**Longitudinal Insights into the Neurophysiology of Cyberbullying Involvement in Adolescence: A Bayesian Approach Using EEG Spectral Power**

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Data availability

LABS is an ongoing longitudinal study with data collection still in progress, and therefore data is currently unavailable. Upon completion of LABS data collection, data will be made available.

**Abstract**

The impact of cyberbullying on mental health is a significant concern among adolescents, yet there is limited research on the neurophysiological markers of cyberbullying. This study aims to address this by exploring whether resting state electroencephalography (EEG) power, among traditional frequency bands (delta, theta, alpha, beta), predicts cyberbullying experiences over time. Participants (*N=*167 with *n*=904 datapoints; aged 12.0-17.9 years) completed EEG and other assessments at 4 monthly-intervals for five years. Results revealed several associations between EEG power across brain regions and various cyberbullying roles. Key findings include a decrease in EEG power across all frequency bands over time across the entire sample, aligning with typical developmental patterns. However, in early adolescence, cyberbully-victims exhibited lower delta power compared to other groups, which may suggest heightened emotional reactivity. Conversely, later in adolescence there were decreases in delta power among cyberbullies, potentially reflective an adaptive stress response. Longitudinally, cyberbully-victims retained more alpha power over time (i.e. into later adolescence) in frontal and central regions, suggesting greater cognitive effort in processing emotional experiences. Conversely, cyberbullies showed a relative steeper decline in alpha power (into later adolescence) in frontal regions, possibly linked to impulsivity and higher levels of general aggression. Longitudinal analyses highlight the importance of early interventions to target cognitive and emotional processes that may be implicated in cyberbullying in order to reduce the impact of cyberbullying and protect the mental health of adolescents. Future research should involve larger, more diverse samples to improve our knowledge of complex relationships in this research area.

**Keywords:** Neurophysiology; electroencephalography; cyberbullying; adolescence; social connectedness**Longitudinal Insights into the Neurophysiology of Cyberbullying Involvement in Adolescence: A Bayesian Approach Using EEG Spectral Power**

**1.1** Adolescence is characterised by significant brain changes that coincide with the emergence of various mental health issues. During this period, regions of the brain responsible for emotional regulation and inhibition undergo substantial development, which may contribute to behaviours like bullying (Steinberg, 2005; Steinberg, 2013). Stressful social environments and events like cyberbullying can disrupt brain maturation and increase the risk of depressive symptoms, suicidal ideation, and other mental health issues (Bilsen, 2018; John et al., 2018; Tyborowska et al., 2018). Cyberbullying, facilitated by the widespread use of technology and social media, has become a significant issue among adolescents (Kowalski et al., 2014). Unlike traditional bullying, cyberbullying occurs electronically and can target individuals persistently and anonymously (Kowalski et al., 2014). The prevalence of cyberbullying among adolescents is high, with approximately 59% of students aged 12-17 experiencing cyberbullying in some way in the previous school term (Mcloughlin et al., 2019). Various factors such as personality traits, psychological disposition, and social functioning may influence cyberbullying behaviours (Shaikh et al., 2020). Exposure to cyberbullying is associated with severe mental health outcomes, including depression and anxiety (Sampasa-Kanyinga et al., 2018), eating disorders (Prince et al., 2024), and suicidality (John et al., 2018). There are several different roles involved in cyberbullying, which include cyberbully perpetrators (who perpetrate cyberbullying), cybervictims (victims of cyberbullying), cyberbully-victims (experience both perpetration and victimisation), and cyberbystanders (witness cyberbullying) (Guo et al., 2021). Although all cyberbullying groups are at an increased risk of negative mental health outcomes (Kowalski et al., 2014), cyberbully-victims are a particularly high-risk group (Lozano-Blasco et al., 2020). The repetitive and pervasive nature of cyberbullying content, which can be shared infinitely online, contributes to its detrimental effects on adolescents' psychological well-being (Bauman, 2010; McLoughlin & Hermens, 2018). While there is an abundance of research on the psychosocial consequences of cyberbullying, studies investigating its neurobiological underpinnings are limited. Despite this, emerging research indicates that exposure to cyberbullying can lead to long-term changes in brain morphology and alterations in brain activity (McLoughlin et al., 2020; Mills et al., 2023; Muetzel et al., 2019). Regions such as the temporal gyrus, default mode network, and putamen show greater activity in participants viewing cyberbullying scenarios (McLoughlin et al., 2020), suggesting the brain is uniquely sensitive to negative stimuli. Neurobiological findings such as these highlight the potential for cyberbullying experiences to impact brain structure and function, emphasizing the need for further research into the neural mechanisms involved.

