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Crowdsourced EEG experiments: A proof of concept for remote EEG acquisition using EmotivPRO Builder and EmotivLABS

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ABSTRACT

The development of online research platforms has made data collection more efficient and representative of populations. However, these benefits have not been available for use with cognitive neuroscience tools such as electroencephalography (EEG). In this study, we introduce an approach for remote EEG data collection. We demonstrate how an experiment can be built via the EmotivPRO Builder and deployed to the EmotivLABS website where it can be completed by participants who own EMOTIV EEG headsets. To demonstrate the data collection technique, we collected EEG while participants engaged in a resting state task where participants sat with their eyes open and then eyes closed for 2 min each. We observed a significant difference in alpha power between the two conditions thereby demonstrating the well-known alpha suppression effect. Thus, we demonstrate that EEG data collection, particularly for frequency domain analysis, can be successfully conducted online.

1. Introduction

The use of online research platforms for cognitive science has seen an increase in the past decade, with 10%–30% of articles in cognitive science journals using online data collection marketplaces [1]. Currently, the most commonly used online participant recruitment agencies include Amazon Mechanical Turk (MTurk), Prolific Academic, and CrowdFlower. These platforms provide researchers access to 10 k - 500 k of unique participants with diverse demographics [2]. The use of these online marketplaces has also been made more accessible to coding-naive researchers through javascript hosting platforms such as Pavlovia and Google SDK, and experiment builders such as PsychoPy3 (www.psychopy.org), jsPsych (www.jspsych.org), and Gorilla Experiment Builder (www.gorilla.sc). Research has shown these platforms to be accurate and precise with regards to display duration and response time logging across many hardware configurations [3]. The proliferation of these online research tools has benefited researchers through access to larger and more diverse participant samples, increased experimental administration efficiency, and streamlined participant recruitment, all while yielding quality and reliable data similar to that collected in laboratory experiments [4,5].

A significant concern with in-person data collection is that the current literature is dominated by convenience samples consisting of narrow demographic profiles [6]. Practical constraints of testing in traditional university laboratories often result in participant samples of convenience (e.g., first-year psychology students). Online testing alleviates some of this concern by giving access to a

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broader diversity of participants. Online testing also mitigates public health concerns as studies can be conducted without physical contact. This is particularly important considering the COVID-19 pandemic in which experimental research was severely disrupted [7]. By eliminating physical contact, online testing provides an alternative for continuing safe human-participant research during a public health crisis. While studies involving "hands-on" experiments, such as cognitive neuroscience research, have been disproportionately disrupted, unfortunately many of these types of experiments cannot be conducted online. This is because they use methods such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and functional near-infrared spectroscopy (fNIRS) that require expensive, specialized devices that cannot be widely deployed or are unavailable to the general public.

Traditionally, EEG data is collected in a dedicated laboratory using expensive research-grade equipment that requires lengthy set up times, inordinate physical contact, and significant amounts of participant organization and administration. However, technological advances in the commercial EEG sector have resulted in the development of low-cost, wireless, consumer-grade EEG devices. Some of these systems have been adopted by the research community (see review by Sawangjai et al. [8]) resulting in more accessible and widespread EEG research. For example, Emotiv, Neurosky, InteraXon and OpenBCI have all released various consumer grade EEG systems that are all cost-effective (less than $1000 USD) and available to both scientific researchers as well as the general public.

EEG hardware advances only represent part of the solution with respect to online testing potential. Another requisite is an online platform capable of simultaneously presenting experiments and recording EEG data. Emotiv has recently developed an online platform, EmotivPRO Builder, that lets users build experiments within a browser-based graphical user interface. These experiments can then be published and made available to a contributor pool composed of Emotiv EEG system owners. Researchers can also use the EmotivLABS platform to collect data locally (for laboratory testing), making it a versatile tool for EEG experiment administration and data collection.

In the decade since the release of the first iteration, EPOC has been widely used by the scientific research community (for a review see Williams et al. [9]). EPOC is a 14-channel wireless EEG system that uses saline-soaked felt pads for signal conduction and has been empirically validated against research-grade systems (e.g., Neuroscan) and shown to record research-quality data [10–12]. Another system, EPOC Flex, is a 32-channel system that allows users to configure sensor placements within a traditional headcap. This system has also been validated against Neuroscan and shown to measure reliable auditory and visual event-related potentials (ERP), steady-state visual evoked potentials (SSVEP), and changes in alpha signatures [13].

