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Prediction of Alpha Power Using Multiple Subjective Measures and Autonomic Responses

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ABSTRACT

Alpha oscillations are associated with various cognitive functions. However, the determinants of alpha power variation remain ambiguous, primarily due to its inconsistent associations with autonomic responses and subjective states under different experimental conditions. To thoroughly examine the correlations between alpha power variation and these factors, we implemented a range of experimental conditions, encompassing attentional and emotional tasks, as well as a resting-state. In addition to the electroencephalogram data, we gathered a suite of autonomic response measurements and subjective ratings. We employed multiple linear regression analysis, utilizing autonomic responses and subjective reports as predictors of alpha power. We also subtracted the aperiodic components for better estimation of the power of periodic alpha oscillations. Our results from two separately conducted experiments robustly demonstrated that the combined use of autonomic response measurements and subjective ratings effectively predicted the parietal-occipital periodic alpha power variation across a range of conditions. These predictions were supported by leave-one-participant-out cross-validation and cross-experiment validation, confirming that multiple linear relationships can be generalized to new participants. This study demonstrates the links of alpha power variations with autonomic responses and subjective states, suggesting that during investigations of the cognitive functions of alpha oscillations, it is important to consider the potential influences of autonomic responses and subjective states on alpha oscillations.

1 | Introduction

Alpha oscillations, typically observed within the 8–13 Hz range on electroencephalogram (EEG) recordings from the occipital areas, increase when participants close their eyes (Adrian and Matthews 1934; Berger 1929). The magnitude of these oscillations represents various cognitive processes, such as visual attention (Foxe and Snyder 2011; Worden et al. 2000), illusory jitter perception (Amano et al. 2008; Minami and Amano 2017), task errors (O'Connell et al. 2009), memory performance (Klimesch 1999), and decision criteria (Samaha et al. 2020). Recent studies suggest that manipulating alpha power can boost cognitive functions (Di Gregorio et al. 2022; He et al. 2022). Although the link between alpha power and cognitive function has become more evident, the origin of alpha power variation remains ambiguous.

Previous studies have indicated that alpha power is associated with autonomic nervous system (ANS) activity and subjective states. For instance, alpha power has been reported to be positively correlated with respiratory amplitude (Yuan et al. 2013), pupil size (Montefusco-Siegmund et al. 2022), mental fatigue (Tran et al. 2020), and sleepiness (Kaida et al. 2006). Conversely, it is negatively correlated with the low-frequency/high-frequency (LF/HF) ratio of heart rate variability (Chang and Huang 2012; Ishii et al. 2013), electrodermal activity (Barry et al. 2020), attention level (Chang and Huang 2012), and emotional arousal (Kim et al. 2021; Luft and Bhattacharya 2015). Furthermore, alpha power is reportedly modulated by respiratory phases (Kluger et al. 2021) and spontaneous blinks (Bonfiglio et al. 2011). It is noteworthy that some discrepancies arise in correlation studies, particularly in terms of the LF/HF ratio, mental fatigue, and sleepiness (Ishii et al. 2013; Kawashima et al. 2024; Luft and Bhattacharya 2015; Strijkstra et al. 2003). In addition, besides the occipital region, the alpha power in the central and frontal regions also showed associations with ANS activity and subjective states, including heart rate variability (Takahashi et al. 2005) and emotional arousal (Weinreich et al. 2016).

There are several challenges in establishing relationships among alpha power, ANS responses, and subjective states. First, several studies have focused on specific measurements, thereby preventing a holistic understanding of these relationships. For instance, although Chang and Huang (2012) explored alpha power variations across attention levels, they did not measure variations in potential task-induced mental fatigue. Second, experimental conditions, such as resting-state or cognitive tasks, can introduce variability in their relationships. Third, recent findings have revealed that the power spectrum of neural oscillations consists of both periodic and aperiodic components, with the latter potentially confounding previous narrowband alpha power calculations (Donoghue et al. 2020). Finally, the results of previous studies may not be generally applicable as they only analyzed the averaged effects and did not examine generalization across participants.

This study aimed to elucidate the relationship of alpha power variation with ANS activity and subjective states. We adopted a comprehensive approach utilizing EEG, electrocardiogram (ECG), respiration, electrodermal activity (EDA), eye tracking, and subjective metrics such as fatigue, attention, and emotional arousal. Data were collected in a resting state and under various task conditions. To focus on the periodic component of alpha power, we segregated and subtracted the aperiodic components of alpha oscillation by parameterizing the EEG power spectrum. Multiple linear regression analysis was used to predict alpha power from multiple autonomic and subjective measurements. Furthermore, unlike previous studies, this prediction was validated using a leave-one-participant-out cross-validation method to ensure robustness across novel participants. To ensure the reproducibility of the results, the same experiment was conducted twice on independent participants.

2 | Method

Two experiments, employing the same methodology, were conducted independently. The second experiment was specifically designed to validate the reproducibility of the results.

2.1 | Participants

In Experiment 1, eight male participants, all students or faculty members at the University of Tokyo, volunteered for the experiment. One participant (No. 2) was excluded due to excessive noise in the EEG recordings. The ages of the remaining seven participants ranged from 22–39 years (Mean = 27.29 years). This study was approved by the Ethics and Safety Committee of the University of Tokyo (approval number: 22-303). Written informed consent was obtained from all the participants prior to the commencement of the study. All study methods adhered to the relevant guidelines and regulations.

Experiment 2 served as a verification of Experiment 1, aiming to ascertain the reproducibility and robustness of the results obtained in Experiment 1. We conducted a power analysis guided by our findings of prediction of periodic alpha power in Experiment 1, and the results indicated that, with a significance criterion of $\alpha = 0.05$ and power = 0.8, the minimum sample size is $N = 5$. Based on this result and to ensure the replication of the results in Experiment 1, we recruited eight more participants for Experiment 2, who were all students at the University of Tokyo and volunteered for the experiment. One participant (No. 9) was excluded due to failure in EDA data measurement. The ages of the remaining seven participants ranged from 21–25 years (Mean = 22.6 years). Written informed consent was obtained from all participants prior to beginning the experiment.

2.2 | Stimuli and Procedure

The main experiment consisted of eight 5-min recording blocks. Figure 1 provides an overview of these blocks, which included a combination of resting-state recordings along with attentional and emotional tasks. The first block was the pre-task resting-state recording, during which the participants were instructed to keep their eyes open and fixate on the center of the screen. The following six blocks consisted of two attention (high/low attention) blocks and four emotion (combination of high/low valence and high/low arousal) blocks. The order between the two task types and within each task type was counterbalanced. The final block was a post-task resting-state recording, and the procedure was the same as that used for the pre-task recording. Breaks spanning 5 min with relaxation videos were provided between the blocks to help the participants reset to the cardiovascular baseline (Piferi et al. 2000).