Electroencephalography (EEG) is a method used to investigate neurophysiology in a temporally sensitive way, which means it may be an ideal method for investigating complex socio-cognitive processes (Bell & Cuevas, 2012), such as cyberbullying. Analysis of the EEG power spectrum can provide insight into patterns of brain activity associated with various cognitive and emotional processes (Dressler et al., 2004). This method dissects the EEG signal into distinct frequency bands by estimating power spectral density (uV2/Hz) within the bands, which are associated with different functions (Dressler et al., 2004; Xiao et al., 2018). Frequency bands are typically delineated based on oscillation frequency: delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), and beta (14-30 Hz) (Abo-Zahhad et al., 2015). The delta band has the slowest EEG waves, typically observed during periods of sleepiness or unconscious sleep. Delta waves have been associated with affective processes, impulse control, and stress response, with decreased frontal delta power having been linked to with increased emotional reactivity and stress response (Knyazev, 2007). This may mean an increased likelihood to experience cybervictimisation or perpetrate cyberbullying, due to difficulties regulating emotions or reactivity to conflicts (Bunnett, 2021; Guo, 2016). Theta waves emerge during deep relaxation, and it is thought that reduced theta power may indicate challenges in challenges in behavioural inhibition and impulse control behaviours (Pscherer et al., 2021). As these tendences are critical factors in aggression (Pscherer et al., 2021), reduced theta power may underlie a tendency to perpetrate cyberbullying (Guo, 2016). Alpha waves are prevalent during relaxed wakefulness, contributing to regulating attentional processes, social attention, engagement, and perspective-taking (Pscherer et al., 2021). Therefore, reduced alpha power may demonstrate deficits in these processes, and therefore increase risk of cyberbullying involvement (Kowalski et al., 2014). Beta waves are associated with regular consciousness, active concentration, and cognitive arousal and engagement in tasks (Klimesch, 1999). Decreased beta power in posterior regions has been found to correlate with deficits in cognitive control and altered decision-making processes in the social context (Engel & Fries, 2010; Klimesch, 1999), which may also contribute to participation in cyberbullying behaviours (Ybarra & Winkielman, 2012). Combined, previous research suggests that mechanisms associated with the four frequency bands, such as alterations in emotional and social processing, and differences in inhibitory control and impulsivity, may be present in individuals that are likely to experience cyberbullying or cybervictimisation. However, comprehensive investigations into EEG and cyberbullying are required to better inform the literature and draw more robust conclusions (Mills et al., 2023).

Despite the various negative psychosocial outcomes that can result from cyberbullying involvement, social connectedness, **which refers to** the sense of belonging and connection to others, plays a crucial role in buffering the adverse effects of cyberbullying (Arató et al., 2021; McLoughlin & Hermens, 2018). Strong social ties provide emotional support, which can enhance resilience and help individuals cope with the stress and emotional strain associated with cyberbullying (McLoughlin et al., 2018). Individuals with robust social networks are more likely to receive support during distressing experiences, potentially mitigating the negative psychological impacts of cyberbullying (Hawkley & Cacioppo, 2010). Additionally, recent findings indicate that lower social connectedness in early adolescence is linked to structural differences in white matter, suggesting a neurobiological basis for these social dynamics (Driver et al., 2023). Notably, a lack of social support may intensify the psychological distress experienced by those exposed to cyberbullying (Chen, 2020), increasing their vulnerability to negative mental health outcomes. Psychological distress is a measure of a person’s current emotional experience or psychological strain (Australian Institute of Welfare, 2023) and may be a valuable indicator for predicting future mental health disorders (Kessler et al., 2003; Lawrence et al., 2015). Research suggests that exposure to cyberbullying is associated with higher levels of psychological distress for adolescents (Sampasa-Kanyinga et al., 2018; Skilbred-Fjeld et al., 2020). Research has found links between resting-state EEG power dynamics and psychological distress in and adolescent sample (Sacks et al., 2023). Additionally, exposure to stress during adolescence can disrupt brain maturation, which may increase the risk of developing mental health issues (Tyborowska et al., 2018).

**1.2 Rationale**

Adolescence is a pivotal stage for neurological and psychosocial development, making it a critical period for examining the impacts of cyberbullying on brain function. However, there is a notable gap in the understanding of the neurophysiological consequences of cyberbullying, particularly using longitudinal methodologies. Most studies to date have focused on cross-sectional data, limiting the ability to discern how cyberbullying impacts brain development over time. By utilising EEG to measure resting-state brain activity, this study seeks to identify neurophysiological patterns associated with cyberbullying roles (victims, bullies, and bully-victims). This approach aims to uncover whether specific EEG band power can predict behaviours such as cyberbullying over time. Furthermore, this study aims to examine the impact of sex, social connectedness, and psychological distress, on any relationships between EEG brain power and cyberbullying involvement. By investigating psychosocial factors, this research can provide a more comprehensive understanding of the interplay between neurophysiological and psychosocial variables in the context of cyberbullying.

**2.0 Methods**

**2.1 Design and Participants**

The Longitudinal Adolescent Brain Study (LABS) investigates adolescent mental health by tracking neurobiological changes (via EEG and magnetic resonance imaging (MRI), with co-occurring self-report, cognitive and neuropsychological data, between the ages of 12-17 (Beaudequin et al., 2020; Boyes et al., 2022). Assessments were completed with trained researchers at the Thompson Institute, University of the Sunshine Coast (UniSC). Participants enter LABS at 12 to 15 years old, and attend assessments every 4 months for up to 5 years, resulting in a maximum of 15 timepoints. Participants receive a $30 voucher as reimbursement for their time, and all participants have the opportunity for a debrief with the researcher if required. Participants were required to be proficient in spoken and written English. Individuals suffering from major medical conditions, neurological disorders, intellectual disabilities or who had sustained a head injury (with loss of consciousness more than 30 minutes) or who were unable to enter the MRI scanner were excluded from the study. Ethics approval for LABS was granted by the UniSC Human Research Ethics Committee (Approval A181064). Written consent from both the participant and caregiver was obtained following an assessment of their understanding the research project information sheet, and prior to commencing the study.

**2.2 Measures**

The sub-set of self-report and neuroimaging (EEG) data included in the current study are described below. The self-report was completed independently by the participant on an iPad, with a researcher present if assistance was required.