Taken together, the issues of representative sampling and public health clearly outline the benefits of an online EEG data collection platform that would increase the capacity to study underrepresented groups while also maintaining safe interactions during disease outbreaks. Thus, the purpose of this paper was to present a novel online EEG data collection platform. To do this, we used a simple resting state task to determine whether we could detect a well-known EEG phenomenon - alpha suppression - which is the decrease of alpha power when the eyes are open compared to when they are closed [14–16].

2. Materials and methods

2.1. Participants

Participants were self-selected from the existing traffic on the EmotivLABS website. To contribute, participants must have possessed an Emotiv EEG headset. They also must have had an internet connection of at least 5 Mbps. To promote the study, we sent a one-time email to existing headset owners that included a link to the study. Participants were instructed to take the study at their convenience. The experiment was published to EmotivLABS on November 9th, 2020 and remained available until August 14th, 2021. Participants were not incentivised and participation was completely voluntary. This study was approved by the Ethics Committee of Macquarie University (Ref: 5201831203493). All participants provided web-based informed consent before proceeding with the experiment.

2.2. Sample size

During the period in which the experiment was active on EmotivLABS website, 105 recordings were initiated by 60 unique participants. Of the 60 unique participants, only 28 participants successfully completed both Eyes Open and Eyes Closed conditions. For cases in which a single participant made two successful recordings, the first recording was retained and the second was excluded in the analysis. Overall, we received data from four INSIGHT, one EPOC, six EPOC+, and six EPOCX systems. We also received data from one EPOCFLEX, but it was excluded from analysis as it cannot be pooled with the other headsets due to the differing sensor count. Thus, 26 complete EEG recordings from 26 unique participants were processed and analyzed. Statistical analysis was conducted separately for INSIGHT ($N = 14$) and EPOC/EPOC+/EPOCX ($N = 12$) headsets.

Overall, there were 77 recordings that did not meet the criteria for this study. In 14 cases participants skipped the EEG quality (EQ) gate, which is powered by a machine-learning algorithm that assesses EEG signal characteristics (further description of EQ provided in the Data Acquisition section).Thirty-seven recordings were abandoned without completing the EQ gate. In another 26 recordings participants passed the gate but abandoned the experiment before completion. Finally, one recording was a duplicate where a participant completed the experiment twice.

2.3. Participant demographics

Of the 26 participants, 25 specified their age (Fig. 1A). These ranged from 18 to 64 ($M = 37.7$, $SD = 12.9$). Genders included twenty males, five females, and one unspecified gender (Fig. 1B). Twenty-one participants were right-handed, four were left-handed, and one ambidextrous based on self-reported writing hand. Education levels ranged from high school to doctoral degree (see Fig. 1 and Table 1 for demographic profiles). Participant recordings were initiated from the United States (n = 8), Australia (n = 2), Sweden (n = 2), Argentina (n = 2), Iran (n = 2) and one each from Czech Republic, Egypt, Spain, United Kingdom, Singapore, Turkey, Lithuania, Finland, Mexico, and an unspecified country.

2.4. Data acquisition software: EmotivPRO Builder and EmotivLABS

The experiment was built using EmotivPRO Builder which is a web-based interactive platform that allows users to build experiments using a graphical user interface. The experiment was published to EmotivLABS "Citizen Science" (https://labs.emotiv.com/), where the study was publicly visible to all visitors. All instructions and stimuli were delivered to the participant through this online platform.

2.5. EEG devices

Participants in this study used one of the following EEG devices: EMOTIV INSIGHT, EPOC, EPOC+, or EPOCX. Although EPOC, EPOC+, and EPOCX are different models, they have a similar form factor and sensor configuration and only differ slightly in their technical specifications. Thus, for simplicity we subsequently refer to all three systems collectively as EPOC.

All Emotiv systems are wireless and connect to the participant's computer through EmotivPRO software using either an USB Receiver Dongle or the computer's native Bluetooth adapter (See Table 2 for headset details). The EPOC and INSIGHT headsets sample the EEG data internally at 2048 KHz. Before the data is transmitted wirelessly to the recording computer, the data is downsampled to either 256 Hz or 128 Hz. This is done after a dual notch filter at 50 Hz and 60 Hz and an antialiasing filter has been applied to reduce mains-line noise and the aliasing of frequencies higher than 64 Hz into the transmitted data.

2.6. Data acquisition

After initiating the experiment, the participant was guided through the headset connection process. To ensure data quality, the participant is required to pass an EEG quality (EQ) "gate".