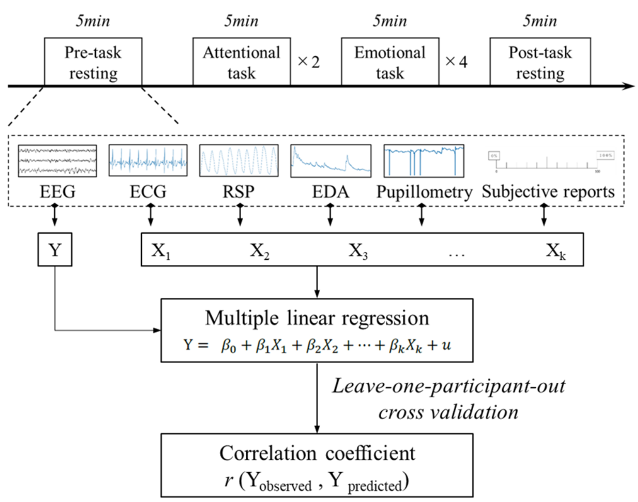

FIGURE 1 | Overview of the experimental procedure and analytical workflow. Abbreviations: ECG, electrocardiogram; EDA, electrodermal activity; EEG, electroencephalogram; RSP, respiration.

As depicted in Figure 2, for an attentional task, we used the multiple object tracking paradigm (Meyerhoff et al. 2017). Initially, 20 white circles appeared for 1.5 s, after which the target circles turned red for 1.5 s. Each circle was 20 pixels in size. The high- and low-attention conditions comprised five and one target circle, respectively. Subsequently, all circles turned white for 2 s before moving randomly within a 20 cm × 20 cm square, covering a visual angle of 25° for 10 s. The movement speed was 2.16 deg/s. Finally, the participants identified a randomly prompted circle as a target or non-target by pressing '1' or '2' on the keyboard using their right hand. In each attention block, 16 multiple object tracking task trials were performed.

For the emotional task, images were sourced from the International Affective Picture System (IAPS) (Lang et al. 2008). Four groups of images were selected based on normative valence and arousal ratings and subsequently classified into four emotional conditions: high-valence, high-arousal (HVHA); high-valence, low-arousal (HVLA); low-valence, high-arousal (LVHA); and low-valence, low-arousal (LVLA). Sixty images were selected for each emotional condition. During image selection, we avoided images with extreme ratings that could evoke strong feelings of fear, disgust, or reluctance. The ranges and means of the normative valence and arousal ratings for the four groups of images are demonstrated in Table 1. To account for the luminance effect, the mean and standard deviation of pixel value across images were equalized using the method described by Mathôt and Vilotijević (2022). In each emotional task block, 60 images in one of the four emotion conditions were randomly presented for 5 s without a blank, and the participants passively viewed the images.

Upon arrival, the participants were briefed on the experimental procedures and data collection methods. They were subsequently prepared for physiological data collection, including EEG, ECG, respiration, EDA, and eye-tracking. Prior to the main experiment, practice trials of attentional and emotional tasks, each consisting of six trials, were administered to ensure that the participants were familiar with the task procedures.

The experiment was conducted in a soundproof booth with the participants seated in front of a color monitor (ZOWIE XL2546, 1920 × 1080 pixels, 60 Hz refresh rate, 24.5 in.) controlled by a PC running Psychtoolbox 3 (Kleiner et al. 2007); on MATLAB software (The MathWorks Inc.). A chin rest, placed 45 cm from the screen, ensured a consistent viewing distance.

2.3 | Psychophysiological Measures

During each 5-min block, we continuously recorded EEG, ECG, respiration, EDA, and eye-tracking data and collected the subjective reports. Table 2 lists the types of measurements and metrics computed.

2.3.1 | EEG

EEG recordings were conducted using StarStim (Neuroelectrics, Barcelona, Spain) paired with NIC2 software (Neuroelectrics, Barcelona, Spain). Dry electrodes were used to measure the EEG recordings. The 20 recording sites were based on the 10–20 International Electrode Placement System and included Fp1, Fp2, Fz, F3, F4, F7, F8, Cz, C3, C4, T7, T8, Pz, P3, P4, P7, P8, Oz, O1, and O2. The reference electrode was placed on the right earlobe. The sampling rate was set to 500 Hz. In NIC2, the quality of EEG signals was assessed using a quality index, which

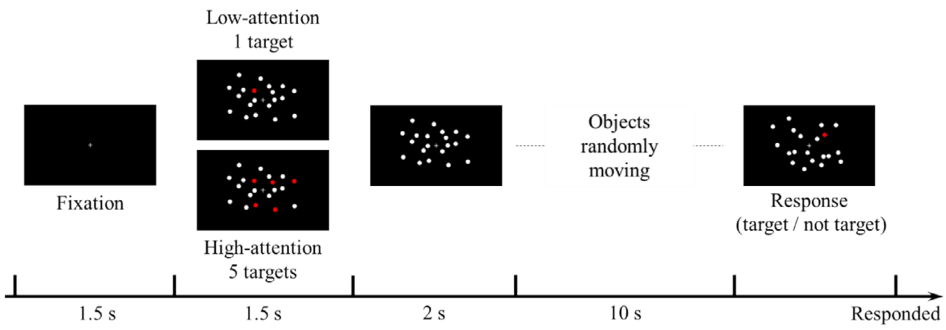

FIGURE 2 | Illustration of a single trial in the attentional task (Multiple Object Tracking Task). Initial fixation lasts for 1.5 s, followed by the display of 20 circles for 1.5 s, with either 1 or 5 target circles highlighted in red. Subsequently, all circles turn white for 2 s. After these circles move arbitrarily for 10 s, motion stops and one random circle is colored red. Participants are then prompted to respond using a keyboard.

TABLE 1 | Normative ratings (range, mean and standard deviation) of the four groups of images from the International Affective Picture System (IAPS).

	Valence ratings range (*Mean* ± SD)	Arousal ratings range (*Mean* ± SD)
High valence high arousal (HVHA)	6–7.5 (6.74 ± 0.35)	5.5–6.5 (5.90 ± 0.31)
High valence low arousal (HVLA)	6–7.5 (6.73 ± 0.44)	3.5–4.5 (4.05 ± 0.27)
Low valence high arousal (LVHA)	2.5–4.2 (3.32 ± 0.51)	5.5–6.5 (5.94 ± 0.26)
Low valence low arousal (LVLA)	2.5–4.6 (3.75 ± 0.57)	3.5–4.5 (4.13 ± 0.27)

TABLE 2 | Summary of EEG, autonomic, and subjective metrics.

Regression variable	Metrics		Unit
Dependent variable (Y)	EEG	Alpha power (8–13 Hz)	log (V^2/Hz)
		Alpha power (periodic)	log (V^2/Hz)
		Aperiodic (exponent)	N/A
		Aperiodic (offset)	N/A
Independent variable (X)	Autonomic	Heart rate	per minute
		HRV LF/HF ratio	N/A
		Respiration rate	per minute
		Respiration amplitude	V
		EDA 0.045–0.25 Hz power	μS^2
		Pupil size	mm
		Blink rate	per minute
		Microsaccade rate	per minute
	Subjective	Mental fatigue	N/A
		Sleepiness	N/A
		Attention level	N/A
		Arousal	N/A
		Valence	N/A

Abbreviations: EDA, electrodermal activity; EEG, electroencephalogram; HRV LF/HF, heart rate variability, the ratio of LF and HF power.

depends on the line noise, main noise and offset, and was kept below 0.8 during recording.