**2.2.1 Berlin Cyberbullying Cybervictimisation Questionnaire (BCyQ)**

The BCyQ  (Schultze-Krumbholz & Scheithauer, 2009) uses a 5-point Likert scale from 1 to 5 (1= never to 5 = several times a week) to assess self-reported experiences of cyberbullying over the last 6 months. The scale consists of 35 items; 17 for cybervictimisation and 18 for cyberbullying perpetration. The cybervictim subscale ranges from 17 to 85, and the cyberbully perpetration subscale ranges from 18 to 90, with higher scores in each subscale indicating greater frequency of the respective behaviour. An individual scoring 18 or above on the cybervictim subscale was classified as a ‘cybervictim’, while an individual scoring 19 or above on the cyberbully perpetration subscale was classified as a ‘cyberbully’. An individual who scored in this threshold on both subscales was classified as a ‘cyberbully-victim’. Finally, individuals who scored both 17 on the cybervictim scale and 18 on the cyberbully scale were classified as the ‘no experience’ group.

**2.2.2 Social Connectedness Scale (SCS)**

The SCS (Lee et al., 2008; Lee et al., 2001) is a 15-item self-report scale revised from the original 8-item scale developed by Lee and Robbins (1995). The SCS uses a 6-point Likert scale, has good reliability (α = .91), and total scores range from 15 to 90. Higher scores are reflective of higher levels of social connectedness, with lower score reflecting lower levels of social connectedness. The SCS has been previously been used in research on adolescent populations (Chaturvedi et al., 2015; Grieve et al., 2013).

**2.2.3 Psychological Distress (K10)**

The Kessler-10 Psychological Distress Scale (K10) (Kessler et al., 2003) is a 10-item self-report questionnaire, measuring non-specific psychological distress (Andrews & Slade, 2001; Chan & Fung, 2014; Kessler et al., 2003). The K10 is a valid measure of psychological distress in adolescents and adults over the past 30-days. Responses are measured on a five-point scale (1 = none of the time to 5 = all of the time), resulting in an overall score of 10-50. Total scores are used to identify an individuals' level of non-specific psychological distress and likelihood of psychological disorders, particularly depression and anxiety. Lower scores indicate low psychological distress and lower risk of disorder, and higher scores indicate increased likelihood of mental disorder (Chan & Fung, 2014; Sunderland et al., 2011). The K10 10 item scale is one of the most widely used tool to assess psychological distress (Iorfino et al., 2017), and had been validated in adolescents aged 12 to 19 (Chan & Fung, 2014).

**2.3 Electroencephalographic analysis and pre-processing**

An in-house EEG data processing pipeline, EEG-pyline, was used for signal pre-processing and spectral analysis (Anijärv, 2022). The specific code (i.e., Jupyter notebook) used for this study can be found in the ‘studies’ folder within the GitHub repository. All raw files were first cropped to include only the 4-minute resting state portion, before the signals were re-referenced to an average reference and filtered using a 0.5-30 Hz band-pass filter (Finite Impulse Response with Hamming window, one-pass, zero-phase, non-causal). EOG artefacts, such as eye movements, were eliminated by calculating signal-space projection (SSP) vectors from specific EOG channels acquired during EEG recording and applying these projections to the EEG signal to remove the artefacts. These steps were performed using the MNE package for Python (Gramfort et al., 2013). The time series was divided into equal-sized consecutive 5-second epochs with no overlap. Epochs were cleaned from artefacts across all channels using the Python package Autoreject (Jas et al., 2016, 2017). The power spectra of each sample were visually inspected as a final processing quality check. Samples with power spectra showing clear artifacts were excluded from the analysis.

**2.4 Spectral analysis**

The processed EEG signals were transformed into the frequency domain (1-30 Hz frequency range) by estimating power spectrum density (PSD) using Welch’s method (Welch, 1967), with a 2.5-second Hamming window (50% overlap, 7.5 seconds of zero-padding). Average PSD values (µV2/Hz) were calculated for channels and regions across four frequency bands: delta (1-3.9 Hz), theta (4-7.9 Hz), alpha (8-12 Hz), and beta (12.1-30 Hz). Channels were grouped into regions; Left and right frontal, left and right temporal, left and right posterior, and frontal, central and posterior midline (See Figure 1). Moreover, signal reliability for each band was assessed by computing z-scores with median and absolute median deviation across all epochs to determine whether PSD values varied over time. Since participants were in a resting state, power spectra were anticipated to remain within two absolute median deviations across epochs.

**< Insert Figure 1 here >**

**2.5 EEG power outlier removal**

We manually inspected the EEG power spectra to remove any bad EEG data not picked up by automated cleaning pipeline. In addition, for each EEG frequency band (delta, theta, alpha beta), those with a log EEG power greater than 1.5 times the interquartile range (IQR) were flagged as outliers. Visual inspection showed that this method did a good job of removing extreme power values.

**2.6 Bayesian Model**

We employed a Bayesian mixed-effects model to investigate the relationship between EEG power and various factors across adolescence. The model was implemented using the brms package in R (version 2.22.0; Bürkner, 2017), which provides an interface to Stan for Bayesian inference (rstan version 2.32.6, Stan version 2.32.2, (Stan Development Team, 2024). Separate models were fit for each EEG frequency band (delta, theta, alpha, and beta) to capture potential differences in these relationships across frequency ranges and to reduce the model size.

