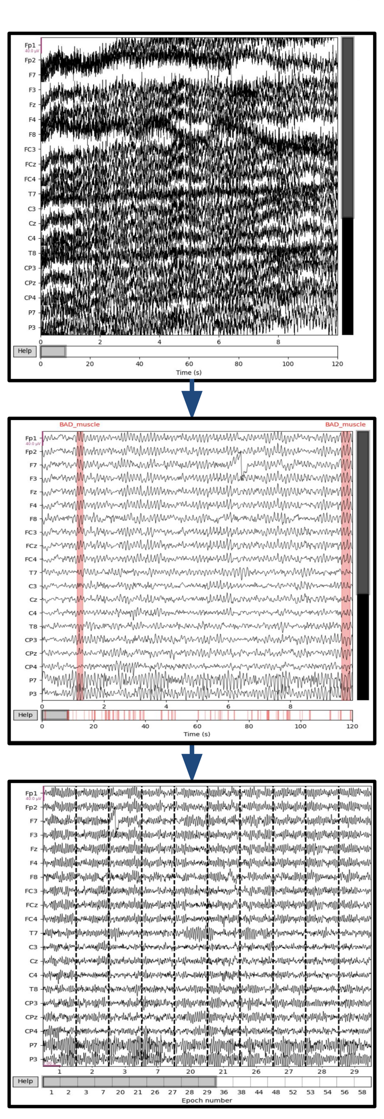

Figure 4. Processing of raw data (top) going through cleaning and epoching. Artifacts are labeled with red bands and channels are cleaned (middle). Data is epoched at 2 secs. to prepare for DFT, which is applied on each window (bottom). PSD is created from epoched data (see Figure 5 left)

2. Visualization Steps

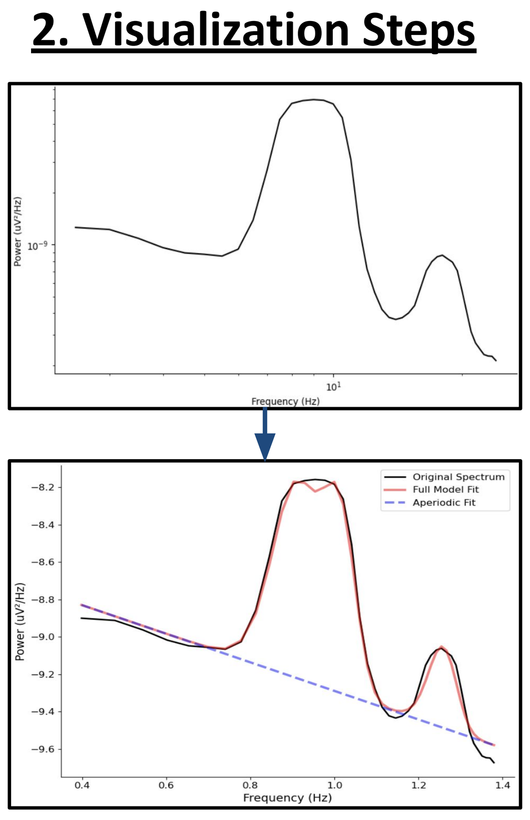

Figure 5. Visualization of PSD using **multitaper** with default params (top) and aperiodic slope, shown by dotted line, fitted using Python library **FOOOF** (bottom). FOOOF calculated the value β, or the exponent to f in the power law (see Figure 3), as .7632, indicating normal decrease in power as frequency increases.

