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RESEARCH REPORT

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Day-to-day individual alpha frequency variability measured by a mobile EEG device relates to anxiety

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Abstract

The individual alpha frequency (IAF) has previously been identified as a unique neural signature within the 8–12 Hz alpha frequency band. However, the day-to-day variability of this feature is unknown. To investigate this, healthy participants recorded their own brain activity daily at home using the Muse 2 headband, a low-cost consumer-grade mobile electroencephalography (EEG) device. Resting-state recordings of all participants using a high-density (HD) EEG were also collected in lab before and after the at-home data collection period. We found that the IAF extracted from the Muse 2 was comparable to that of location-matched HD-EEG electrodes. No significant difference was found between these IAF values before and after the at-home recording period for the HD-EEG device. Similarly, there was also no statistically significant difference between the beginning and end of the at-home recording period for the Muse 2 headband over 1 month. Despite the group-level stability of IAF, the individual-level day-to-day IAF variability carried mental health-relevant information: Exploratory analyses revealed a relationship between IAF day-to-day variability and trait anxiety. We also noted that the IAF systematically varied across the scalp and although the Muse 2 electrodes do not cover the occipital lobe where alpha oscillations were the strongest, IAFs measured in the

Abbreviations: BDI, Beck Depression Inventory; BISBAS, Behavioral Activation Scale and Behavioral Inhibition Scale; EEG, electroencephalography; EHI, Edinburgh Handedness Questionnaire; HD, high density; IAF, individual alpha frequency; MINI, Mini International Neuropsychiatric Interview; STAI, State–Trait Anxiety Inventory.

Lauren Sidelinger and Mengsen Zhang have equal contribution. Flavio Frohlich and Stacey Daughters have equal contribution.

temporal lobe and occipital lobe were strongly correlated. Altogether, these results show that mobile EEG devices are useful for studying IAF variability. The relationship between day-to-day variability of region-specific IAF and the dynamics of psychiatric symptoms, particularly anxiety, should be further investigated.

KEYWORDS
anxiety, EEG analysis, EEG frequency band analysis, EEG spectral analysis, human EEG alpha and theta oscillations

1 | INTRODUCTION

Alpha oscillations (8–12 Hz) were first discovered in the parietal and occipital regions of the brain and are highest in amplitude when the eyes are closed (Berger, 1929). Later studies found that alpha oscillations are not restricted to the occipital regions (Gastaut & Bert, 1954; Hari et al., 1997; Pfurtscheller & Neuper, 1994) and are involved in a variety of cognitive functions including working memory, attention and creativity (Klimesch, 2012; Lustenberger et al., 2015; Riddle, Scimeca, et al., 2020). An important feature of alpha oscillations is the individual alpha frequency (IAF), defined as the frequency with the highest power in the alpha range specific to a person. IAF has been implicated in various neurological and psychiatric disorders, such as schizophrenia, as individuals with these disorders are known to have lower IAF values (Ramsay et al., 2021). More recently, it has been noted that the people in the general population with high schizotypy traits have a slower IAF in parieto-occipital regions. This was observed in both the left and right hemispheres (Trajkovic et al., 2021). IAF is also being evaluated as a biomarker for both pain and intellectual disabilities (Furman et al., 2020; Pérez-Elvira et al., 2021). Furthermore, IAF has been observed to have a variety of functions in visual perception such as in the temporal resolution of visual perception (Samaha & Postle, 2015), the perception of a jitter frequency (Minami & Amano, 2017), conscious visual perception (Di Gregorio et al., 2022) and the temporal window of integration (Cecere et al., 2015). Additionally, IAF has important implications in cognition such as being causally related to feature binding (Zhang et al., 2019) and modulating the ability of practice to improve performance in a working memory task (Bertaccini et al., 2022). These studies on cognition and perception found these relationships with IAF by utilizing non-invasive brain stimulation to make causal and correlative findings. In addition to alpha oscillations being targeted by non-invasive brain stimulation to better understand cognition and perception, alpha oscillations have also become a target of non-invasive brain stimulation studies for several disorders (Ahn, Mellin, et al., 2019; Ahn, Prim, et al., 2019; Alexander et al., 2019; Force et al., 2021; Fröhlich, 2015; Mellin et al., 2018; Prim et al., 2019; Riddle et al., 2022; Riddle, Rubinow, & Frohlich, 2020; Zhang et al., 2022). Understanding spontaneous alpha dynamics would allow for a more informed and individualized approach to target engagement (Kurmann et al., 2018).

Although studies have suggested that IAF could be a heritable trait (Smit et al., 2006), changes in IAFs have been observed on different time scales, and the functional relevance of the IAF is not yet fully understood. Over the time scale of years, the IAF in adults exhibits a gradual and steady decline in frequency with age (Grandy et al., 2013). In contrast, studies analysing second-to-second dynamics of alpha oscillations have found significant fluctuations in the IAF, perhaps representing state-like features such as different levels of neuronal activation or fluctuations in arousal (Mierau et al., 2017; Stitt et al., 2018). However, how IAF fluctuates in the intermediate time scales remains unknown. Having a better understanding of IAF stability on a day-to-day basis is critical for evaluating IAF as a trait-like component.

To our knowledge, there is no previous study that examines the day-to-day fluctuations in IAF over a month-long period nor how such fluctuations relate to behavioural features. This is not surprising due to the low feasibility of daily recordings using high-density electroencephalography (HD-EEG), which would consume substantial time and resources. To address this feasibility issue, we utilized mobile EEG devices participants could use at home. Although primarily marketed to consumers, these low-cost EEG devices present a unique opportunity for research to include increased data collection over long periods of time. One of these devices is the Muse 2 headband, a dry-electrode device with four recording electrodes. The Muse 2 headband has been used in previous research from predicting stroke severity to assessing visual attention (Krigolson et al., 2017; Wilkinson

et al., 2020). However, most of these studies have been conducted in lab under the supervision of study personnel. This does not take advantage of the opportunity mobile EEG devices offer for long-term at-home data collection, arguably their greatest strength in research settings. It also does not investigate the acceptability of these devices to participants. The Muse device has been successfully used previously to extract IAFs in thousands of participants across different ages (Hashemi et al., 2016). However, this study did not examine day-to-day dynamics of the IAF nor how these dynamics related to behavioural features.

In this study, we used at-home EEG recording with the Muse 2 headband to examine the day-to-day variability of IAF. Given that alpha oscillations have been involved in a wide range of cognitive functions and psychiatric symptoms (Gotlib, 1998; Klimesch, 2012; Knyazev et al., 2004, 2006; Lustenberger et al., 2015; Riddle et al., 2022; Riddle, Scimeca, et al., 2020; Zhang et al., 2022), we assessed participants' depressive symptoms, trait and state anxiety and behavioural activation and inhibition to understand how the variability of the IAF might relate to them. At the same time, we sought to understand the feasibility and acceptability of participants using this device at home without supervision and to evaluate the quality of the at-home recordings with Muse by comparing spectral features to those of in-lab recordings with HD-EEG.

2 | MATERIALS AND METHODS

The study was approved by the Institutional Review Board at the University of North Carolina at Chapel Hill. Subjects gave their written informed consent prior to the start of the experiment.

2.1 | Participants

Twenty healthy volunteers were recruited for this study. Participants were recruited from the Raleigh–Durham–Chapel Hill community. Inclusion criteria included (1) aged between 18 and 70 years old, (2) daily access to a smartphone with an existing data plan, and (3) willingness and ability to download and install the study-associated app on their personal smartphone. Participants were excluded if they (1) had a DSM-V psychological disorder as determined by the Mini International Neuropsychiatric Interview (MINI) (Lecrubier et al., 1997), (2) self-reported a current diagnosis of a neurological illness, (3) were taking any medication associated with the treatment of a mental health condition or a neurological illness, (4) had a history of brain surgery or brain implementations, (5) had any previous significant head injury where unconsciousness exceeded 5 min, (6) had suicidal ideation as determined by the MINI (Lecrubier et al., 1997) and the Beck Depression Inventory (BDI) (Beck et al., 1996), (7) an unstable health condition and (8) dermatological issues that would affect wearing the EEG headset.

Two participants withdrew during the study due to issues with compensation and time commitment (Figure S1). The present analyses are based on the 18 participants who completed the study, who were ages 19–69 with a mean of 28.8 years and a standard deviation of 12.3. 66.7% of participants were female. Six percent of participants were African American, 6% were Asian, and 88% were White.

2.2 | Study design

The study included two in-lab sessions and 4 weeks of at-home sessions (Figure 1). The first in-lab session was scheduled a day before the first at-home session, and the second in-lab session was scheduled as soon as possible after the last at-home recording session. The at-home sessions span approximately 4 weeks at the frequency of once per day.

There were five components to the first in-lab session: (1) Participants completed self-report questionnaires, (2) participants went through a clinical interview to ensure no criteria for a mental health condition were met, (3) participants were directly assisted and shown how to use the Muse device for an initial recording, (4) a research-grade HD-EEG recording was captured, and (5) participants were supervised while completing a final recording using the Muse device (Figure 2).

Participants first completed self-report questionnaires and the MINI semi-structured interview (Lecrubier et al., 1997). Behavioural self-report questionnaires included the BDI (Beck et al., 1996), State–Trait Anxiety Inventory (STAI) (Spielberger, 2010), Behavioral Activation Scale and Behavioral Inhibition Scale (BISBAS) (Carver & White, 1994) and the Edinburgh Handedness Questionnaire (EHI) (Veale, 2014). A demographics self-report questionnaire was also collected. If participants endorsed criteria for a psychological disorder during the MINI they were excluded from the study.