In order to test the exploratory hypotheses the model was formulated as follows using a Gaussian family with identity link function:

log\_power ~ age + sex + region \* age \* (social connectedness + distress + cyber) +

    (1 + age + social connectedness + distress + cyber | id) +

    (1 + age + social connectedness + distress + cyber | region:id)

Where the log\_power is the log-transformed and standardised EEG power (mean = 0 and std = 1), age represents the age of the participant centred at 12 years of age (earliest age of entry into LABS). Sex (reference level males) is the participant's sex. Region represents the EEG channel at midline (Fz, Cz, Pz) and region on the scalp left- and right-frontal, left- and right-temporal and left- and right-posterior (as per Figure 1). The reference region was set to the Cz for its overall lower power level.  ‘Social connectedness’ represented the standardised SCS score, distress represented the K10 score (centred at 10 for no psychological distress), and cyber was a categorical variable describing cyberbullying experience (No experience, cyberbully, cybervictim and cyberbully-victim, reference level ‘No experience’). Random intercepts and slopes were included for individual participants (id, between subject variability) and the interaction between participants and EEG scalp region (region:id, within subject variability). This model structure allowed us to test various exploratory hypotheses concerning the complex interactions between age, brain region, and psychosocial factors on EEG. The inclusion of random effects accounts for individual variability and channel/region-specific differences within individuals. The model resulted in 109 fixed effects parameters, encompassing main effects and interactions for age, sex, nine EEG scalp regions, social connectedness, psychological distress, and four cyberbullying experience levels, while the Bayesian approach mitigates multiple comparisons issues. Default uniform brms priors were used.

**2.6.1 Model fitting**

The model was fitted using 4 chains, each with 10,000 iterations (5,000 warmup), resulting in 20,000 post-warmup samples. Posterior predictive checks and model diagnostics using leave-one-out cross validation were performed to assess model fit and convergence (see Supplementary Information).

**2.6.2 Model evaluation**

Models were evaluated with posterior predictive checks (see Supplementary Information), Widely Applicable Information Criterion (WAIC) and Leave-one-out Cross Validation (LOO) with moment matching and sub sampling due to computational constraints (4000 observations, 1000 posterior draws resulting in 20000 by 4000 subsampled log-likelihood values from 8099 total observations).

**2.6.3 Inference**

Rather than directly interpreting model coefficients (109 in total), we leveraged the flexibility of Bayesian inference to conduct direct hypothesis tests. Specifically, we used posterior predictive contrasts to examine specific effects of interest (using the epred\_draws() function from the Tidybayes R package; Kay & Mastny, 2023) to estimate expected outcomes under different parameter combinations This approach, enabled by the Bayesian framework, allows for intuitive and direct probabilistic statements about our hypotheses without the need for multiple comparison corrections typically required in frequentist analyses. We calculated expected posterior differences in EEG power between cyberbullying experience levels at early (age 13) and later (age 16) adolescence, as well as changes in these differences across adolescence, across EEG bands, and scalp regions at the median level of social connectedness and psychological distress. Results were considered significant if the probability of direction (pd) exceeded 0.975, providing a stringent threshold for evidence in favour of our hypotheses (Makowski et al., 2019). Ages 13 and 16 were chosen as representative of early and later adolescence as these ages were well represented in our cohort. We chose to use Bayesian credible intervals of 89% unless noted otherwise, which represents the probability at which the range of parameter estimate(s) falls, given the observed data and priors.

**2.6.4 EEG Topographical plots**

Scalp topographical maps of the relative median EEG power differences in each frequency band were plotted to better understand the EEG scalp region differences. Only regions with sufficient evidence of a difference were plotted (probability of direction > 97.5% corresponding to a two-tailed frequentist p-value < .05 using the relation ).

Relative median power differences were computed as follows: Model contrasts yielded log power differences (as we modelled log power), such that Δln(p) = ln(p₂) - ln(p₁) = ln(p2/p1). Differences in log power were converted to relative difference by exponentiating and subtracting one: =

**2.6.5 EEG band power developmental trajectories**

To investigate the developmental effects, we computed Bayesian posterior expected values for early (13-year-olds) and later (16-year-olds) adolescence across different levels of cyberbullying exposure and brain regions, while controlling for social connectedness, distress, and sex. This approach enabled us to capture the nuanced dynamics of neurodevelopmental changes in relation to cyberbullying experiences across EEG scalp regions. Specifically, the computed difference in expected log power between 16 and 13 years was transformed to give relative power retained across adolescence, which was then contrasted across levels of cyberbully experience for each EEG scalp region.

**3.0 Results**

For ease of interpretation of our longitudinal data sample, *N* will refer to participants, and *n* will refer to datapoints. Descriptive statistics are displayed in Table 1, with total *N* participants per age group, as well as *n* per age group. The final sample was 53% (*N* = 94, *n* = 479) female, with an age range of 12.0 to 17.9 years. Across the datapoints 3% (n = 25) were cyberbullies, 12% (n = 105) were cyberbully-victims, 19% (n = 177) were cybervictims, and 66% (n = 597) reported no recent cyberbullying experience. All bands exhibited relative decline from early to later adolescence (Table 2).

**3.1 Demographics**

**< Insert Table 1 here >**

**< Insert Table 2 here >**

**3.2 Bayesian Model Diagnostics**

All models showed excellent convergence, with R-hat values of 1.00 for key parameters across all frequency bands. Bulk and tail effective sample sizes (ESS) were robust ranging from 6148 – 14293 (see Supplementary Information). Posterior predictive checks revealed good agreement between observed and simulated data across all frequency bands, suggesting adequate model fit (see Supplementary Figure S1).