EEG signal processing was performed using the MNE-Python package (version 1.2.3) (Gramfort 2013). A bandpass filter from 1–100 Hz was applied to the signals, which were subsequently re-referenced to the average of all channels. Independent component analysis was conducted, and the components were identified using the automated mne-iclabel method available in the MNE-ICALabel package (version 0.4) (Li et al. 2022). The mne-iclabel method automatically labels components by estimating their probability values as being one of 'brain', 'muscle artifact', 'eye blink', 'heart beat', 'line noise', 'channel noise', or 'other' components. The identified components of blinks and muscle artifacts were discarded from subsequent analyses. To ensure the consistency of preprocessing across blocks (conditions) within participants, the aforementioned preprocessing was applied to the full 40-min dataset (comprising eight blocks of 5 min each) for every participant. After preprocessing, the data were re-segmented into eight original blocks.

The preprocessed data were further processed to calculate the four EEG metrics, as shown in Table 2. To achieve a higher frequency resolution in power spectrum measurements, data from each block were divided into non-overlapping 5-s epochs. Noisy epochs were rejected by visual inspection, leading to the exclusion of an average of four epochs (6.70%) per block in Experiment 1 and five epochs (8.48%) in Experiment 2. Power spectrum density was computed using the multitaper method (Slepian 1978), targeting a frequency resolution of 0.2 Hz. The multitaper method was formulated to improve the signal-to-noise ratio for power estimation (Lendner et al. 2020) and has been used before parameterizing the power spectrum in recent studies (Azizi et al. 2023; Maschke et al. 2023). Spectral analysis was conducted separately on the parietal-occipital (Pz, P3, P4, P7, P8, Oz, O1, O2), central (Cz, C3, C4, T7, T8) and frontal (Fz, F3, F4, F7, F8, Fp1, Fp2) regions. In each block of EEG data, the power spectrum densities were calculated for each channel, averaged over epochs, and then further averaged over channels within each region. To investigate the aperiodic and periodic components separately, the power spectrum density was parameterized using the FOOOF algorithm (version 1.0.0) (Donoghue et al. 2020). Settings for the algorithm were set as follows: peak width limits: (0.5, 12.0); max number of peaks: inf; minimum peak height: 0.0; peak threshold: 2.0; and aperiodic mode: 'fixed'. The setting parameters were selected for better detection of peaks and higher goodness (R^2) of model fit. The resulting goodness of fit (R^2) was 0.9948 ± 0.0009 (*mean* ± SE) in Experiment 1 and 0.9903 ± 0.0011 in Experiment 2. The spectra were parameterized over a 1–40 Hz frequency range, distinguishing and quantifying both aperiodic (exponent and offset) and periodic (alpha relative power) components. Specifically for the parietal-occipital region, the periodic alpha power was derived as Power_total—Power_aperiodic, within a frequency range determined by individual alpha frequency ± bandwidth for each participant. For each participant, individual alpha frequency (IAF) and bandwidth were based on the parameterized outcomes of the pre-task resting-state EEG power spectrum. Specifically, the IAF was defined as the peak frequency with the largest power within a range of 8–13 Hz. In Experiment 1, IAF was found in every participant, while in Experiment 2 this failed in one participant because no peaks were detected. In this case, the EEG spectrum in the post-task resting condition was used to determine the IAF. For the frontal and central regions, we did not calculate the periodic alpha power because alpha peaks in these regions could not be detected for every participant. Along with the exponent, offset, and periodic alpha power, an unparameterized 8–13 Hz alpha power metric was also derived before power spectrum parameterization, which was achieved by averaging power within the 8–13 Hz range. In summary, the following EEG metrics were calculated for each 5-min block: unparameterized 8–13 Hz alpha power, exponent, and offset in the parietal-occipital, central, and frontal regions, and periodic alpha power in the parietal-occipital region.

2.3.2 | ECG, Respiration, EDA

ECG, respiration, and EDA were recorded using the BIOPAC MP 160 system (Systems Inc., Goleta, USA) coupled with the AcqKnowledge 5 software. The signals were sampled at a rate of 2000 Hz. Three Ag/AgCl adhesive electrodes were positioned on the chest, and ECG data were collected. Respiration was measured using a sensor attached to a plastic band positioned around the participant's chest where respiratory expansion peaks. The EDA signals were recorded using two isotonic pregelled electrodes placed on the index and middle fingers of each participant's left hand.

Autonomic signals, including ECG, respiration, and EDA, were analyzed utilizing the neurokit2 package (Makowski et al. 2021). ECG data were processed using a fifth-order high-pass Butterworth filter featuring a 0.5 Hz cut-off frequency (the default method). Peaks in the ECG signal were identified, and artifacts were corrected using the approach detailed by Lipponen and Tarvainen (2019). Consequent intervals between such peaks (R-R interval) were extracted, and spectral analysis was subsequently conducted to quantify the power value in the LF (0.04–0.15 Hz) and HF (0.15–0.4 Hz) bands. The ratio was then calculated as LF/HF, which is a commonly used metric for measuring the balance between sympathetic and parasympathetic activities (Shaffer and Ginsberg 2017). For every 5-min block, both heart rate and HRV LF/HF ratio were computed.

The respiratory data were linearly detrended and further processed using a fifth-order low-pass IIR Butterworth filter with a 2 Hz cut-off frequency (Khodadad et al. 2018). We then calculated the mean respiratory rate and amplitude for each 5-min block.

Lastly, EDA data processing involved a fourth-order low-pass Butterworth filter with a 3 Hz cut-off to eliminate high-frequency noise. The spectral power within the 0.045–0.25 Hz frequency range was then determined, which is considered to reflect sympathetic activity (Posada-Quintero et al. 2016).

2.3.3 | Pupillometry

Binocular pupil size and eye movement were measured using the EyeLink 1000 Plus system (SR Research Ltd., Ontario, Canada) in a desktop mount setup. The EyeLink PC was networked to the primary PC via an Ethernet connection and operated using commands from the EyeLink toolbox. Data were recorded at a sampling rate of 500 Hz.

For data processing of pupil size and blinks, we utilized the pupillometry package in Python, which can be accessed at [https://ihrke.github.io/pypillometry/html/index.html]. In the pupil size time series, blink events were detected based on two criteria: sequences comprising consecutive zeros and sequences found between two instances where the velocity profile shifted from negative to positive (*blinks_detect*() function). Consecutive blinks occurring within a 130 ms interval were merged together to deal with blinks in quick succession (*blinks_merge*() function). To address data gaps during blinks, pupil size was interpolated using a cubic spline fit, as described by Mathôt (2013). Following preprocessing, we calculated the mean pupil size and blink rate for each 5-min block. The mean pupil size was obtained by averaging binocular values over the 5-min block. The blink rate was calculated by dividing the total number of blinks by five.