Upon meeting the inclusion criteria for the study, the participants downloaded the 'Mind Monitor' app (Clutterbuck, n.d.) on their personal smartphones and were reimbursed for this purchase. This app connected to the Muse device via Bluetooth to give feedback on the connection quality of the different electrodes and allowed

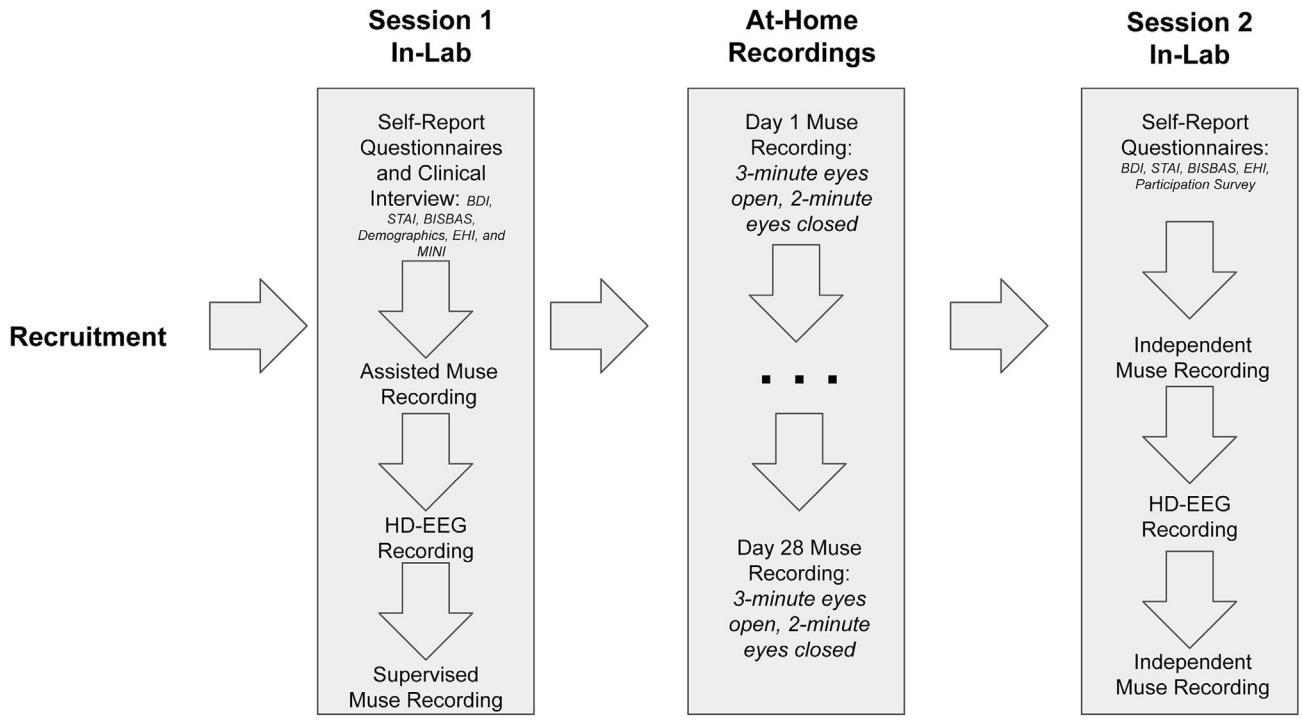

FIGURE 1 Study design. This figure shows the study timeline and what was involved in each stage.

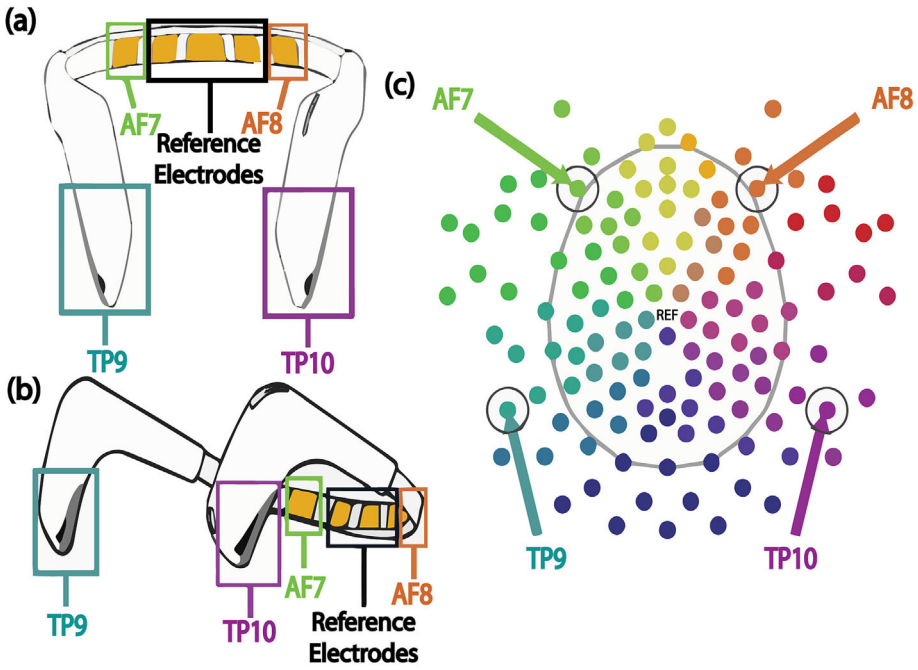

FIGURE 2 The electrodes' layout of MUSE and HD-EEG. (a,b) The Muse device has four recording electrodes: AF7, AF8, TP9 and TP10. Above are the locations of each of these electrodes and the reference electrodes on the device. When recording, participants placed electrode gel on each of these electrodes to ensure increased connection quality. (c) Above is the location of each electrode in the EGI system with AF7, AF8, TP9 and TP10 highlighted.

participants to easily send data from recordings to a study-specific email.

Study personnel then demonstrated how to navigate the app and set up the Muse 2 EEG headband. Although designed as a dry electrode device, preliminary testing found that applying electrode gel increased the quality of the recording such that alpha oscillations visible in the raw recordings were observed. More specifically, gel was added to each of the recording electrodes and spread across the three reference electrodes. Participants were shown how to apply electrode gel and how to check for a high-quality connection using feedback from the device. A 3-min eyes-open, 2-min eyes-closed resting-state EEG recording was then collected using the device. Once completed, a 3-min eyes-open and 2-min eyes-closed recording was collected using research-grade HD-EEG.

Participants then used the Muse 2 device with supervision from study personnel. If study personnel observed any mistakes or missed steps, they would intervene and make suggestions to the participant. Participants then took the Muse 2 device home and were asked to record the 3-min eyes-open and 2-min eyes-closed resting-state EEG every day for 4 consecutive weeks. Participants were given the opportunity to make up for missed days by extending the at-home recording period of the study.

A study website with tutorial videos and information sheets was made available to participants if they required further assistance in using the device. Study personnel periodically checked the data quality of recordings and reached out to participants offering advice if the quality was subpar. These checks were conducted once per participant within the first week after their at home recording period started.

After this at-home data collection portion, participants returned for their second and final in-lab session. There were four components to this second session: (1) self-report questionnaires, (2) an initial independent recording using the Muse device, (3) a recording using the HD-EEG and (4) a final independent recording using the Muse device.

The session started with self-report questionnaires. The same behavioural self-report questionnaires from the first session were used in addition to a survey about their participation in the study and the acceptability of the device. Participants were asked to rate statements from strongly disagree to strongly agree. Statements included 'I enjoyed participating in this study', 'setting up and performing the daily EEG recording was straightforward' and 'the EEG sessions interfered with my daily life'. If a participant marked agree or strongly agree to a statement, that statement was said to be true to them, whereas if a participant marked disagree or strongly disagree, the opposite of that statement was said to be true to them. The participants then independently recorded their resting state data from the Muse device. Afterwards, the study personnel collected a resting-state recording from the HD-EEG using the same protocol as in the first session. The study was completed with a final independent recording from the participant with the Muse 2 headband. Participants were compensated for each attended session and had an increase in compensation linearly related to the number of completed mobile recordings.

2.3 | EEG data and preprocessing

Research-grade HD-EEG data were collected using a 128-channel electrode net at 1000 Hz (HydroCel Geodesic Sensor Net) and EGI system (NetAmps 410, Magstim Electrical Geodesics Inc., OR, USA). The Cz electrode served as the reference electrode in this system. Prior to the start of each HD-EEG recording, the impedance of each electrode was below 50 kΩ. Two types of preprocessing pipeline were used in this study: a *minimal* preprocessing pipeline and an *extensive* preprocessing pipeline. The minimal preprocessing pipeline was used to compare HD-EEG to Muse data, as the Muse data are not suitable for advanced artefact rejection commonly used for HD-EEG data. The extensive preprocessing pipeline followed common procedures used for HD-EEG processing. The extensively preprocessed HD-EEG data were used for sanity checks to ensure spectra and IAFs computed from minimally preprocessed HD-EEG were not substantially different. The minimal preprocessing pipeline includes visual inspection of the time series to remove bad channels and segments and spherical interpolation of bad channels. The extensive preprocessing pipeline extends the minimal preprocessing pipeline to include (1) low-pass filtering and down-sampling to 250 Hz, (2) automated artefact rejection using the Artifact Subspace Reconstruction method (Mullen et al., 2013) and (3) manual ICA rejection of eye movement artefacts, heartbeats, muscular artefacts and channel noise. All preprocessing were performed using EEGLAB (Delorme & Makeig, 2004) in Matlab.