The models explained a substantial proportion of variance in EEG power across all frequency bands. Bayesian R² values were highest for theta (R² = 0.83, 95% Credible Intervals (CI) [0.83, 0.84]) and beta (R² = 0.81, 95% CI [0.80, 0.81]) bands, with alpha (R² = 0.79, 95% CI [0.79, 0.80]) and delta (R² = 0.77, 95% CI [0.76, 0.77]).

Subsampled LOO-CV results corroborated the WAIC findings, with the beta band model demonstrating the best out-of-sample predictive performance (LOOIC = 1043.7, SE = 42.4), followed by delta (LOOIC = 2130.2, SE = 36.8), theta (LOOIC = 2263.7, SE = 41.3), and alpha (LOOIC = 6896.7, SE = 34.1). Pareto k diagnostics indicated that over 99.5% of observations across all models fell within the "good" range (k ≤ 0.7), with only a small fraction 0.2 – 0.4% identified as bad, suggesting reliable LOO-CV estimates.

These convergent diagnostics collectively support the validity and reliability of our Bayesian models for inferring relationships between EEG power, age, and psychosocial factors (i.e. distress, social connectedness, cyberbullying) across adolescence. Simplified models that excluded social connectedness and distress were found to be inferior to the model presented according to leave-one-out cross-validation (LOO) criteria. However, coefficients revealed no main effects for covariates; sex, social connectedness or distress, in the model (Supplementary Table S3). However, there were links between cyberbullying experiences and EEG power across various brain regions, suggesting that associations between EEG and cyberbullying involvement are present even after controlling for these variables.

**3.3 Early adolescence cyberbullies relative median power differences**    
Our Bayesian mixed-effects model revealed significant relative median power differences across various EEG frequency bands and scalp regions among early adolescents (13 years old) with different cyberbullying experiences (Table 3, Figure 2).

**< Insert Table 3 here >**

**3.3.1 Delta band differences**

In the delta band, cyberbullies exhibited significantly increased power compared to those with no cyberbullying experience, particularly in the right temporal region (20.7%, 89% CI [4.6%, 39.1%], pd = 98.32%, p < .05) and at Cz (22.3%, 89% CI [6.0%, 41.0%], pd = 98.76%, p < .05). This pattern of increased central and right temporal delta activity in cyberbullies is evident in the topographical plot (Figure 2, first row).

Conversely, cyberbully-victims demonstrated significantly decreased delta power compared to those with no experience, most notably at Cz (-14.5%, 89% CI [-23.0%, -5.4%], pd = 99.29%, p < .05) and in the right posterior region (-12.5%, 89% CI [-20.8%, -3.3%], pd = 98.36%, p < .05). This reduction in delta power for cyberbully-victims was particularly pronounced when compared to cyberbullies, with substantial decreases observed across multiple regions, including right temporal (-18.5%, 89% CI [-30.7%, -4.0%], pd = 97.59%, p < .05), left temporal (-19.9%, 89% CI [-32.3%, -5.5%], pd = 98.41%, p < .05), Fz (-21.6%, 89% CI [-33.5%, -7.5%], pd = 99.02%, p < .05), and most markedly at Cz (-30.1%, 89% CI [-40.9%, -17.4%], pd = 99.98%, p < .001). These differences are clearly visible in the topographical plots (Figure 2, third row).

**3.3.2 Theta band differences**

In the theta band, similar patterns emerged, with the cyberbully group showing increased power at Cz compared to those with no experience (21.6%, 89% CI [4.3%, 41.2%], pd = 97.9%, p < .05). Cyberbully-victims, however, exhibited decreased theta power at Cz relative to both those with no experience (-14.7%, 89% CI [-23.0%, -5.4%], pd = 99.19%, p < .05) and cyberbullies (-29.7%, 89% CI [-40.8%, -16.7%], pd = 99.94%, p < .01).

**3.3.3 Beta band differences**

Cybervictims showed decreased beta power in the right temporal region compared to cyberbully-victims (-11.9%, 89% CI [-20.0%, -3.2%], pd = 98.35%, p < .05). Additionally, both cybervictims and cyberbully-victims exhibited reduced beta power at Cz compared to cyberbullies (-16.7%, 89% CI [-28.0%, -3.6%], pd = 97.64%, p < .05 and -18.5%, 89% CI [-30.4%, -4.7%], pd = 98.16%, p < .05, respectively).

The topographical analysis in Figure 2 summarises these power differences across cyberbullying experiences and frequency bands. In summary, at early adolescence the most pronounced differences were observed in the delta and theta bands, with cyberbullies showing *increased* power and cyberbully-victims showing *decreased* power, particularly in central and temporal regions.

**< Insert Figure 2 here >**

**3.4 Later adolescence cyberbully relative median power differences**    
The Bayesian model also found significant differences in EEG band powers for later adolescents (16-year-old) with different cyberbullying experiences. The results are summarised in Table 3 and visualised topographically in Figure 3.

**3.4.1 Delta band differences**

In the delta band, cybervictims exhibited significantly higher relative median power compared to cyberbullies in the left frontal region (23.0%, 89% CI [7.0%, 41.7%], pd = 99.1%, p < .05) and at the Fz electrode (26.6%, 89% CI [10.1%, 45.2%], pd=99.7%, p < .01). A similar pattern was observed for cyberbully-victims compared to cyberbullies at Fz (24.1%, 89% CI [6.7%, 43.8%], pd=98.86, p < .05). Notably, cyberbullies showed significantly reduced delta power at Fz compared to those with no cyberbullying experience (-15.2%, 89% CI [-25.0%, -4.2%], pd=98.36, p < .05).