For data processing of microsaccade, Microsaccade Toolbox in R was used (Engbert et al. 2015). In this algorithm, a binocular microsaccade is detected by its velocity, and the velocity threshold is computed based on the standard deviation of the velocity distribution. The minimum duration was set as 8 ms (Leopold and Logothetis 1998). To check the quality of detection, correlation coefficients between the amplitude and peak velocity of microsaccades were calculated, which was confirmed to be higher than 0.75 for every participant. For each 5-min block, the microsaccade rate was calculated by dividing the total number of binocular microsaccades by five.

2.3.4 | Subjective Measurement

Following each block, the participants rated their subjective state by completing a questionnaire consisting of five subjective items: mental fatigue, sleepiness, attention level, arousal, and valence. Mental fatigue, sleepiness, and attention level were measured using a visual analog scale, ranging from 0 to 100 (Chang and Huang 2012; Mizuno et al. 2011). A score of 0 signified no feeling of fatigue or sleepiness, or 0% attentional investment; whereas a score of 100 denoted extreme fatigue, extreme sleepiness, or 100% attentional investment. Arousal and valence were measured using the 9-point Self-Assessment Manikin (Bradley and Lang 1994).

2.4 | Statistical Analysis

2.4.1 | Changes in EEG, Autonomic, and Subjective Metrics Across Conditions

To capture within-participant variations in EEG, autonomic, and subjective metrics across experimental conditions, we applied within-participant z-score normalization using metrics from all eight experimental blocks for each participant.

To investigate the effect of conditions on each metric, we utilized a one-way repeated-measures ANOVA (eight conditions: pre-task resting state, post-task resting state, low attention, high attention, emotional HVHA, HVLA, LVHA, and LVLA). Condition effects were further examined using paired t-tests, with p-values adjusted using Benjamini-Hochberg's method. In the ANOVA and paired t-test analysis of EEG and pupillometry metrics of Experiment 1, the data of one (No. 5) and two (Nos. 1, 7) participants were discarded due to measurement error. In the analysis of ECG, respiration, and EDA metrics of Experiment 2, the data of one (No. 12) participant were discarded, while specifically for EDA metrics, one more participant (No. 11) was excluded because all of them were outliers. In the analysis of pupillometry metrics, one (No. 11) participant was discarded, while specifically for the analysis of microsaccade, one more participant (No. 16) was excluded because only monocular data were available in the low-attention condition.

2.4.2 | Prediction of Alpha Power Using Multiple Linear Regression Analysis

We constructed multiple linear regression models to predict the alpha power, with autonomic ($X_{autonomic}$) and subjective ($X_{subjective}$) metrics as independent variables (Table 2).

Regressions were performed separately for the four EEG metrics, unparameterized 8–13 Hz alpha power ($Y_{8\text{–}13\_power}$), periodic alpha power ($Y_{periodic\_power}$), and two aperiodic components, exponent ($Y_{exponent}$) and offset (Y_{offset}). For the $Y_{8\text{–}13\_power}$, regressions were also performed separately for 8–13 Hz alpha power in three brain regions: parietal-occipital, central, and frontal regions. To ensure that there was no multicollinearity among the independent variables, the variance inflation factor (VIF) was checked to be below 5 for each variable.

In Experiment 1, from 56 blocks (7 participants × 8 conditions), five incomplete blocks (pre-task, post-task resting-state, and HVHA blocks of No. 1's pupillometry data, post-task resting-state block of No. 5's EEG data, and HVHA block of No. 7's pupillometry data) were excluded due to measurement errors. Thus, a total of 51 blocks were fitted to the regression model. In Experiment 2, from 56 blocks (7 participants × 8 conditions), two incomplete blocks (post-task resting-state block of No. 12's ECG, respiration and EDA data, high attention block of No. 11's pupillometry data) were excluded due to measurement errors. Therefore, a total of 54 blocks were fitted to the regression model.

We employed the leave-one-participant-out cross-validation approach to evaluate the prediction accuracy of the models, which means that X and Y variables from 48 blocks (6 participants × 8 conditions) were used for model training, and those from the remaining eight blocks (1 participant × 8 conditions) were used for the tests. The exact number of blocks used in the model training and tests differed slightly if there was an incomplete block. The multiple regression analysis was performed using the scikit-learn package in Python.

Furthermore, a cross-experiment validation analysis was performed to further examine the robustness of our results. The workflow for the cross-experiment validation analysis is shown in Figure 3. First, we fitted multiple linear regression models on the data from Experiment 1, each time leaving one participant out, resulting in seven models. This method allows us to construct a model less prone to overfitting compared to creating a single model using all the data (Yamashita et al. 2020). We then used blocks from Experiment 2 as the validation set. This gave us seven predicted values for each Y variable. We calculated a final predicted value for each Y variable by averaging the seven predicted values. Finally, prediction performance was assessed using Pearson correlations between observed and predicted values. We also conducted this procedure with Experiments 1 and 2 reversed.

3 | Results

3.1 | Changes in EEG, Autonomic, and Subjective Metrics

Initially, we assessed whether there were significant variations in EEG, autonomic, and subjective metrics across different experimental conditions. ANOVA results revealing a significant effect of the condition are detailed here, whereas a complete

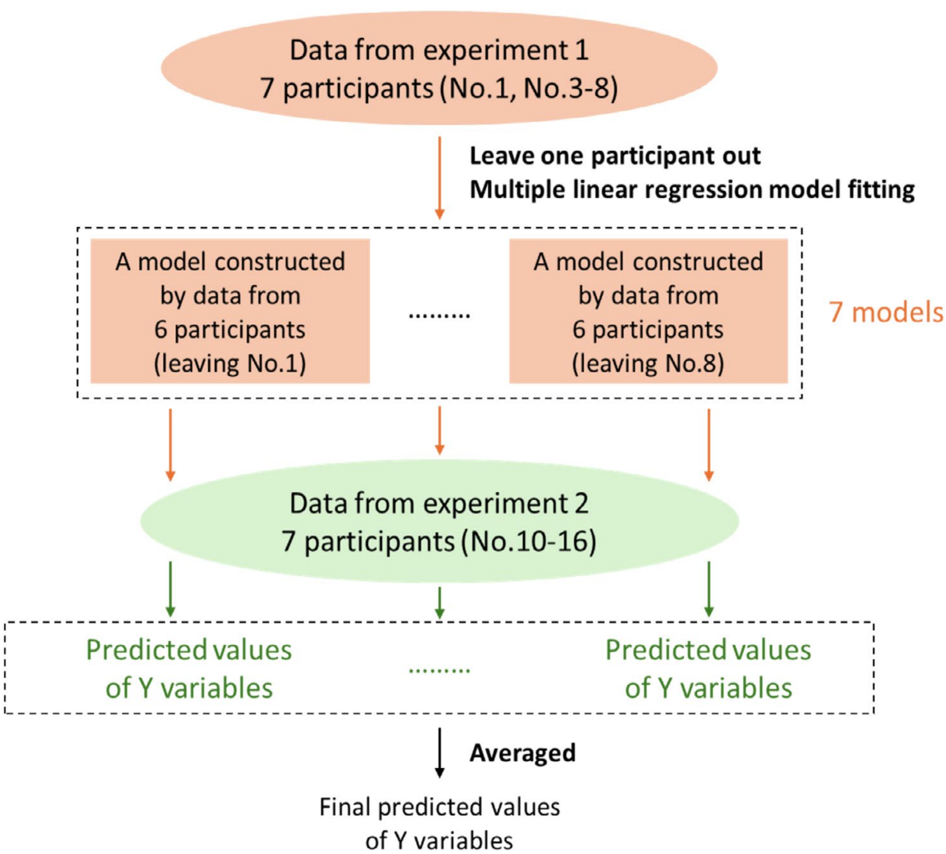

FIGURE 3 | The workflow for cross-experiment validation analysis, illustrating one of the two directions (Exp1 → Exp2).