Mobile EEG data were collected using the Muse 2 headband at 256 Hz (see Figure S5 for a summary on the distribution of timestamps with respect to the expected sampling rate). Prior to the start of each recording, visual feedback was given by the Mind Monitor app regarding signal and connection quality as assessed via the variance in the raw EEG signal. Using this visual feedback, participants were able to minimize the variance and improve the connection quality. Data were rejected at points the Muse device estimated to be eye blinks. Across all participants, the blink detection rates were 5.9 ± 6.3 blinks per minute in eyes-closed recordings and 13.8 ± 10.6 blinks per minute in eyes-open recordings (significantly higher in eyes-open recordings, $t(34) = 2.71$, $p = 0.01$). Data segments were rejected within ± 1 s windows around the time of each blink detection; the percentage of sample points rejected were $13.5\% \pm 14\%$ for eyes-closed recordings and $32.4\% \pm 21.0\%$ for eyes-open recordings (significantly higher in eyes-open recordings, $t(34) = 3.19$, $p = 0.003$). In the present study, IAFs were estimated from eyes-closed data—results recording eyes-open data are included to provide context for understanding the rejection rates. The algorithm used by Muse for eye blink detection is proprietary and not shared with us, which was thus only used for data collected from the Muse device, not for data collected from the HD EEG device. Results of the blink rejections were verified by

visually inspecting the power spectra before and after rejection to ensure that spectral changes in the low-frequency range (<5 Hz) were as expected from eye blink removal. Large artefacts were automatically rejected, and bad recordings were determined by visual inspection of the power spectra. Because of the tendency of alpha to be most prominent in occipital areas and the low quality of the data collected from the frontal electrodes (Figure 3), we primarily used data from TP9 and TP10 electrodes on the Muse device for IAF analysis (Lozano-Soldevilla, 2018).

2.4 | Spectral analysis and peak frequency extraction

The power spectral density was estimated using the Welch method on the detrended data. For this, a Hann window of 2 s with 1/8 s overlap was used for both Muse and EGI. The frequency of interest was from 1 to 30 Hz in intervals of 0.1 Hz. The aperiodic components in the power spectra were removed using FOOOF (Donoghue et al., 2020). Power spectra were visually inspected for each recording session. A frequency band within the alpha range (7–13 Hz) was manually determined whereby visual inspection ensured that the alpha peaks were successfully captured and that no artificial peaks due to spectra leakage from other frequency bands were recorded. In this band, the peak with the highest power was extracted automatically and was defined as the IAF. For peak detection, we used the 'findpeaks' function in MATLAB to avoid artificial 'peaks' falling on the edges of the window due to any presence of a trend within the window. Here, we use the peaks in the flattened (aperiodic component removed) power spectra instead of the peak parameters estimated by FOOOF as IAF to avoid adding reconstruction errors resulting from any non-Gaussianity of spectral peaks to IAF estimations.

2.5 | Statistical analysis

IAF values were compared within subjects using paired *t*-tests. For recording quality assessment, spectral correlations were made using Pearson correlation coefficients in the frequency range of 4–20 Hz between each pair of recordings; an average correlation coefficient was then computed for each subject and each electrode for further comparisons (ANOVA, with Tukey HSD for post hoc comparisons). This range was selected because (1) we are primarily interested in the spectral quality in the alpha frequency range, where we will estimate the IAF, and (2) this range is generally least affected by ocular and motion artefacts, as we are interested in the consistency of the measurements of brain signals instead of the artefacts. In the low-frequency range (<4 Hz), spectra are often dominated by high-power ocular and motion artefacts with consistent spectral signatures. Were we to extend the window to below 4 Hz, data may appear consistent due to the consistency of artefactual spectral features, in which case spectral consistency would not be a good estimator of signal quality for within-device comparisons. Thus, we have chosen the spectral correlation between 4 and 20 Hz for quality assessment. Relationships between behavioural data and IAF variability were assessed using a Spearman correlation coefficient and the standard deviation of the day-to-day IAF.

For statistically insignificant *t*-tests ($p > 0.05$), we used Bayesian *t*-tests (Rouder et al., 2009) and reported the Bayes factors (BF) to provide additional information regarding whether the null hypothesis is preferred (e.g. Muse IAF is equal to HD-EEG IAF). The BF (Jeffreys, 1998; Kass & Raftery, 1995) is the ratio between the marginal likelihood of the null hypothesis and that of the alternative hypothesis:

$$B_{01} = \frac{M_0}{M_1}$$

where M_0 and M_1 are the marginal likelihood of the null hypothesis and the alternative hypothesis, respectively. For one-sample *t*-tests (Rouder et al., 2009) used in the present study, the marginal likelihoods are defined as

$$M_0 = \int_0^\infty f_0(y|\sigma^2)\, p_0(\sigma^2)\, d\sigma^2$$

and

$$M_1 = \int_0^\infty f_1(y|\mu,\sigma^2)\, p_1(\mu,\sigma^2)\, d\sigma^2\, d\mu$$

where f is the probability density function for observing data y, given the parameters σ^2 and μ and p denotes the prior distribution. The Bayes factors (BF_{01}) used in the present study were computed using JASP (Quintana & Williams, 2018), given the default prior (Cauchy distribution with a scale factor of 0.707). Based on Lee and Wagenmakers' (2014) classification scheme, BF_{01} between 1 and 3 indicates anecdotal evidence supporting

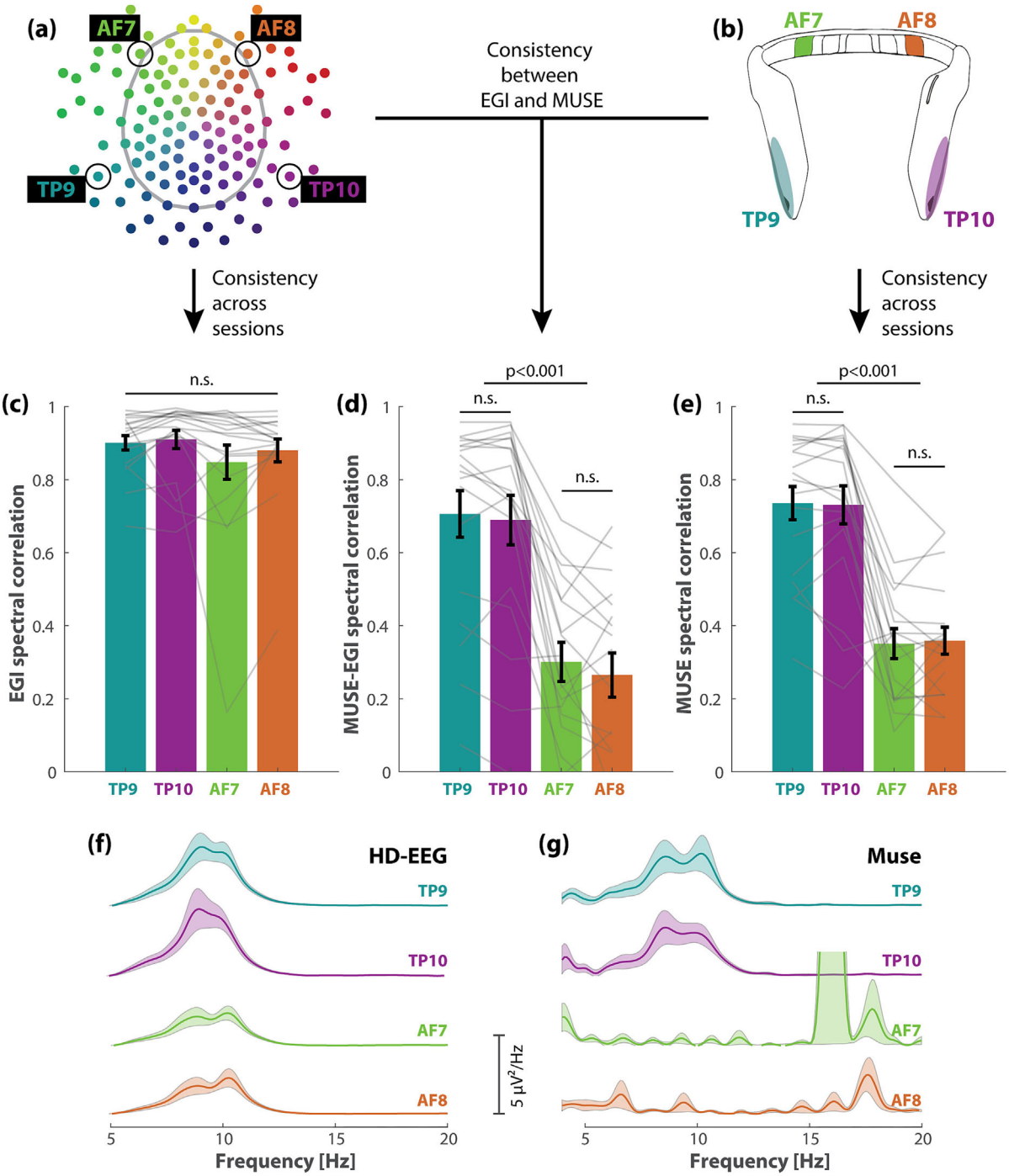

FIGURE 3 Assessing recording quality via spectral correlations. (a) HD-EEG layout with highlighted AF7, AF8, TP9 and TP10 electrodes. (b) Muse layout with highlighted AF7, AF8, TP9 and TP10 electrodes. (c) Spectral correlations between sessions for each highlighted HD-EEG electrode. (d) Averaged spectral correlations between each Muse recording and each HD-EEG session for specific electrodes. (e) Average spectral correlations between each Muse recording for electrodes of interest. (d,g) Error bars indicate standard errors. (f) Average HD-EEG spectra across all sessions and participants. (g) Average Muse spectra across all sessions and participants. (f,g) Colour bands indicate standard errors. The 1/f-removed spectra are shown between 0 and 6 $\mu V^2/Hz$.

the null hypothesis, BF_{01} between 3 and 10 indicates moderate evidence supporting the null hypothesis, and $BF_{01} > 10$ provides stronger support for the null hypothesis.