3. Next Steps

Calculate rest of the slopes and observe the change in slope values vs. increasing age grouped by conditions

Results

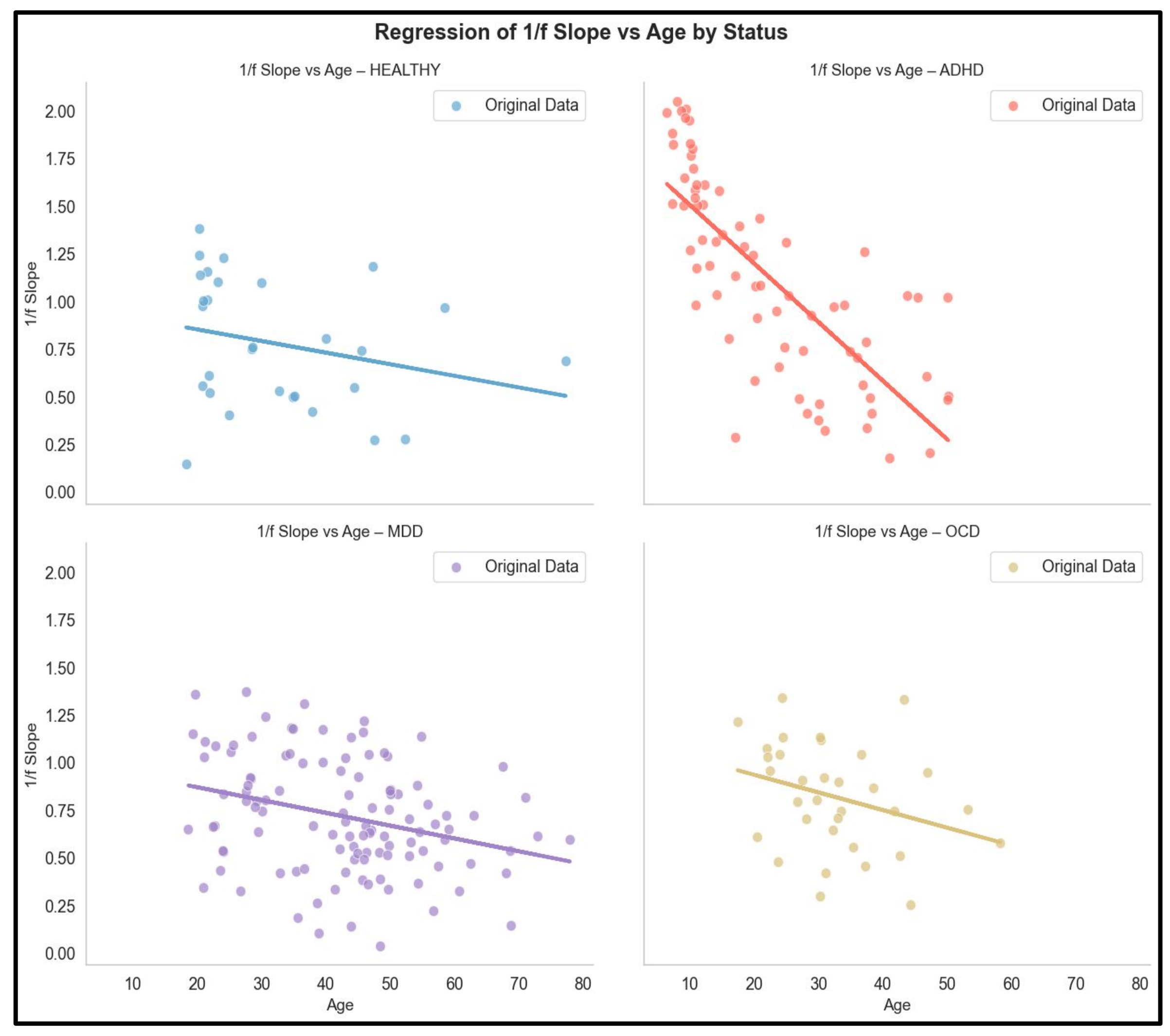

Figure 6. Aperiodic slope graphed as a function of age using linear regression. All regressions have a negative slope, with ADHD having the most negative slope and thus the most downward trend in aperiodic slope as age increases.