report of the ANOVA and paired t-test outcomes is available in Figures S1–S3 (Experiment 1) and S4–S6 (Experiment 2).

Among the EEG metrics, a significant main effect of the condition was evident for 8–13 Hz alpha power in the parietal-occipital region ($F(7, 35) = 6.44$, $p < 0.001$, $\eta_g^2 = 0.18$; $F(7, 42) = 5.30$, $p < 0.001$, $\eta_g^2 = 0.03$) and the central region ($F(7, 35) = 5.31$, $p < 0.001$, $\eta_g^2 = 0.10$; $F(7, 42) = 2.24$, $p = 0.049$, $\eta_g^2 = 0.02$) in both Experiments 1 and 2. The main effect of the condition was also significant for periodic alpha power in the parietal-occipital region in both experiments ($F(7, 35) = 24.61$, $p < 0.001$, $\eta_g^2 = 0.45$; $F(7, 42) = 6.43$, $p < 0.001$, $\eta_g^2 = 0.23$). These observations indicate significant alpha power differences across eight task conditions. Specifically, in Experiment 1, paired t-tests demonstrated significant differences between the resting-state and task-state conditions in terms of the periodic alpha power (Figure S1a) and 8–13 Hz alpha power (Figure S1b) in parietal-occipital regions, but these effects were not observed in Experiment 2 (Figure S4a,b). No significant differences were observed in the context of aperiodic components (both exponent and offset) in either of the brain regions.

For autonomic measures, significant main effects for condition were observed for respiration rate ($F(7, 42) = 2.64$, $p = 0.024$, $\eta_g^2 = 0.14$; $F(7, 35) = 2.93$, $p = 0.016$, $\eta_g^2 = 0.21$), pupil size ($F(7, 28) = 9.08$, $p < 0.001$, $\eta_g^2 = 0.53$; $F(7, 35) = 26.35$, $p < 0.001$, $\eta_g^2 = 0.51$) in both experiments. Furthermore, as shown in Figures S2f and S5f, in both experiments, paired t-tests demonstrated reduced pupil size in the four emotional task conditions compared to others, indicating that pupils constricted in response to the emotional images. This is consistent with the decrease in pupil size during IAPS image viewing in a previous study (Bradley et al. 2008), at least partly originating from the pupil light response (Mathôt 2018).

In the context of subjective measures, the main effect of the condition was significant for attention ($F(7, 42) = 8.18$, $p < 0.001$, $\eta_g^2 = 0.33$; $F(7, 42) = 6.04$, $p < 0.001$, $\eta_g^2 = 0.29$), arousal ($F(7, 42) = 3.30$, $p = 0.007$, $\eta_g^2 = 0.17$; $F(7, 42) = 5.23$, $p < 0.001$, $\eta_g^2 = 0.34$), and valence ($F(7, 42) = 2.40$, $p = 0.037$, $\eta_g^2 = 0.25$; $F(7, 42) = 10.07$, $p < 0.001$, $\eta_g^2 = 0.58$) in both experiments. These results indicated that subjective states were indeed modulated by attentional and emotional tasks.

In addition, we investigated the bivariate correlations among EEG, autonomic, and subjective metrics, mirroring approaches from previous studies. Pearson's correlation coefficients were calculated, and the results were presented in Figure S7 as a correlation matrix for each experiment. In Experiment 1, both 8–13 Hz alpha power and periodic alpha power were positively correlated with blink rate, microsaccade rate, and sleepiness, and negatively correlated with attention level. However, in Experiment 2, no significant correlations were found for either 8–13 Hz alpha power or periodic alpha power.

3.2 | Prediction Performance of EEG Metrics in the Parietal–Occipital Region

We then attempted to predict alpha power using both autonomic and subjective measures. Prediction performances, evaluated using leave-one-participant-out cross-validation, are detailed in terms of Pearson correlation coefficients between observed and predicted values.

Figure 4 compares the prediction performances of the regression models fitted to the four EEG metrics in the parietal-occipital region in Experiments 1 and 2. We found that the prediction performance of regression models for $Y_{8\text{–}13\_power}$ ($r = 0.54$, $p < 0.001$; $r = 0.33$, $p = 0.015$) and $Y_{periodic\_power}$ ($r = 0.69$, $p < 0.001$; $r = 0.38$, $p = 0.005$) using both $X_{autonomic}$ and $X_{subjective}$ as independent variables was significant in both experiments. This result indicates that variations in 8–13 Hz and periodic alpha power in the parietal-occipital region across a variety of conditions, resting-state and task-state, can be predicted using variations in autonomic and subjective responses. This also suggests that the prediction was generalized across participants. For the aperiodic components, the $Y_{exponent}$ ($r = 0.05$, $p = 0.74$; $r = -0.13$, $p = 0.35$) and Y_{offset} ($r = 0.10$, $p = 0.49$; $r = 0.08$, $p = 0.58$) did not exhibit a significant results in both experiments. To compare these performances, we performed a statistical test on the differences between correlation coefficients. The results revealed that in both experiments, the prediction performance of $Y_{periodic\_power}$ significantly surpassed that of the $Y_{exponent}$ ($z = 3.90$, $p < 0.001$; $z = 2.68$, $p = 0.007$), whereas there was no marked difference between $Y_{periodic\_power}$ and $Y_{8\text{–}13\_power}$ ($z = 1.20$, $p = 0.23$; $z = 0.29$, $p = 0.77$). In summary, 8–13 Hz and periodic alpha power in the parietal-occipital region were effectively predicted using $X_{autonomic}$ and $X_{subjective}$, which performed better than the aperiodic components (exponent). Furthermore, the periodic alpha power achieved the highest prediction performance ($r = 0.69$; $r = 0.38$) in each experiment.