For comparisons of IAFs across the scalp, the term 'global IAF' describes the IAF value with the greatest power across the scalp during an eyes-closed resting-state recording.

3 | RESULTS

3.1 | High acceptability of at-home recording

We observed that participants generally found that the device was easy to use, the daily recordings were not a burden, and participation in a study of this type was enjoyable. Eighty-nine percent of participants reported that they enjoyed participating in the study, 89% thought setting up the Muse EEG device for the daily recording was straightforward, and 72% noted that the recordings did not interfere with their daily life.

3.2 | IAF estimated using HD-EEG and Muse were comparable at mastoid electrodes

The quality of the data captured from each electrode of interest was evaluated using spectral correlations prior to the rejection of low-quality sessions. High spectral correlations were found for the data from HD-EEG for AF7, AF8, TP9, and TP10 (Figure 3c). Contrarily, only TP9 and TP10 on the Muse device were consistent across sessions, whereas AF7 and AF8 dropped off significantly (Figure 3e). For a direct visual comparison, the average spectra from the two devices are shown in Figure 3f,g. These spectral correlation values represent the average of all correlation values between all Muse sessions. High spectral correlations were then found between Muse and HD-EEG for TP9 and TP10, but, again, AF7 and AF8 had significantly lower correlations (Figure 3d). The spectral correlations here were calculated by averaging all the correlation values between the Muse and HD-EEG recordings. Considering the poor correlations of AF7 and AF8 spectra and that eyes-closed alpha oscillations are generally strong in the posterior regions, only TP9 and TP10 were used in further data analyses. This is expected because alpha waves are most prominent in posterior areas of the scalp, and TP9 and TP10 were expected to be used for primary comparisons. Furthermore, we computed the percentage of rejected at-home sessions for each subject to assess how recording quality varied across subjects. Some participants consistently sent in poor-quality data, whereas others consistently sent in high-quality data. Approximately 28% of all participants had greater than 25% of their at-home sessions rejected due to subpar quality as assessed by visual inspection of artefacts.

IAF values were extracted from power spectra with aperiodic components removed. Although some participants have been previously observed to lack a systematic alpha peak (Haegens et al., 2014), all participants in this study had clear alpha peaks. Examples of these power spectra and the extracted peaks are shown across all recording electrodes for HD-EEG (Figure 4a) and all days from the Muse TP10 electrode (Figure 4b) of the same participant. Visually, Muse spectra were consistent across days (Figure 4b), and the IAFs in Muse (marked by 'x') are comparable to that of HD-EEG (Figure 4a) in both frequency and amplitude. The IAF dynamics over all at-home recording sessions of each subject are shown in Figure S2.

Extracted IAFs from location-matched electrodes were compared between the Muse at-home recordings and the HD-EEG in-lab sessions using a paired *t*-test. For the TP9 IAF, no statistically significant difference was found between the first Muse at-home recording and the first HD-EEG session ($t(17) = 1.73$, $p = 0.102$, $BF_{01} = 1.19$, SD = 0.30 Hz; Figure 5a) or between the final Muse at-home recording and the second HD-EEG session ($t(17) = -0.24$, $p = 0.816$, $BF_{01} = 3.87$, SD = 0.40 Hz; Figure 5b). Similar comparisons between Muse and HD-EEG were made for IAF extracted from TP10, where no significant difference was found between the first Muse at-home recording and the first HD-EEG session ($t(17) = -0.66$, $p = 0.520$, $BF_{01} = 3.40$, SD = 0.36 Hz; Figure 5c) or between the final Muse at-home recording and the second HD-EEG session ($t(17) = 1.53$, $p = 0.144$, $BF_{01} = 1.13$, SD = 0.45 Hz; Figure 5d). To examine whether the difference in IAF estimation between Muse and HD-EEG depends on the frequency, we show the Bland–Altman plots for IAF differences between two devices across subjects and sessions in Figure 5e,f for TP9 and TP10, respectively. There was no significant correlation between the inter-device difference in IAF and the average IAF at TP9 ($r = -0.25$, $p = 0.14$) or TP10 ($r = -0.05$, $p = 0.78$). Thus, there was no evidence that Muse's accuracy was biased for specific frequencies. We performed the same analyses for alpha power at IAF and found no significant difference between Muse and HD-EEG (Figure S3).

The first and final collected values for both electrodes for both recording devices were compared to measure the stability of the IAF across the 4-week period. The IAF extracted from the first at-home recording using the Muse 2 headband was compared to that of the final at-home recording. For TP9, no significant difference was found ($t(17) = -0.30$, $p = 0.77$, $BF_{01} = 3.95$, SD = 0.40 Hz; Figure 6a). For TP10, there was no significant difference ($t[17] = -0.56$, $p = 0.58$, $BF_{01} = 3.57$, SD = 0.50 Hz; Figure 6b). Additionally, the IAFs extracted from the HD-EEG recordings in the first and second session were also compared using a paired *t*-test. For TP9, no significant difference was found ($t(17)$

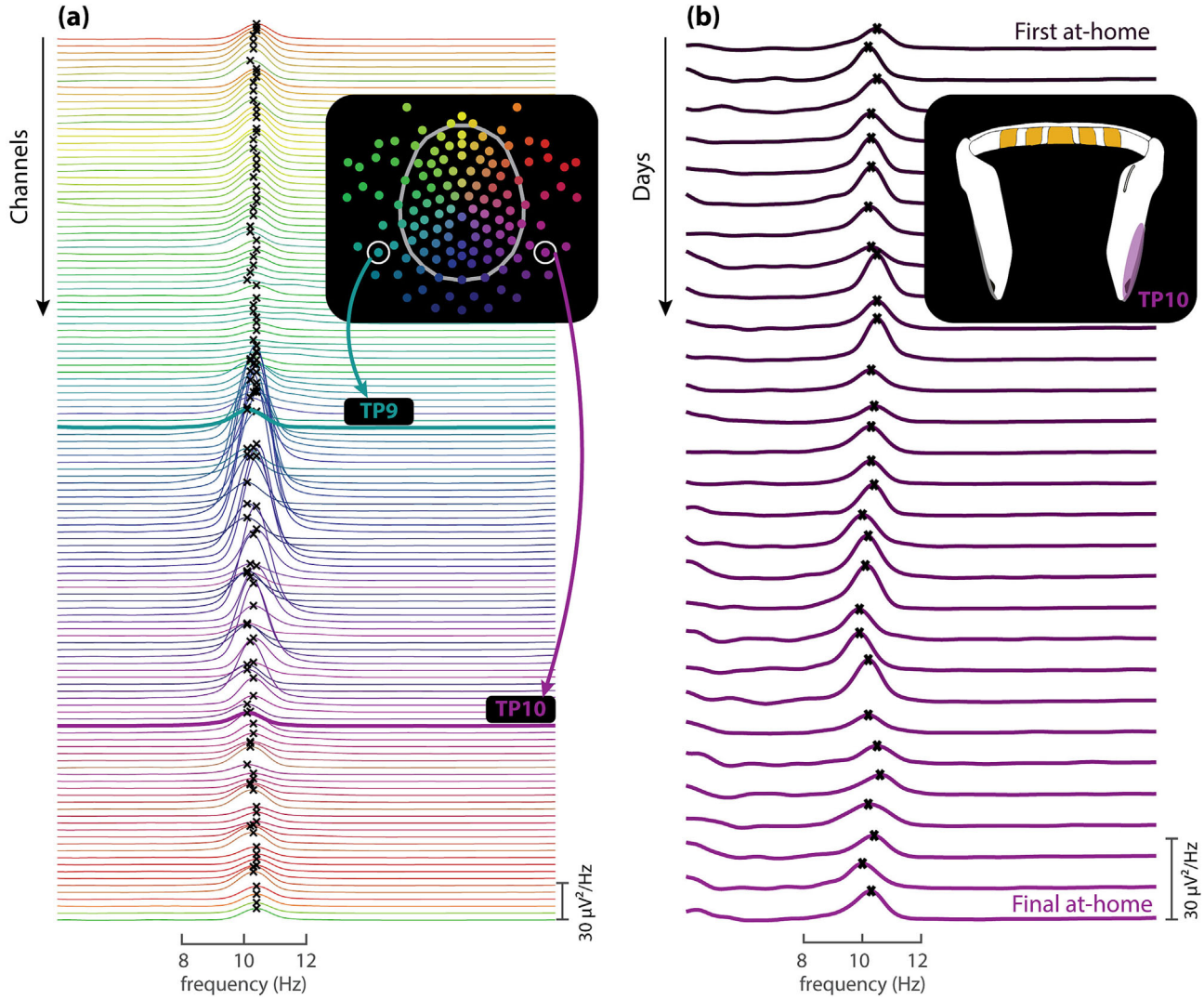

FIGURE 4 Example power spectra from HD-EEG and MUSE. (a) Example power spectra from the first session of one participant for all electrodes of the HD-EEG system. 'x' marks the extracted IAF for each channel. (b) Example power spectra for all days of at-home recordings from TP10 on the Muse device for the same participant.