**3.4.2 Alpha band differences**

The most pronounced differences were observed in the alpha band. Cybervictims demonstrated markedly higher alpha power compared to cyberbullies across multiple regions: right posterior (29.8%, 89% CI [6.3%, 58.1%], pd=98.12, p < .05), right frontal (37.2%, 89% CI [12.5%, 67.8%], pd=99.5, p < .01), left frontal (43.8%, 89% CI [17.9%, 75.3%], pd=99.83, p < .01), Fz (60.6%, 89% CI [31.4%, 95.6%], pd=99.98, p < .001), and Cz (38.9%, 89% CI [13.9%, 70.1%], pd=99.46, p < .05). Cyberbully-victims exhibited a similar pattern of elevated alpha power compared to cyberbullies.

Conversely, cyberbullies showed significantly reduced alpha power compared to those with no cyberbullying experience across all examined regions, with the most substantial difference at Fz (-35.6%, 89% CI [-46.4%, -22.6%], pd=99.99, p < .001).

**3.4.3 Beta band differences**

In the beta frequency range, both cybervictims and cyberbully-victims displayed significantly higher power compared to cyberbullies in the left frontal region (24.3%, 89% CI [8.5%, 42.5%], pd=99.46, p < .05; and 23.8%, 89% CI [7.2%, 42.7%], pd=99.16, p < .05, respectively) and at Fz (23.2%, 89% CI [7.4%, 41.1%], pd=99.22, p < .05; and 25.3%, 89% CI [8.3%, 44.6%], pd=99.3, p < .05, respectively).

**< Insert Table 4 here >**

In summary, for later stage adolescence Figure 3 shows the most striking patterns are observed in the alpha band, where cybervictims and cyberbully-victims show greater median power compared to cyberbullies, particularly in frontal and central regions. Conversely, cyberbullies exhibit less alpha power globally, compared to those with no cyberbullying experience. These findings suggest distinct neurophysiological profiles associated with different cyberbullying experiences in later adolescence compared to early adolescence.

**< Insert Figure 3 here >**

**3.5 Differences in adolescent EEG band power developmental trajectories by cyberbully experience**

Our Bayesian mixed-effects model revealed significant age-related differences in the developmental trajectories of EEG band power as a function of cyberbullying experience. These differences were observed across multiple frequency bands and scalp regions, suggesting widespread differences in neural trajectories associated with cyberbullying. All EEG frequency bands were found to decline in power over adolescence and so the changes outlined below represent differences in EEG band power between cyberbullying categories, in addition to the overall changes in power across adolescence.

**3.5.1 Delta band trajectories**

In the delta band, we observed the most widespread effects across the scalp. Cyberbully-victims retained more power compared to cyberbullies. The most substantial differences were observed in the frontal midline (Fz: 58.1% or 1.58 times more power retained than cyberbullies, 89% CI [27.7%, 95.5%], pd=100%, *p* < .0001) and central midline (Cz: 54.5%, 89% CI [25.0%, 92.8%], *p* < .01) regions. Notably, cyberbullies exhibited a larger decline of delta power compared to adolescents with no cyberbullying experience in temporal and frontal regions (cyberbullies experienced an ~20 – 25% more delta power decline).

**3.5.2 Theta band trajectories**

Theta band trajectories also differed significantly, with cyberbully-victims showing greater theta power retention compared to cyberbullies, most prominently in the central midline region (Cz: 55.0%, 89% CI [24.3%, 93.5%], pd=99.96, *p* < .001). Cyberbullies demonstrated greater theta power decline compared to the no-experience group in frontal and central midline areas (~20% more decline compared to the no-experience group, pd ~ 98.3%, *p* < .05).

**3.5.3 Alpha band trajectories**

Alpha band developmental trajectories revealed striking differences, particularly in frontal and midline regions. Cyberbullies exhibited markedly more decline in alpha power compared to others, with the most substantial differences observed at Fz (86.5% more power retained for cyberbully-victims, 89% CI [39.9%, 148.9%], *p* < .001) and Cz (82.1%, 89% CI [35.9%, 143.2%], *p* < .001). Cyberbullies showed significantly more alpha power decline compared to the no-experience group, most notably in the right frontal region (-32%, 89% CI [-48.1, -13.2], pd=99.46%, *p* <.05) and at Fz (-38.0%, 89% CI [-51.8, -19.7], pd=99.8, *p* < .01).

**3.5.4 Beta band trajectories**

Beta band trajectories also differed significantly, albeit with a more localised pattern. Cyberbully-victims demonstrated more retained beta power compared to cyberbullies, particularly in frontal and central midline regions (Cz: 43.3 more power retention, 89% CI[17.0, 75.2], pd=99.78%, *p* <.01). Consistent with the other EEG band power trends, cyberbullies showed greater power decline compared to the no-experience group but more localised in the right frontal and central midline areas (~-20%,  pd~98%, *p* < .05).

In summary, our results reveal a clear differentiation in EEG power developmental trajectories across cyberbullying experiences. Figure 4 shows that while differences were observed across multiple scalp regions, the most consistent and pronounced effects were found in the frontal and central midline areas (Fz and Cz). In particular, cyberbullies experienced greater decline in median power across all bands (delta, theta, alpha beta) compared to those with no-experience and those that experienced some form of cybervictimisation. This difference was primarily localised to the fronto-central regions (Fz, Cz). Whereas cyberbully-victims tended to retain more median power compared to the no-experience group, predominantly in the central region Cz. These findings provide compelling evidence for an association between cyberbullying experiences and adolescent brain development, as indexed by EEG band power.