3.3 | Prediction Performance of 8–13 Hz Alpha Power in Three Channel Regions

Second, in addition to the parietal-occipital region, we examined whether the 8–13 Hz alpha power in the central and frontal regions could be predicted. Periodic alpha power was not calculated in the central and frontal regions, because alpha peaks could not be detected for every participant. Figure 5 compares the prediction performances of $Y_{8\text{–}13\_power}$ across the three channel regions in Experiments 1 and 2. The results showed that significant prediction performances were also observed for $Y_{8\text{–}13\_power}$ in the central ($r = 0.33$, $p = 0.02$) and frontal ($r = 0.33$, $p = 0.02$) regions in Experiment 1, but not in Experiment 2 (central: $r = -0.10$, $p = 0.46$; frontal: $r = -0.11$, $p = 0.43$). This indicates that the prediction of 8–13 Hz alpha power was only reproduced in Experiment 2 in the parietal-occipital region, but not in the central and frontal regions.

3.4 | Cross-Experiment Validation

To further examine the robustness of our results, we conducted a cross-experiment validation. This validation assessed whether models constructed with data from one experiment could predict outcomes in the other experiment. All EEG metrics, such as 8–13 Hz alpha power, periodic alpha power, exponent, and offset, were examined.

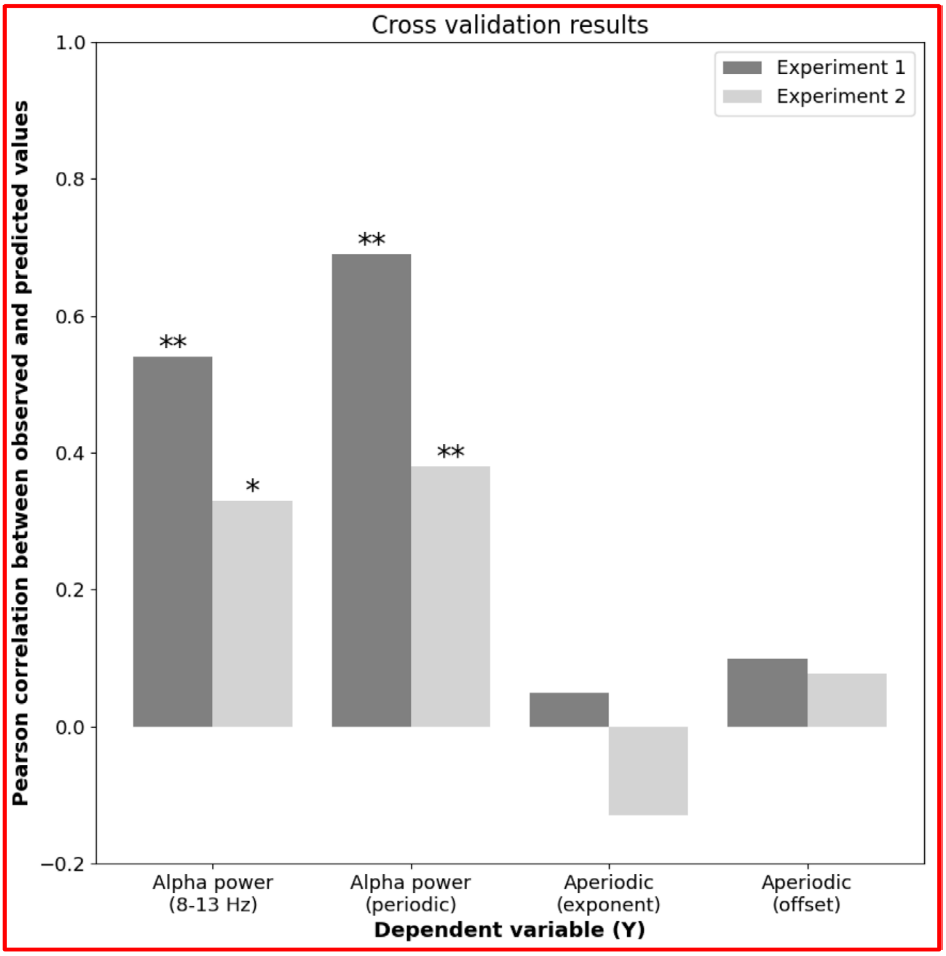

FIGURE 4 | Prediction results of leave-one-participant-out cross-validation using both autonomic and subjective metrics as independent variables (X), in Experiments 1 and 2. The four EEG metrics in the parietal-occipital region were the dependent variables (Y). Significance of the correlations is denoted by asterisks above the bars (*$p<0.05$, **$p<0.01$).

Figure 6 compares the prediction performances of regression models fitted to four EEG metrics in the parietal-occipital region, in both directions of cross-experiment validation. In both directions, the $Y_{8–13\_power}$ (Exp1 → Exp2: $r=0.35$, $p=0.009$; Exp2 → Exp1: $r=0.35$, $p=0.013$) and $Y_{periodic\_power}$ (Exp1 → Exp2: $r=0.49$, $p<0.001$; Exp2 → Exp1: $r=0.50$, $p<0.001$) showed significant prediction performance. This indicates that the regression models for 8–13 Hz and periodic alpha power constructed in one experiment are generalizable to the independent dataset from the other experiment. The aperiodic components, both $Y_{exponent}$ (Exp1 → Exp2: $r=-0.10$, $p=0.47$; Exp2 → Exp1: $r=-0.04$, $p=0.79$) and Y_{offset} (Exp1 → Exp2: $r=0.21$, $p=0.13$; Exp2 → Exp1: $r=0.13$, $p=0.35$), did not exhibit significant prediction performance in either direction of cross-experiment validation. In summary, these results further confirm that alpha power can be robustly predicted using autonomic and subjective measures.

4 | Discussion

This study explored the relationships of alpha power variations with changes in autonomic responses and subjective reports. EEG data, autonomic measures, and subjective reports collected under various conditions were analyzed. To focus on the periodic component of alpha power, the aperiodic component of alpha power, which displays 1/f-like behavior and represents non-oscillatory activity, was isolated and subtracted. Apart from the bivariate correlations often assessed in previous studies, we constructed multiple linear regression models to predict alpha power using autonomic responses and subjective reports as predictors. Importantly, the prediction accuracy of the regression model was evaluated by leave-one-participant-out cross-validation, so that the association between alpha oscillations and autonomic/subjective responses invariant across participants could be studied. Our results indicated that the periodic component of alpha power in the parietal-occipital region can be significantly predicted using autonomic measures and subjective reports. The robustness of this prediction was confirmed in a cross-experiment validation analysis.