$= -0.88$, $p = 0.39$, $BF_{01} = 3.22$, SD = 0.35 Hz; Figure 6c). TP10 comparisons were also found no significant difference ($t(17) = 1.45$, $p = 0.17$, $BF_{01} = 0.73$, SD = 0.44 Hz; Figure 6d). Finally, the changes in IAF between Muse and HD-EEG for each electrode were compared. Changes in TP9 for Muse versus HD-EEG were not significant ($t(17) = -1.00$, $p = 0.33$, $BF_{01} = 2.82$, SD = 0.42 Hz; Figure 6e). Changes in TP10 for Muse versus HD-EEG were marginally significant ($t(17) = 1.82$, $p = 0.09$, $BF_{01} = 0.83$, SD = 0.50 Hz; Figure 6f). No significant correlations were observed between the behavioural self-report questionnaires and the changes in IAF for the first and second session for both Muse and HD-EEG (see Table S1 and Table S2 for correlation coefficients and *p*-values from Session 1 and Session 2, respectively). We performed the same analyses for alpha power extracted at IAF. We found no significant change in alpha power over the course of 4 weeks in either Muse or HD-EEG; there was no significant difference in the changes in alpha power between Muse and HD-EEG (Figure S4).

For all the above analyses, HD-EEG spectra were computed from minimally processed EEG data (e.g. no ICA-based artefacts rejection) to ensure a fair comparison with Muse spectra, for which advanced artefact rejection techniques are not applicable due to low density of electrodes. Nevertheless, we performed additional analysis to examine whether using extensively preprocessed data following a standard EEG preprocessing pipeline (see Section 2) will produce more stable estimates of IAF across two sessions. To do so, we extracted the global IAF (peak with the highest spectra power across scalp

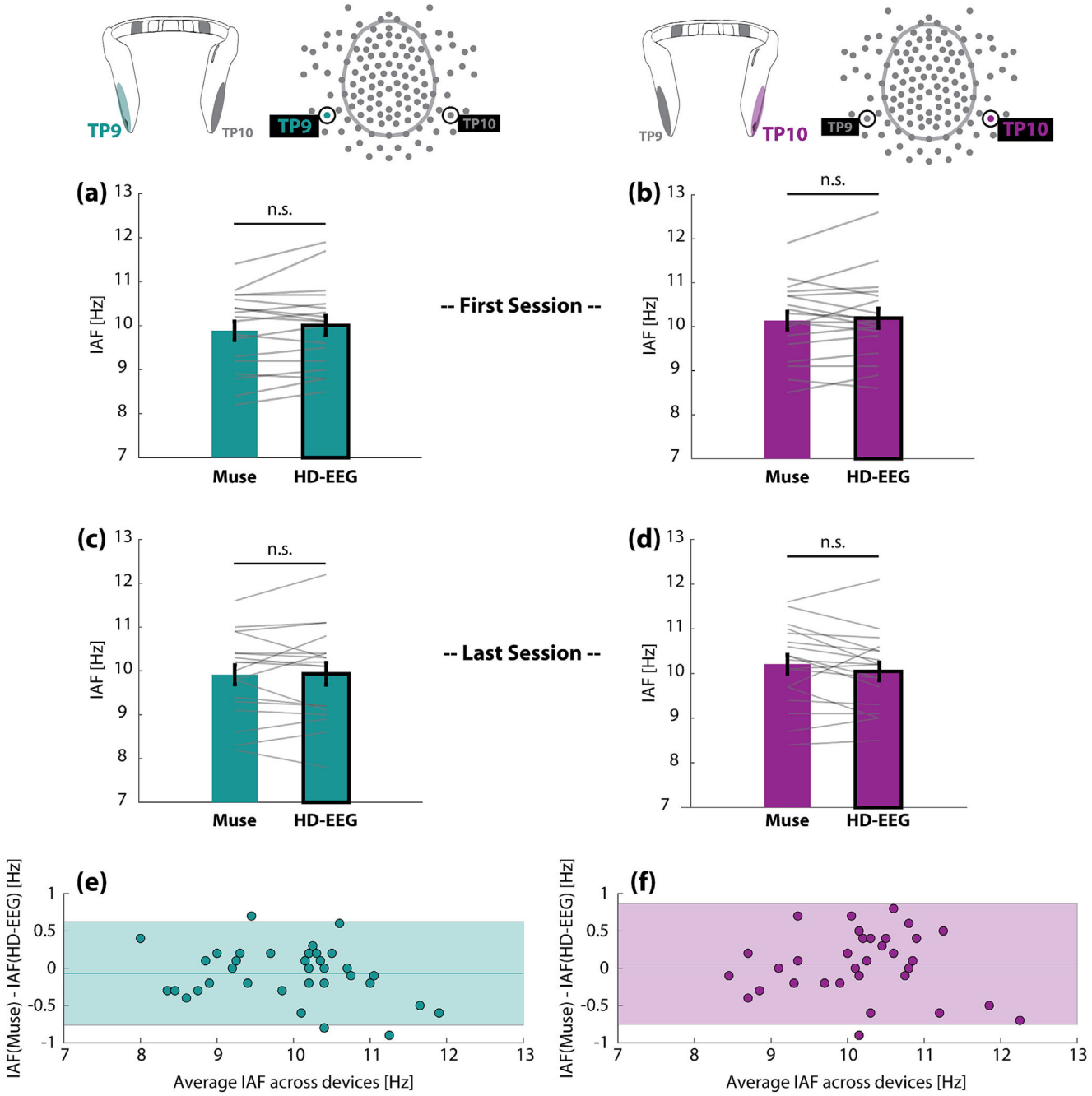

FIGURE 5 IAFs extracted from HD-EEG and Muse are comparable. Maps of the location of TP9 and TP10 on both the Muse device and HD-EEG system are included for reference purposes. (a) Extracted IAF from the TP9 Muse electrode of the first at-home recording versus the extracted IAF of the HD-EEG TP9 of in-lab session 1. (b) IAF of Muse TP10 during the first at-home recording versus that of HD-EEG during the first in-lab session. (c) Muse TP9 IAF from final at-home recording versus HD-EEG TP9 IAF from in-lab session 2. (d) TP10 Muse IAF from final at-home recording versus HD-EEG TP10 IAF from the second in-lab session. (e) Bland–Altman plot for IAF at TP9 measured in both devices and sessions, where each dot represents a specific subject session. The x-coordinate of each dot reflects the average IAF between Muse and HD-EEG, and the y-coordinate of each dot reflects the difference in IAF between the two devices. The coloured horizontal line indicates the mean difference between devices for all samples, and the coloured area indicates the ±1.96 standard deviation from the mean. (f) Bland–Altman plot for IAF at TP10 measured in both devices and sessions. Detailed interpretation of the graph follows (e).

electrodes; see Figure 8) from spectra computed from both minimally and extensively preprocessed HD-EEG data. For the first session, 15 out of 18 participants showed identical IAF for both preprocessing pipelines (at 0.1 Hz spectral resolution); two out of 18 participants showed a 0.1 Hz higher IAF in the extensively