**< Insert Table 5 here >**

**< Insert Figure 4 here >**

**4.0 Discussion**

Cyberbullying is a prevalent issue in adolescence. While extensive research has focussed on the psychosocial consequences of cyberbullying, there has been a lack of research on the impacts of cyberbullying on neurophysiological measures, including its longitudinal impacts. In order to address this research gap, the present study investigated associations between EEG power and different types of cyberbullying experience at early and later adolescence, using a Bayesian mixed-effects model. The model incorporated the four traditional frequency bands: delta, theta, alpha, and beta, which have each been linked to various cognitive and emotional processes, such as social processing, cognitive control and emotional regulation (Aggensteiner et al., 2022; Engel & Fries, 2010; Knyazev, 2007). The model also controlled for individual differences in psychological distress and social connectedness. The current study also evaluated the longitudinal changes in EEG according to cyberbullying involvement, to elucidate potential neurodevelopmental impacts of cyberbullying experiences.

Frequency statistics from the BCyQ (Schultze-Krumbholz & Scheithauer, 2009) in the current study align with prevalence statistics from an Australian study, with rates between 15% and 40% for cybervictimisation, and 5 to 25% for cyberbullying perpetration in Australian high school students (Trompeter et al., 2022), thereby confirming that our sample is representative of the Australian adolescent population in regards to cyberbullying involvement.

**4.1 EEG power**

There were links between cyberbullying experiences and EEG power across various brain regions and frequency bands, even after controlling for sex and psychosocial variables (psychological distress, social connectedness). While social connectedness and psychological distress have been identified as predictors of cyberbullying involvement in broader literature (Kowalski et al., 2014; Sampasa-Kanyinga et al., 2018; Spears et al., 2015), the results from the current study suggest that relationships between EEG power and cyberbullying involvement are independent to levels of social connectedness or psychological distress. Additionally, all EEG frequency bands demonstrated decreased power across time, with the 16-year-old sample exhibiting generally lower power across all four bands. This is in support of existing literature and a signature of typical neurodevelopment in adolescence (Giertuga et al., 2017).

**4.1.1 Delta band**

In early adolescence, cyberbully-victims demonstrated decreased delta power compared to those with no experience, at the temporal midline region and right posterior regions. This may be reflective of increased anxiety, heightened vigilance and reactivity (Knyazev, 2007). As temporal regions are responsible for several social and emotional processes, decreased delta power may suggest defecits in these regions that are responsible for social processes (Adolphs, 2009). Cyberbully-victims had higher median delta power retention across time from 13 to 16 years in frontal and central midline regions, which may be reflective of previous utilisation of emotional regulation (Lapomarda et al., 2022). This may indicate adaptive neurophysiology to cope with the emotional strain of cybervictimisation. Additionally, higher delta has been linked to more proactive aggression (Aggensteiner et al., 2022), again suggestive of an adaptive strategy to combat or redirect aggression from the perpetrator. This may help explain how victims become cyberbully-victims, who have been evidenced to be a particularly high-risk group for negative outcomes (Lozano-Blasco et al., 2020).

As increased delta power has been associated with affective processes, such as anxiety, impulsivity, and aggressive behaviour (Knyazev, 2007), elevated delta power in early adolescent cyberbullies in temporal regions may indicate increased activity in brain areas related to social cognition. Conversely, in later adolescence there was a reduction in delta power in the frontal central regions for cyberbullies, in comparison to victims and those with no experience, suggesting a different neurophysiological profile. Lower frontal delta power has also been linked to psychological pain (Meerwijk et al., 2015), which is supported by cyberbullying research that suggests that even perpetrators are prone to anxiety, depression and other social difficulties (Campbell et al., 2013). A steeper decline in delta power in cyberbullies in temporal and frontal regions may indicate emotional dysregulation and impulsive aggression (Houston & Stanford, 2005). This decline, was approximately 20-25% greater in cyberbullies, which indicates that neurophysiological markers associated with cyberbullying may change over time, potentially influenced by past experiences and emotional and cognitive capacities.

**4.1.2 Theta band**

In early adolescence, theta band patterns were similar to delta band. Specifically, cyberbully-victims exhibited decreased theta power at central midline, compared to those with no experience. There was increased theta power retention in cyberbully-victims compared to other categories in central midline regions, possibly reflective of previous utilisation of emotional regulation (Lapomarda et al., 2022), as well as increased cognitive control (Eisma et al., 2021). Again, increased theta power may be a neural marker of adaptive processes to cope with cybervictimisation experiences. This may be key, as social dynamics become increasingly complex during adolescence (Klimesch et al., 2005).

Cyberbullies showed a 20% greater decline in theta power in frontal and central regions compared to other categories, compared to those with no experience, which may indicate changes in cognitive processes such as emotional regulation (Klimesch, 1999).

**4.1.3 Alpha band**

Interestingly, alpha power did not display any significant differences in early adolescence. However, in later adolescence, cybervictims exhibited increased alpha compared to other categories. As alpha power is reflective of inhibitory control and cognitive load (Klimesch, 2012), increased alpha power in cybervictims across multiple midline regions suggests that cybervictims may recruit increased cognitive resources as an adaptive strategy for processing victimisation experiences. Conversely, reduced alpha power has been linked to impulsivity (Lee et al., 2017) and increased arousal, at resting state (Barry et al., 2009), suggesting that cyberbullies may have increased levels of trait impulsivity, or baseline arousal when compared to those who have no history of cyberbullying perpetration. Such traits may impair abilities for behavioural regulation and inhibition (Knyazev, 2007).