4.1 | Comparison Between Periodic and 8–13 Hz Alpha Power

We analyzed both periodic alpha power, which was parameterized for each individual participant, and conventional 8–13 Hz alpha power. The latter, which lacks individual parameterization, has been reported to be confounded by the

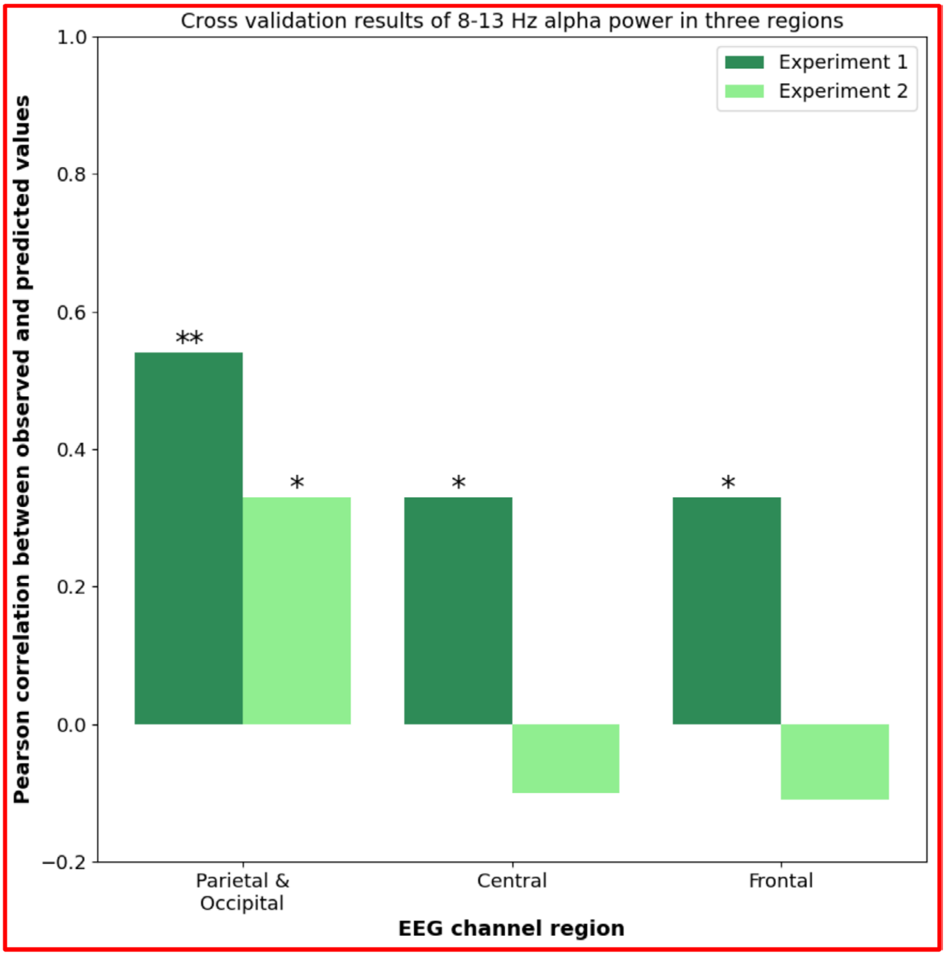

FIGURE 5 | Prediction results of leave-one-participant-out cross-validation using both autonomic and subjective metrics as independent variables (X), in Experiments 1 and 2. The 8–13 Hz alpha power in parietal-occipital, central, and frontal regions was the dependent variable (Y). Significance of correlations is denoted by asterisks placed above the bars (*$p < 0.05$, **$p < 0.01$).

aperiodic component (Donoghue et al. 2020). In addition, calculating alpha power within a predefined frequency range can produce inaccurate results, primarily due to the significant heterogeneity in individual peak frequencies and bandwidths of alpha oscillations. Our results showed that periodic alpha power achieved the highest prediction performance in both within-experiment (Figure 4) and cross-experiment (Figure 6) validations. This result suggests that the periodic component of alpha power has a stronger multiple linear relationship with autonomic and subjective measures than unparameterized alpha power.

4.2 | Investigating Task Effects on Alpha Power Prediction

As shown in Results 3.1, EEG, autonomic, and subjective metrics can vary significantly due to different task conditions. Therefore, it is essential to investigate whether variations in alpha power are solely influenced by the differences in task conditions, independent of the influence of the autonomic and subjective responses. To determine whether types of task conditions (i.e., resting-state, attentional task, and emotional task), autonomic, and subjective measures explained unique or shared variance in periodic alpha power, we modeled them as fixed factors in a linear mixed-effects model, with participants as a random factor. For the fixed factor of task conditions, two dummy variables (task_attention, task_emotion) were used to represent the task conditions, with the resting-state as the baseline condition. More details of the analysis are provided in the Supporting Information, and the results are presented in Tables S1 and S2.

As a result, for Experiment 1, we observed that both the attentional ($\beta = -0.738$, $p < 0.001$) and emotional tasks ($\beta = -0.917$, $p < 0.001$) explained unique variance in alpha power, with negative estimates indicating a suppressive effect on alpha power relative to the resting-state condition (Table S1). In contrast, in Experiment 2, task conditions (task_attention: $\beta = -0.078$, $p = 0.510$; task_emotion: $\beta = 0.050$, $p = 0.773$) did not show a significant effect on alpha power (Table S2). In summary, while task effects were significant and may have influenced the prediction of alpha power in Experiment 1, this result was not confirmed in Experiment 2.

Despite the above linear mixed-effects analysis revealing differences in task effects between Experiments 1 and 2, 8–13 Hz and periodic alpha power could still be predicted using autonomic and subjective measures in a cross-experiment validation

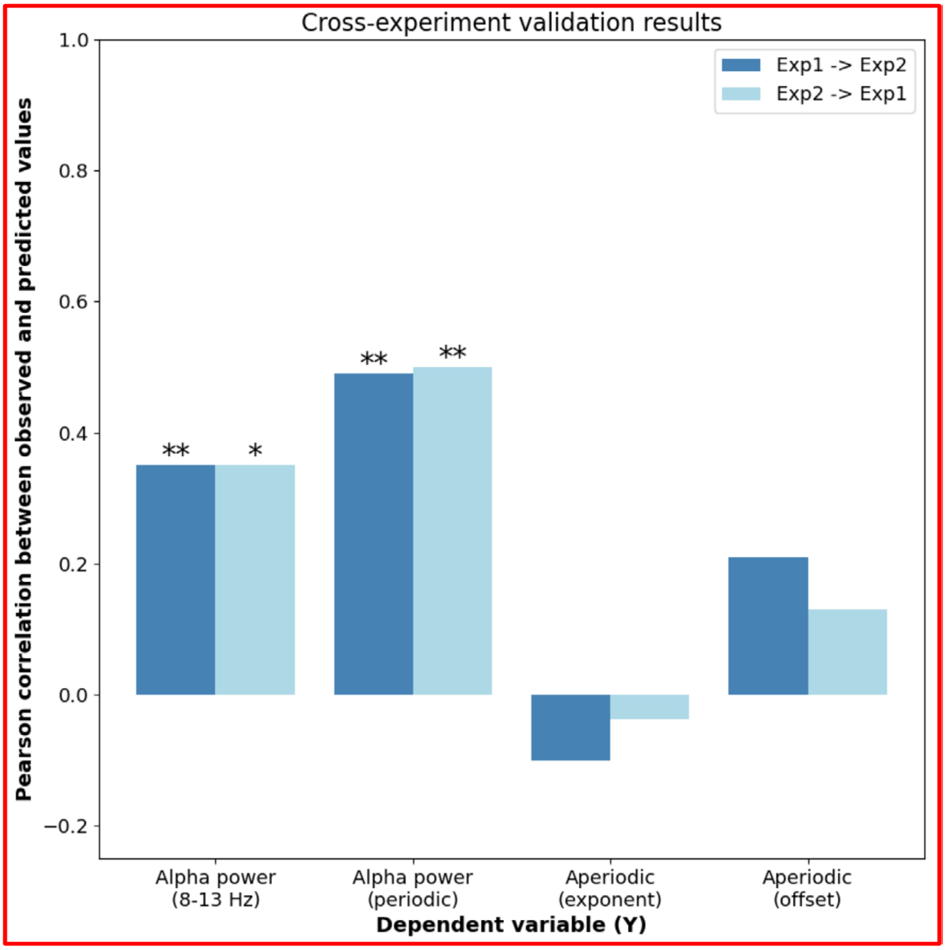

FIGURE 6 | Prediction results of cross-experiment validation using both autonomic and subjective metrics as independent variables (X). The four EEG metrics in the parietal-occipital region were dependent variables (Y). Significance of correlations is denoted by asterisks placed above the bars (*$p < 0.05$, **$p < 0.01$).