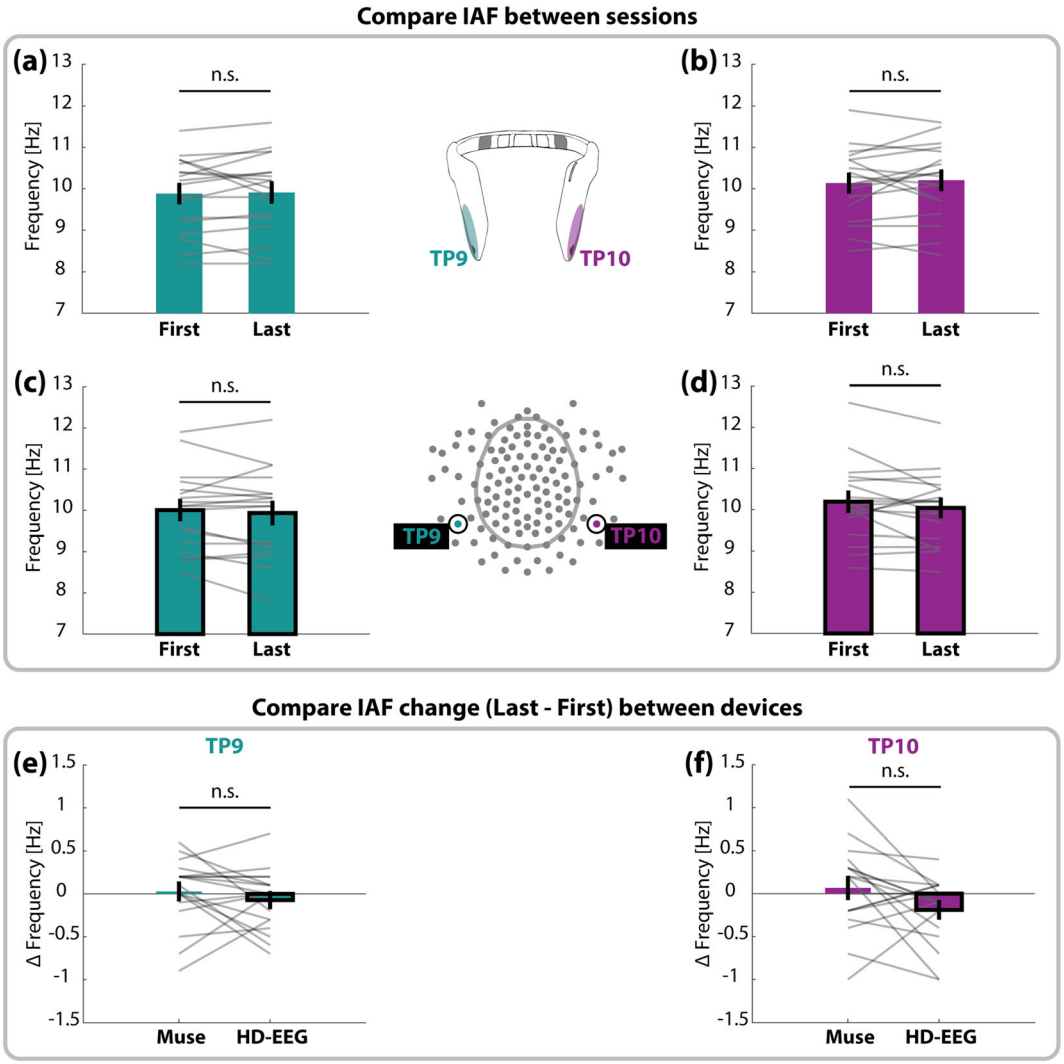

FIGURE 6 Changes in IAF value over 4 weeks are comparable between HD-EEG and Muse. (a) Muse TP9 IAF comparisons of first at-home recording versus final at-home recording. (b) Muse TP10 IAF comparisons of first-at home recording versus final at-home recording. (c) HD-EEG TP9 IAF comparisons of first in-lab session versus second in-lab session. (d) HD-EEG TP10 IAF comparisons of first in-lab session versus second in-lab session. (e) Changes in Muse TP9 IAF versus changes in HD-EEG TP9 IAF. (f) Changes in Muse TP10 IAF versus changes in HD-EEG TP10 IAF.

preprocessed data compared with the minimally preprocessed data; one out of 18 participants showed a 0.2 Hz higher IAF in the extensively preprocessed data compared to the minimally preprocessed data. The difference between the two pipelines is not significant ($t(17) = 1.14$, $p = 0.269$). For the last session, 14 out of 18 participants showed identical IAF across pipelines; three out of 18 participants showed a 0.1 Hz lower IAF in the extensively preprocessed data; one out of 18 participants showed a 0.3 Hz higher IAF in the extensively preprocessed data. The difference between the two pipelines is not significant ($t(17) = -0.27$, $p = 0.790$). Further, we compared the two pipelines in terms of the change in IAF across two sessions, which is also not significant ($t(17) = -1.29$, $p = 0.215$). However, we found greater absolute changes in IAF across sessions in the extensively preprocessed data compared with the minimally preprocessed data ($t(17) = 3.06$, $p = 0.007$). For a breakdown, 11 out of 18 participants showed identical absolute IAF changes; six out of 18 participants showed a 0.1 Hz greater absolute IAF change in the extensively preprocessed data; one out of 18 participants showed a 0.2 Hz greater absolute IAF change in the extensively preprocessed data. This result indicates that extensive preprocessing introduces additional IAF variability across sessions. This is not entirely surprising as (1) common artefacts rarely have spectral peaks in the alpha band with comparable power to the real alpha peak and (2) artefact rejection based on spatial filtering such as Artifact Subspace Reconstruction and ICA often removes some genuine brain signals as

contaminated components are removed (Chang et al., 2018). Thus, in the following analyses, we only used IAF derived from the minimally preprocessed data for HD-EEG.

3.3 | Day-to-day variability of IAF was associated with anxiety

Several exploratory analyses were conducted to examine the correlation between IAF day-to-day variability as measured by standard deviation and various behaviours measured by the self-report questionnaires. All Spearman correlation coefficients and relevant *p*-values are displayed in Figure 7 for significant findings. Correlation coefficients and *p*-values between variability and all self-report behavioural measures for the first and second session can be found in Tables 1 and 2, respectively. Comparisons between the standard deviation of Muse TP9 and STAI Trait Anxiety Score of the first session revealed a significant correlation. Similarly, the standard deviation of Muse TP9 and the STAI Trait Anxiety Score obtained during Session 2 were also significantly related (Figure 7b). The standard deviation of Muse TP10 also had a significant relationship with the STAI Trait Anxiety of in Session 1 (Figure 7c). Finally, the STAI Trait Anxiety Score from Session 2 was significantly related to the standard deviation of Muse TP10 (Figure 7d). Additionally, no significant correlation was observed between the number of rejected sessions and anxiety, thus suggesting that anxiety is not correlated with signal quality. Across 1 month, the average standard deviation for both TP9 and TP10 was 0.28 Hz, with a minimum of 0.16 Hz and a maximum of 0.54 Hz.

3.4 | IAF varied across space

The consistency of the alpha peak across different regions of the brain was also explored. To accomplish this, the

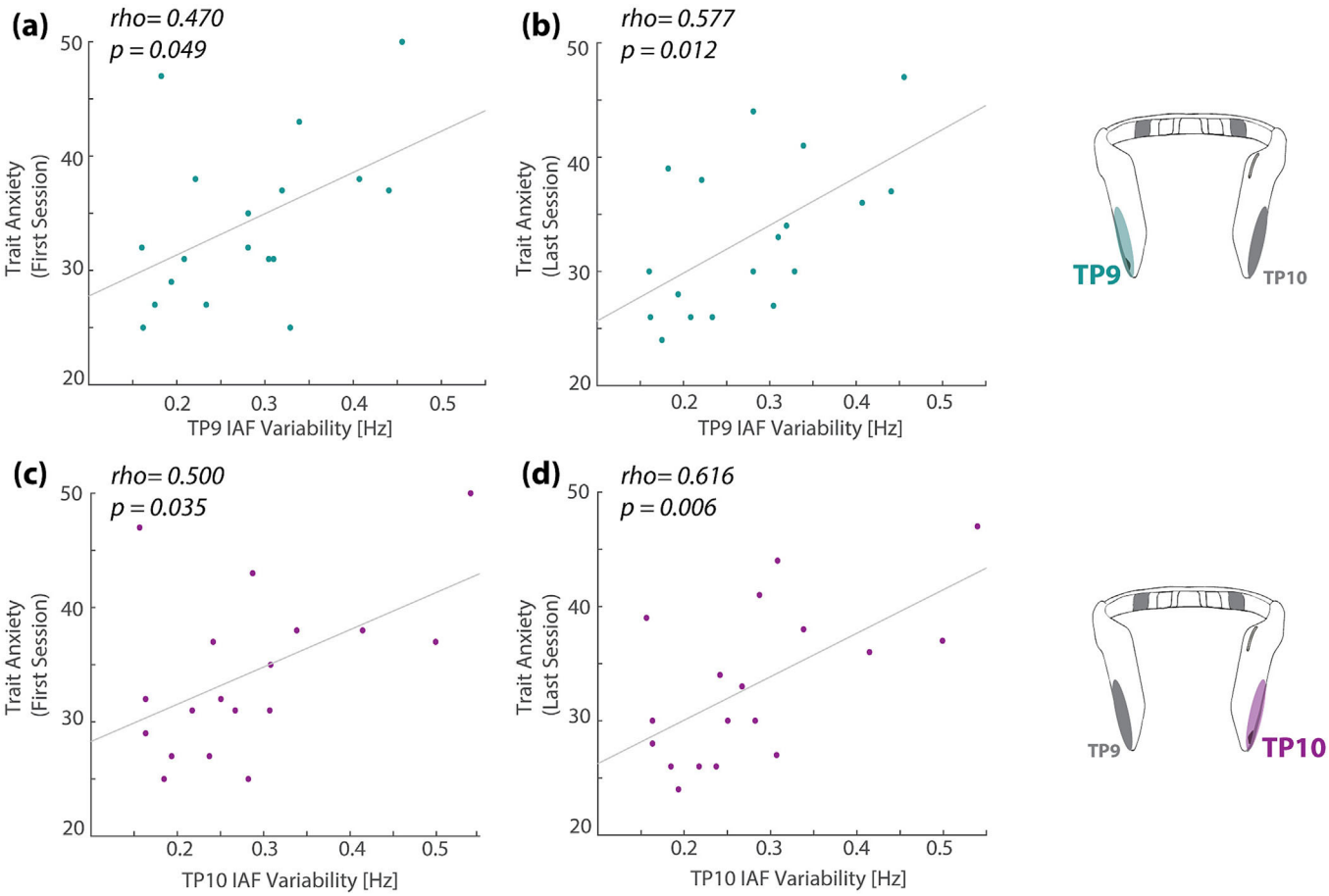

FIGURE 7 At-home IAF variability correlates with trait anxiety. (a) Day-to-day TP9 IAF standard deviation versus in-lab session 1 trait anxiety score (STAI). (b) Day-to-day TP9 IAF standard deviation versus in-lab session 2 trait anxiety score (STAI). (c) Day-to-day TP10 IAF standard deviation versus in-lab session 1 trait anxiety score (STAI). (d) Day-to-day TP10 IAF standard deviation versus in-lab session 2 trait anxiety score (STAI).

TABLE 1 First session correlations between IAF variability and self-report behavioural measures.

	TP9		TP10	
Measure	**rho**	***p***	**rho**	***p***
STAI-Trait	0.470	0.049*	0.500	0.035*
STAI-State	0.412	0.089	0.366	0.135
BDI	0.132	0.601	0.065	0.798
BIS	0.206	0.412	0.221	0.378
BAS-Fun	−0.260	0.298	−0.278	0.264
BAS-Drive	−0.134	0.597	−0.099	0.696
BAS-Reward	−0.089	0.726	−0.059	0.816

TABLE 2 Last session correlations between IAF variability and self-report behavioural measures.