In the alpha band, the most notable difference in trajectories were for cyberbully-victims, where they retained more power at frontal (87% more retained) and central midline (82% more retained) regions, compared to other categories. Increased alpha power has been linked to cognitive and emotional symptoms associated with depression (Fan et al., 2024), which may explain this trajectory, as cybervictimisation has been linked to depression and anxiety, among other mental health issues (Kumar & Goldstein, 2020). However, alpha power has also been associated with relaxed alertness and cognitive engagement (Klimesch, 2012), and therefore may be reflective of increased emotional regulation skills and cognitive processing, which may act as a buffer to the harmful effects of cyberbullying (Extremera et al., 2018). In contrast to this, cyberbullies had a markedly steeper decline in alpha power over time, particularly in right and central frontal regions. Research has linked reduced alpha power to increased general aggression (Aggensteiner et al., 2022), which may mean that individuals with these neurophysiological profiles are more inclined to participate in cyberbully perpetration behaviours (Kowalski et al., 2014).

**4.1.4 Beta band**

The beta band revealed some notable differences between groups in early adolescence. As beta power has been linked to cognitive processing, and functions such as problem solving (Engel & Fries, 2010), lower beta power in cybervictims (compared to bully-victims) may be reflective of reduced engagement in these processes, and difficulty managing emotional distress. From 13 to 16 years, cyberbully-victims demonstrated significantly more beta power retention (43% at central midline) than other categories. As research has linked beta power to negative emotions (Güntekin & Başar, 2010), this difference may be a product of the cybervictimisation experience. Additionally, increased beta power has been found to be a signature of attentional top-down modulation and increased cognitive engagement (Palacios-García et al., 2021), therefore potentially manifesting as rumination on these negative experiences for cybervictims.

Conversely, lower beta power has been linked to impulsivity (Lee et al., 2017), and proactive aggression (Aggensteiner et al., 2022). In the current sample, cyberbullies exhibited a steeper decline in beta power over time, indicating potential impairments to cognitive control, behavioural inhibition and increased levels of proactive aggression. This evidences a need for intervention during the adolescent period, to help reduce continuation of this behaviour among adolescence.

**4.2 Limitations and future directions**

Although this study uncovered several novel findings linking cyberbullying to neurophysiological differences, longitudinally, there are several limitations that should be acknowledged. The current study used self-report measures, which presents a limitation (Fan et al., 2006). For example, adolescents may report incorrect information in questionnaires, which may impact the validity of the self-report data (Crockett et al., 1987). Additionally, individuals may be hesitant to disclose unfavorable information in self-report surveys, due to factors such as guilt, embarrassment, or may answer incorrectly due to carelessness or boredom (Fan et al., 2006). However, due to the nature of cyberbullying research, developing methodology that would combat these limitations remains quite challenging.

Additionally, there are potential variables that were not included in our analyses that could confound the results of perpetration or victimisation. Future research should include variables such as family dynamics, impulsivity, or internet usage to investigate any moderation effects on the neurophysiological impacts of cyberbullying experiences. In addition to this, research is needed to find interventions that target factors outside of these such as social and emotional processing and self-regulation. As many neurophysiological markers of cyberbullying perpetration may be linked to aggression, impulsivity, and cognitive control processes, initiatives that focus on building skills to combat these tendencies from a young age, may help reduce cyberbullying incidence. Conversely, as cybervictimisation groups exhibited neurophysiology that may mark emotional regulation and cognitive demand, initiatives could focus on building skills to help buffer against the harmful effects of cyberbullying.

The neurophysiological findings suggest that cyberbullying experiences over the last 6 months are associated with different types of brain activity, under a resting state condition. If neural patterns could predispose individuals to specific roles in cyberbullying (such as perpetrator, victim, or no experience), certain neural profiles could be targeted in early intervention strategies in vulnerable populations. Alternatively, as research has shown that stress may lead to lasting changes in the brain’s neurodevelopment in adolescence (Tyborowska et al., 2018; Sampasa-Kanyinga et al., 2018), cyberbullying experiences could contribute to persistent alterations in stress reactivity, social processing, or emotional regulation. This highlights the need for effective interventions for adolescents, who undergo such a crucial period of social maturation and neurodevelopment.

**5.0 Conclusion**

This study has uncovered some novel findings linking EEG brain power to cyberbullying experiences, and is the first study to explore the trajectories of these associations over time. The most notable contrasts where in delta and theta bands (slow wave bands) during adolescence, which might suggest that these frequency bands are particularly sensitive at rest to cyberbullying experiences, particularly in central and temporal regions. Increases in delta and theta power could reflect heightened arousal or emotional activation, where decreases might suggest a maladaptive stress response, or deficits regulating emotions. However, we noted that alpha power had the most significant change over time, indicating that this frequency band could be a key marker of the progression of cyberbullying involvement. These results highlight the importance of preventative efforts for cyberbullying, as our results demonstrate longitudinal neurobiological effects that may underlie the known psychosocial and emotional effects. Future research could utilise mediation models to help inform how a variety of complex psychosocial factors might impact cyberbullying involvement, and consequently neurophysiological developmental trajectories. Overall, the findings of this research highlight the extent that neural processes may underpin cyberbullying behaviours, as well as the need for preventative efforts to minimise the impact of cyberbullying on young people's mental health and neural development.

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