Condition	Regression Slope	R^2	R	Mean	Median	StdDev	Min	Max
HEALTHY	-0.0061	0.0659	-0.2568	0.776101	0.747848	0.338188	0.147678	1.381140
ADHD	-0.0308	0.5774	-0.7598	1.125985	1.084107	0.522895	0.175045	2.049509
MDD	-0.0067	0.0912	-0.3019	0.717482	0.672623	0.298469	0.036555	1.372637
OCD	-0.0093	0.0964	-0.3105	0.818232	0.804434	0.284386	0.251569	1.341235

Figure 7. Statistics for regression line from Figure 6 and Characteristics of slopes across conditions

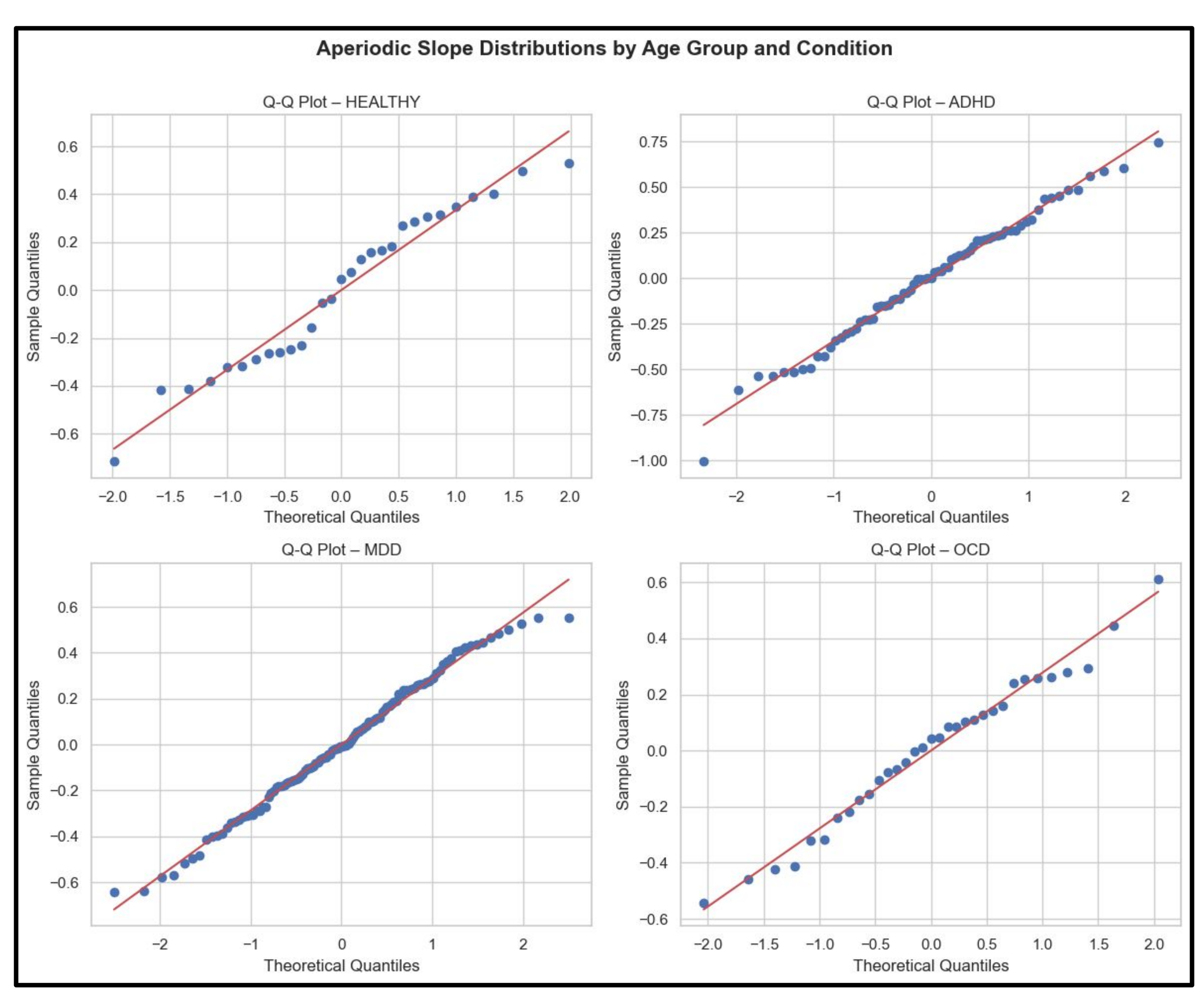