	TP9		TP10	
Measure	**rho**	***p***	**rho**	***p***
STAI-Trait	0.577	0.012*	0.616	0.006*
STAI-State	0.452	0.060	0.452	0.060
BDI	0.102	0.687	−0.034	0.894
BIS	0.318	0.198	0.381	0.119
BAS-Fun	−0.386	0.114	−0.427	0.078
BAS-Drive	−0.103	0.685	0.023	0.929
BAS-Reward	−0.133	0.598	−0.090	0.723

IAF captured from the location-matched electrodes was compared with the IAF with the highest power across all 128 electrodes of the HD-EEG system, termed the 'global IAF'. The global IAF was significantly greater than the TP9 IAF in the first session ($t(17) = -3.36$, $p = 0.004$, SD = 0.66 Hz; Figure 8a) and the second session ($t(17) = -3.06$, $p = 0.007$, SD = 0.68 Hz; Figure 8b). Similar observations were made for TP10. The global IAF was significantly greater than the TP10 IAF for the first session ($t(17) = 3.11$, $p = 0.006$, SD = 0.46 Hz; Figure 8c) and the second session ($t(17) = -3.29$, $p = 0.004$, SD = 0.49 Hz; Figure 8d). Overall, the local IAFs at TP9 and TP10 were lower than the global IAF. Differences in IAF are not, however, observable exclusively in these regions. A range of IAF values is seen across the scalp, varying across different regions (Figure 8e). Although the TP9 and TP10 IAFs were significantly different from global IAFs, the global IAF could be linearly predicted from these temporal electrodes (Figure 9). We observed that the TP9 IAF and global IAF in the first session had a significantly high correlation (rho = 0.79, $p = 9.9e\text{-}5$) and that this relationship could be modelled by $y = 0.90x + 1.52$ (y denotes global IAF; x denotes local IAF here after). Similar correlation findings were made between TP9 IAF and global IAF in the second session (rho = 0.83, $p = 2.3 \times 10^{-5}$) and that this relationship could be modelled by $y = 0.82x + 2.25$. In the first session, the TP10 IAF and the global IAF were significantly correlated (rho = 0.87, $p = 2.1 \times 10^{-6}$), and the relationship could be modelled by $y = 1.03x + 0$. In the second session, the TP10 IAF and the global IAF were also highly correlated (rho = 0.92, $p = 4.3 \times 10^{-8}$) and this relationship could be modelled by $y = 1.18x - 1.35$.

4 | DISCUSSION

In this study, we used the Muse headband, a mobile EEG device, to study IAF stability by daily measurements and compare the at-home recording quality to HD-EEG recorded in the lab. We found that the temporal electrodes of the Muse device, when coated in electrode gel before each recording, are suitable for daily at-home recordings for examining the daily dynamics of IAF, which yield comparable IAF estimates to HD-EEG. IAF was found to be stable over the time scale of a month, and the smaller fluctuations appear to be biologically meaningful due to their correlation with trait anxiety levels.

Studying the stability of IAF depends on the ability of the Muse device to record usable data comparable to a research-grade device. Previous research regarding the quality of the data collected from the device has had mixed results. Those that did not utilize electrode gel observed a greater presence of artefacts than brain activity and overall more variability in the measurements (Przegalinska et al., 2018; Ratti et al., 2017). However, Wilkinson et al. (2020) utilized electrode gel and observed that TP9 and TP10 effectively captured neural oscillations data, whereas AF7 and AF8 were unusable (Wilkinson et al., 2020). These findings are consistent with the high spectral correlations for TP9 and TP10 and low spectral correlations for AF7 and AF8 observed in this study. Even without electrode gel, many studies have utilized this device and claim to have found meaningful results (Cannard et al., 2021; Hashemi et al., 2016; Hawley et al., 2021; Hunkin et al., 2021; Krigolson et al., 2017). We determined that although using electrode gel may decrease the generalizability of the device, the stark improvement in the signal quality makes this a worthwhile trade-off. Notably though, in an acceptability survey conducted at the end of the study, participants noted that the Muse device setup, including the gel application process, was straightforward and relatively easy. Although we recognize that this will decrease the generalizability of the device overall, we suspect that the

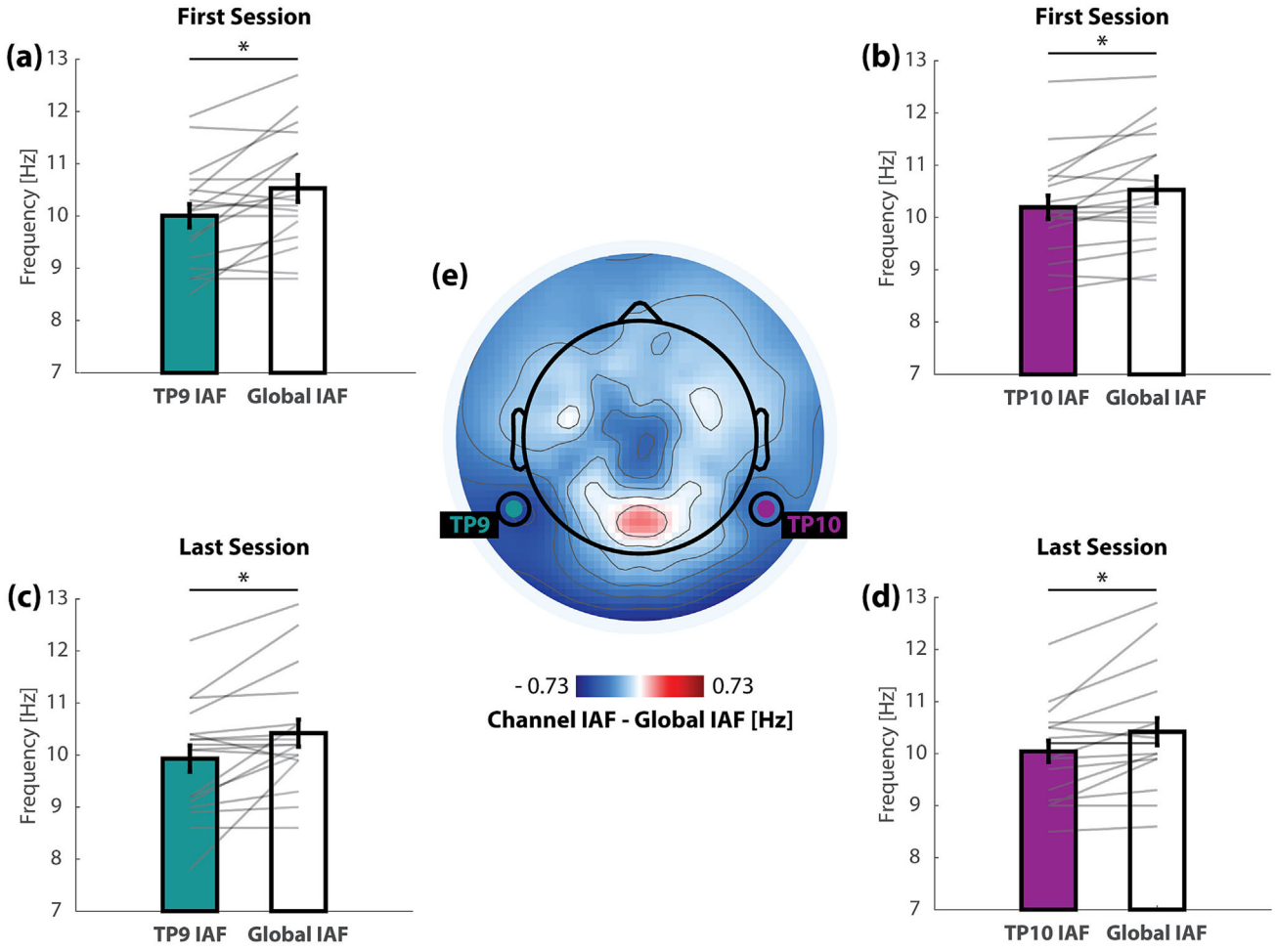

FIGURE 8 Channel IAF values differ from global IAF. (a) In-lab session one HD-EEG TP9 IAF versus HD-EEG global IAF (i.e. the alpha peak with the highest power over all HD-EEG channels). (b) In-lab session one HD-EEG TP10 IAF versus HD-EEG global IAF. (c) In-lab session two HD-EEG TP9 IAF versus HD-EEG global IAF. (d) In-lab session two HD-EEG TP10 IAF versus HD-EEG global IAF. (e) Topography plot showing channel IAF values vary across the scalp.

impact of adding gel on generalizability is limited. Building on existing studies, the present work provides a more comprehensive validation of the quality of the Muse data both by visual inspection and by direct comparison to HD-EEG. Furthermore, by 1/f fitting, we controlled for the contribution of aperiodic signals such that our estimations of IAF and its variability would better reflect the features of alpha oscillations. Previous studies have compared the Muse device to HD-EEG devices but either did not utilize electrode gel (Ratti et al., 2017) or used TP9 and TP10 as reference electrodes (Cannard et al., 2021), limiting the comparability of recording quality. Future research that plans to employ these devices should consider whether they are suitable for the region of interest, as those in anterior regions of the brain may not be effectively captured by this device. This is particularly important for features such as frontal alpha asymmetry that have been associated with mood disorders (Riddle et al., 2021). Studying these regions may be better pursued by utilizing a different mobile EEG device or by exploring ways to improve the signal quality of these electrodes beyond using electrode gel. More specifically, it may be useful to employ a device with a reference electrode further from the frontal recording electrodes. Additionally, the materials used for the AF7 and AF8 electrodes were different from that of TP9 and TP10. The soft silicone material used for TP9 and TP10 may be better at effectively capturing signals compared to the frontal electrodes. All these factors are worth considering when evaluating how to approach a specific region of interest. Regardless, for the study of alpha or other oscillations prominent in regions surrounding TP9 and TP10, the Muse device makes a viable candidate for evaluating neural activity and signatures in these regions.