(Figure 6). This indicates that the significant prediction performance of alpha power cannot be solely attributed to task effects but is actually related to variations in autonomic and subjective measures. Moreover, task effects may also contribute to the prediction of alpha power in addition to influence from autonomic and subjective metrics, as inferred from the higher prediction performance of periodic alpha power in Experiment 1 ($r = 0.69$) than in Experiment 2 ($r = 0.38$) (Figure 4). Additionally, the prediction performance of alpha power in the central and frontal region was significant only in Experiment 1, not in Experiment 2 (Figure 5), which may also be due to significant task effects in Experiment 1.

4.3 | Correlation of Alpha Power in Various Brain Regions With Autonomic/Subjective Responses

While most previous studies have demonstrated correlations between autonomic activity, subjective states, and alpha power in posterior areas, some studies have also revealed associations with alpha power in central and frontal regions (Takahashi et al. 2005; Weinreich et al. 2016). Our current findings indicate that only the alpha power in the parietal-occipital region was predicted by autonomic and subjective responses consistently in both Experiments 1 and 2. The prediction of alpha power in the central and frontal regions was not replicated in Experiment 2. As discussed in the previous section, the prediction of alpha power in the central and frontal regions in Experiment 1 may be attributed to task effects. Further research is required to elucidate the relationship between autonomic/subjective responses and alpha power in the central or frontal regions.

4.4 | Relationship Between Aperiodic Components and Autonomic/Subjective Responses

Since the 1/f-like aperiodic and periodic components are known to have different functions, it has been suggested that they be analyzed separately (Donoghue et al. 2020). While the aperiodic component has been linked to between-participant differences in age (Hill et al. 2022), sex (McSweeney et al. 2021), cognitive speed (Ouyang et al. 2020), and diseases (Wang et al. 2022), recent evidence has shown that it correlates with within-participant variations in consciousness, such as states of wakefulness, anesthesia, and non-REM and REM sleep (Lendner et al. 2020; Miskovic et al. 2019; Waschke et al. 2021). Furthermore, Kluger et al. (2023) demonstrated that changes in the aperiodic component are influenced by the respiratory cycle. Multiple linear regression analyses in the current study revealed that the aperiodic components of alpha power had worse prediction performance compared to the periodic component. Further research is required to understand the mechanisms by which aperiodic components are related to autonomic and subjective responses.

4.5 | Comparison Between Autonomic and Subjective Inputs

Moreover, we were interested in how periodic alpha power in the parietal-occipital region was associated with autonomic response and subjective reports. To explore this, two separate models were tested for each EEG metric: one only included $X_{autonomic}$, and the second only included $X_{subjective}$. The results are shown in Figure S8. Prediction performances for $Y_{periodic\_power}$ and $Y_{8\text{–}13\_power}$ were significant for both $X_{autonomic}$ and $X_{subjective}$ in Experiment 1. On the contrary, the prediction performances were significant for only $X_{subjective}$ in Experiment 2. Therefore, we could not definitely conclude whether alpha power is related more to autonomic changes or to subjective feelings. As for the aperiodic components, Y_{offset} and $Y_{exponent}$, prediction performances were insignificant for both $X_{autonomic}$ and $X_{subjective}$ in both Experiments 1 and 2.

4.6 | Limitations and Future Directions

The current study had several limitations that need to be considered. First, although various autonomic and subjective variables were incorporated into the regression model, determining the importance of each variable based on its regression weights was challenging. This difficulty arises because regression weights can only be correctly interpreted when the causal model is preconceived (Hernán and Robins 2020). Therefore, to discern which factor correlates more with alpha power, future studies should create potential causal models using intervention experiments and evaluate the weights based on these models. Furthermore, although we used ICA to eliminate artifacts such as blinks and muscle activity, residual electromyography (Muthukumaraswamy 2013) may still influence EEG alpha band activity (Urigüen and Garcia-Zapirain 2015). This potentially confounds the relationship between autonomic responses and alpha power. In future studies, this influence could be minimized by examining EEG and physiological responses during non-visual cognitive tasks with the eyes closed. Additionally, acknowledging that multiple components manifest in posterior alpha oscillations, which originate from the occipital–temporal and occipital–parietal regions (Barzegaran et al. 2017), is crucial for future research to discern how each component of the periodic alpha oscillation is related to the autonomic and subjective states. This can be achieved using higher spatial resolution measurements, such as Magnetoencephalography (MEG) coupled with simultaneous autonomic and subjective measurements. Finally, while our study provided preliminary evidence supporting the prediction of alpha power using physiological and subjective responses through leave-one-participant-out cross-validation and cross-experiment validation, there were still inconsistencies between the two experiments, such as the bivariate correlations (Figure S7) and task effects (Tables S1 and S2). This suggests that the current sample size may be insufficient to fully understand the bivariate correlations among alpha power, autonomic responses, subjective responses, and task effects. Therefore, using larger samples in future studies could contribute to a more comprehensive understanding.

5 | Conclusion

This study investigated the relationships of alpha power with autonomic responses and subjective reports. Our results indicate that periodic alpha power in the parietal-occipital region can be effectively predicted by constructing multiple linear regression models using autonomic responses and subjective reports as independent variables. These findings highlight that variations in periodic alpha power of the posterior area reflect changes in autonomic responses and subjective reports. Although numerous studies have emphasized alpha oscillation activity in various cognitive states, our results underscore the need to consider its relationship with autonomic responses and subjective reports, which may vary and affect alpha power variations under different cognitive states.

Author Contributions

Yuting Xu: conceptualization, data curation, formal analysis, investigation, methodology, visualization, writing – original draft. **Ayumu Yamashita:** conceptualization, formal analysis, investigation, methodology, validation, writing – review and editing. **Kyuto Uno:** methodology, writing – review and editing. **Tomoya Kawashima:** conceptualization, investigation, methodology, writing – review and editing. **Kaoru Amano:** conceptualization, funding acquisition, investigation, methodology, supervision, writing – review and editing.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data and code that support the findings of this study will be made available after the paper is accepted. https://osf.io/3qme2/.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.