Figure 8. Q-Q plots of residuals from linear regression between age and aperiodic slope for four conditions. Normality assumption for the residuals appears to be met for ADHD and MDD conditions, while HEALTHY and OCD show some deviations.

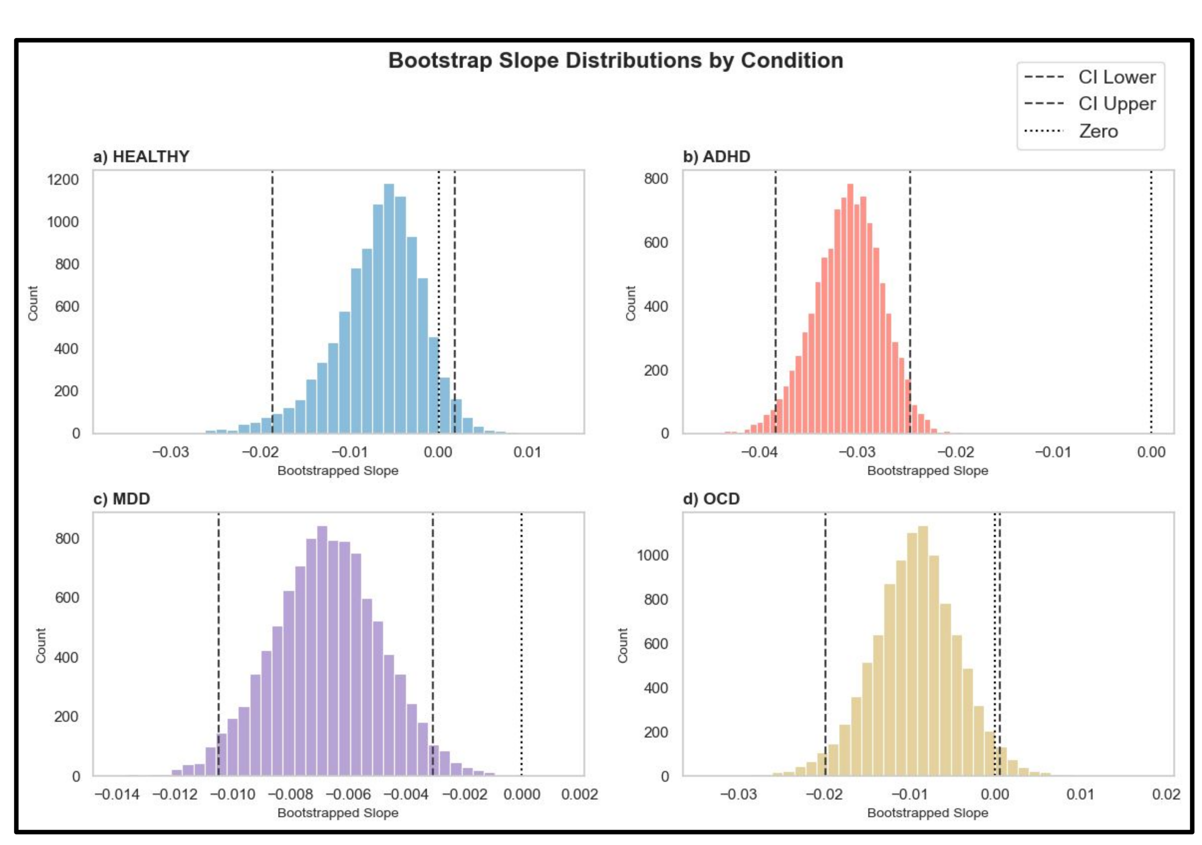

Figure 9. Bootstrapped slope distributions comparing age and aperiodic slope across four conditions derived from **Ordinary Least Squares** regression. Graphed with 95% confidence interval (α = 0.05).
a), d) Zero lies inside CI and invalidates significant age-aperiodic slope relation
b), c) Zero lies outside CI and validates significant age-aperiodic slope relation