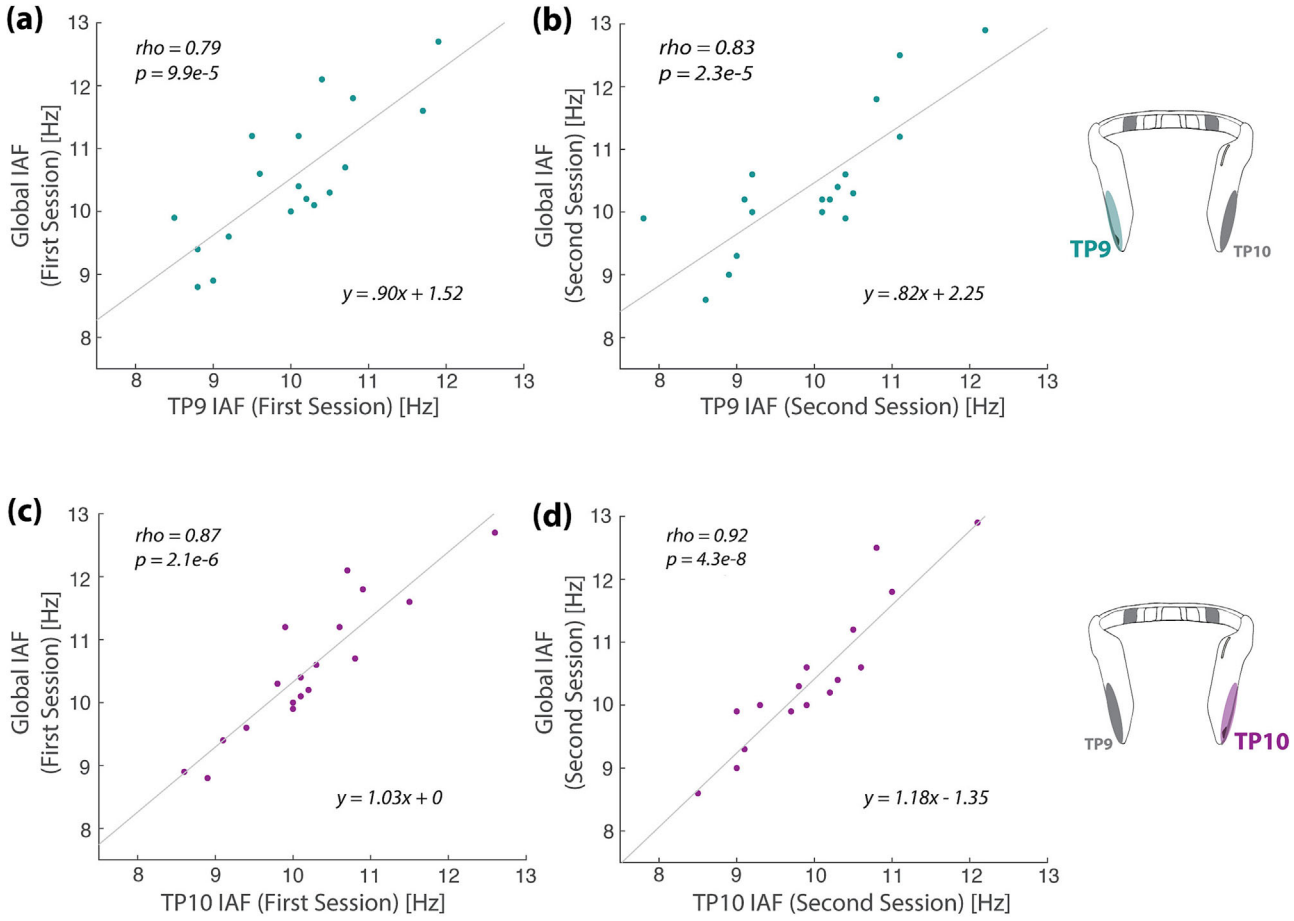

FIGURE 9 Location-matched HD-EEG IAFs correlate with and predict global HD-EEG IAF values. Linear models were used to predict global IAF by channel IAFs: (a) TP9 IAF of the first session, (b) TP9 IAF of the second session, (c) TP10 IAF of the first session, and (d) TP10 IAF of the second session.

In addition to achieving acceptable data quality, we also demonstrated that long-term at-home recording with Muse is feasible. A previous study successfully incorporated at-home recordings using the device to assess mindfulness (Hunkin et al., 2021). It has also been used successfully in a long-term at-home recording study in a clinical population, namely, obsessive–compulsive disorder (Hawley et al., 2021). These studies utilized the mindfulness and mind wandering scores generated by the proprietary software instead of analysing and validating the power spectra collected as is common in EEG studies. In contrast, the present work directly examines the EEG time series and power spectra, providing the opportunity to validate the signal quality of at-home recordings. We found more than 70% of the participants were able to collect high-quality data on a daily basis. This suggests that it is feasible to study day-to-day brain dynamics using mobile EEG device at home. Future work may further improve the signal quality through more frequent data quality checks and intervening with participants early on to minimize misunderstandings regarding device usage.

Given our findings that those with a less stable day-to-day IAF had greater trait anxiety, the variability of the IAF itself may be of interest. To our knowledge, this is the first demonstration of the relation between day-to-day variability of IAF and anxiety, enabled by the use of mobile EEG devices. Trait-like features require long-term studies opposed to single-session analysis. It is thus reasonable to expect that the neural correlates of trait anxiety would better manifest over longer periods of time, such as in the present study. Although IAF has not been previously related to anxiety, alpha oscillations have. Most of these findings, however, were more concerned with power or synchronization rather than frequency (Cantero et al., 2002; Knyazev et al., 2004, 2006). Our findings demonstrate that frequency variability may also play an integral role in the relationship between alpha and anxiety. Future work can incorporate causal manipulations of IAF to investigate the underlying mechanism of this observation.

Given the differences in IAF across different areas of the brain, questions remain about whether the IAF

should be defined as a singular feature of the whole brain or a region-specific property. There is a clear spatial organization whereby posterior regions have the fastest IAF, the temporal lobe has a slower IAF and other regions have in-between values. This finding suggests that alpha oscillations may serve different purposes in different areas of the brain (Zhang & Frohlich, 2022). This is not a new concept—the mu rhythm, although around the same frequency as alpha, has been uniquely associated with the motor cortex (Kuhlman, 1978). There also exists a similar phenomenon with the tau rhythm in the temporal lobes (Niedermeyer, 1990). Perhaps a similar construct exists for other cortices of the brain regarding oscillations in the alpha frequency band. Recent theories have also suggested that alpha may have a broader role in different cognitive functions across the cortex (Klimesch, 2012; Klimesch et al., 2007). Altogether, it could be beneficial to view the alpha oscillation not as a single oscillation but rather as a distributed set of region-specific oscillators engaging in global coordination. The spatial distribution rather than a single value of IAF, together with their behavioural correlates, should be a future point of research.

Several limitations existed within this study. No day-to-day behavioural assessments were conducted at the same time the at-home recordings were submitted to the research team. This limited our ability to understand fluctuations in state anxiety and its potential relationship with IAF variability. This could be an interesting new direction, given our present findings on trait anxiety. Additionally, because exclusively mentally healthy individuals were included in this study, it would be interesting to see if those who meet the criteria for an anxiety disorder have different IAF variabilities. The Muse device also contained only four recording electrodes. This limited the number of regions that could be studied. Furthermore, with this limited number of electrodes, spatial relationships could not be made between oscillations across the scalp. The lack of spatial resolution greatly limited the possibility of using artefact rejection methods such as ICA for the Muse data. Additionally, only alpha oscillations were examined as part of this work. Other oscillations, including theta, beta and gamma, could potentially be studied using the Muse device, and this would be a fascinating new avenue of research given our present findings. It is worth noting, however, that the lack of automated artefact rejection, particularly for eye blinks, could lead to difficulties in studying theta oscillations on long-term scales.

In conclusion, this study demonstrates the potential for using mobile EEG devices for at-home data collection for extended periods of time and the potential for using IAF day-to-day variability as a biomarker. Utilizing these devices could allow for a more comprehensive understanding of brain dynamics. This study opens new possibilities to study day-to-day variability of brain dynamics at home using mobile EEG devices. Further development of this approach could help us better understand the mechanism of psychiatric disorders at various time scales.

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CONFLICT OF INTEREST STATEMENT

LS, MZ and SD have no competing interests to declare. FF is the lead inventor of IP filed on the topics of non-invasive brain stimulation by UNC. FF is a paid consultant for Electromedical Products International and has received honoraria from the following entities: Academic Press, Insel Spital and University of Michigan.

DATA AVAILABILITY STATEMENT

EEG spectra that have gone through our processing pipeline with aperiodic components removed are available on OSF: https://osf.io/jesud/?view_only=73b2b24997894c37a39e3fe2f86e6f06.

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PEER REVIEW

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