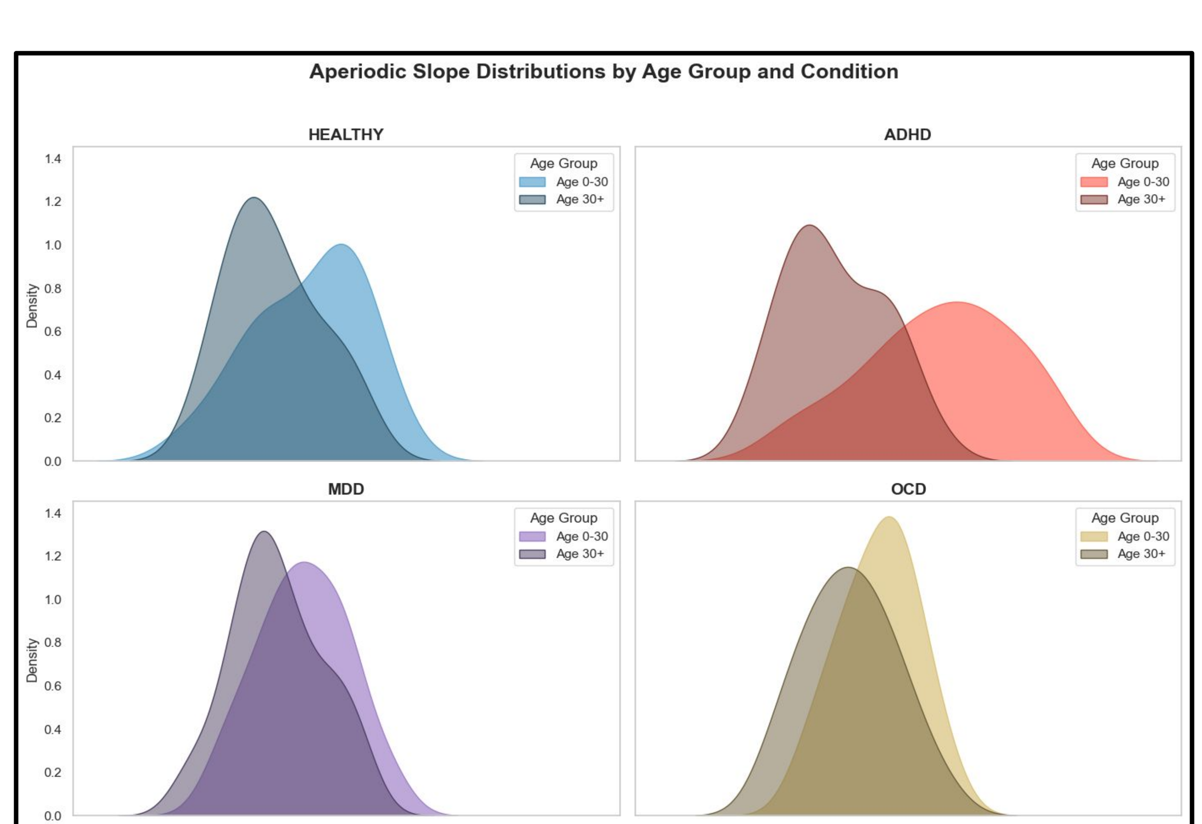

Figure 10. Overlap of aperiodic slope distributions for different age groups across conditions. Each condition has an overlap, with the HEALTHY and ADHD overlaps being the largest.

Discussion

Conclusions:

- Aperiodic slope flattens with age across all groups, supporting validity as an **age-sensitive biomarker** and indicating the neural changes are not unique to neuropsychiatric conditions.
- **Differing bootstrap significance** in age-slope relationships suggests that while age contributes to slope flattening, other disorder-related factors may also play a role.
  - OCD initially looked like it would be statistically significant but due to a **smaller sample size**, the bootstrap interval ended up including zero.
  - Healthy controls showed **non-significant** age-slope trend, possibly due to the smaller sample size or less pronounced cognitive changes compared to the neuropsychiatric.
- Distributions suggest **variability** in median slope values between disorders, which may reflect disorder-specific neural dynamics.
- Ridge regression shows that slopes are insufficient to predict age solely with slope, **Mean Absolute Error** of 10.26 years

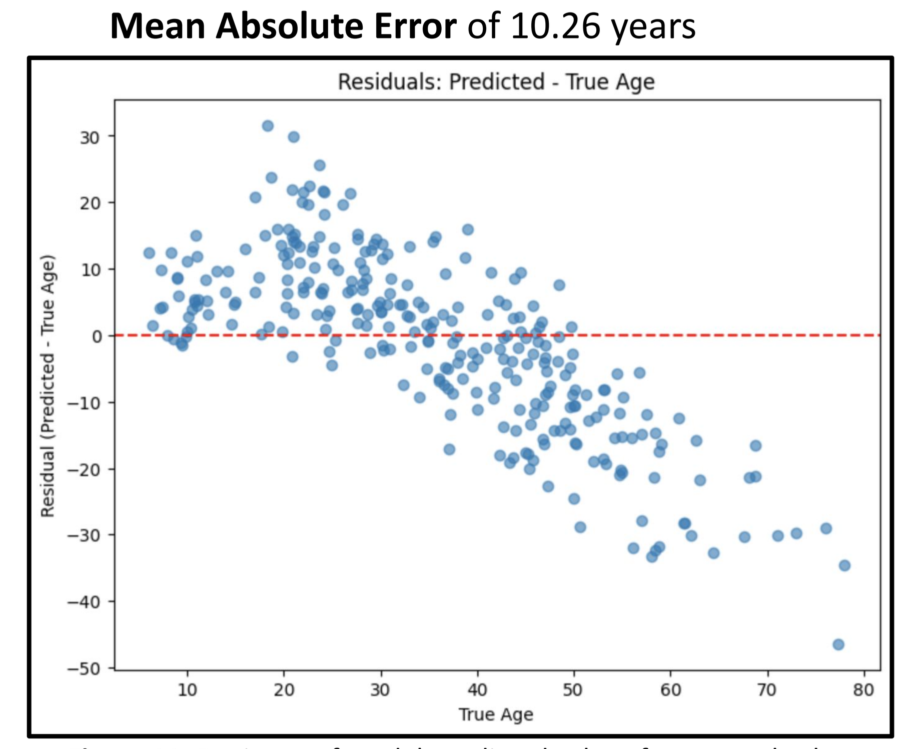

Figure 11. Deviance of model-predicted values from actual values.

Limitations:

- Missing participant meta data and eeg files limited sample size
- Conditions such as burnout and ADD were **underrepresented**, making it difficult to draw conclusions for these populations
- Less data points in later age ranges introduced more **variability** to slope-age graph trends
- Artifact residue after filtering and may have decreased accuracy in results

Future Work:

- Include more data from underrepresented categories (ex: ADD, burnout, ASD).
- Explore region-specific slope differences using spatial EEG mapping to better localize cognitive decline.
- Utilize more sophisticated preprocessing software to optimize artifact removal (**HAPPILEE**)
- Improve model accuracy by inputting more participant metadata
- Analyze other neurophysiological factors, like **offset**, in relation to slope

References

Acknowledgements

We would like to thank Patrick Bloniasz for his amazing mentoring and insights through his neuroscience experience during this project. We also appreciate Dr. Eugene Pinsky and the teaching fellows for all their guidance and support during our time at RISE. Finally, we thank our families who made it possible for us to attend the program.