EQ is a proprietary trained machine learning algorithm, modeled independently for each electrode location to account for local artifacts. EQ is based on EEG signal characteristics (signal amplitude, frequency components, slew rate), contact quality (CQ), and wireless sample loss rate. The EQ model was trained on approximately 40 records of 20–40 min of EEG data in which bad and good (artifact free) EEG segments were visually inspected and labeled by an expert. Segments were labeled as bad if they included one or more of the known noise sources. The algorithm also accounts for CQ, which is a direct analog measurement of the conductance of the circuit between the driven right leg (DRL) electrode and each EEG electrode in turn. CQ helps to ensure that each EEG electrode has good electrical contact with the skin, minimizing the amplitude of extraneous noise sources such as power line and electrostatic coupling. The EQ algorithm ranks each block of 2-s EEG signals as very good, good, poor or very bad, which participants see as dark green, light green, orange or red respectively for each sensor on the screen. They also see a EQ percentage, which is the average EEG quality of the three worst channels. To pass the EQ gate, participants must exceed 82% EQ. EQ and CQ scores are updated twice per second. Please note that high EQ does not guarantee artifact-free data, the EQ gate only acts as a screening tool to help improve the quality of data from the onset.

After passing the EEG Quality Gate, participants were presented with a digital copy of the information and consent form. Participants gave consent by ticking a "yes I provide consent" box and clicking the "next" button.

Participants were next encouraged to ensure they will not be disturbed, to turn off their phone (or place in airplane mode), to check that their computer and EEG headset are adequately charged, and that their computer sound is turned up. The participant was also

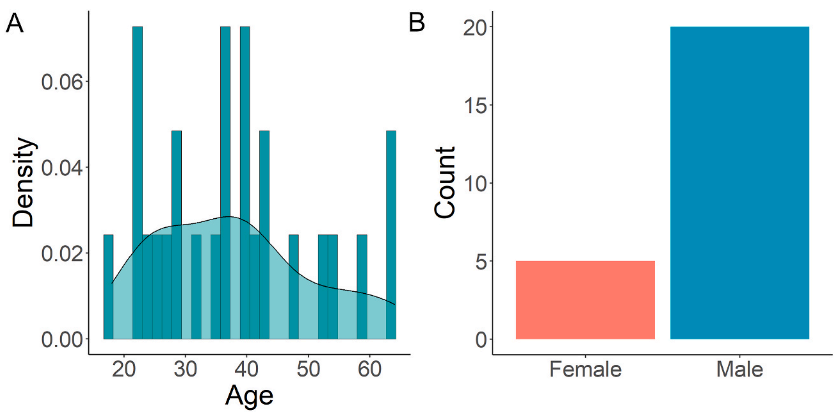
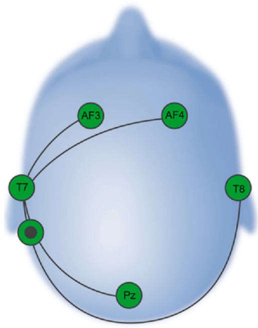
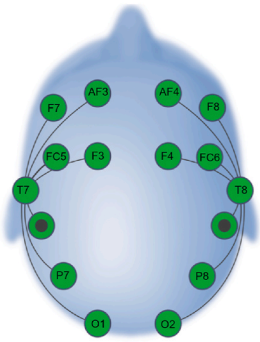


Fig. 1. Demographic profile of participants. A) Age distribution and B) Gender frequency of participants are shown above.

Table 1
Demographic profile of participants.

Factor	N	% of total sample (N = 26)
Handedness		
Right	21	80.8
Left	4	15.4
Ambidextrous	1	3.8
Education Level		
Below High School	1	3.8
High school or equivalent	4	15.4
Bachelor's degree	9	34.6
Vocational/technical training	5	19.2
Professional degree	1	3.8
Masters degree	5	19.2
Doctoral degree	1	3.8

Table 2
EEG devices used in the study.

	INSIGHT	EPOC/EPOC+/EPOC X
Sensor count	5 (+2 references)	14 (+2 references)
Sensor locations		
References	CMS/DRL references on left mastoid process	CMS/DRL references at P3/P4 left/right mastoid process alternative
Sensor Technology	Long life semi-dry polymer	Saline soaked felt pads
Sample Rate	2048 Hz internal downsampled to 128 SPS	2048 Hz internal downsampled to 128 SPS (or 256 SPS in EPOC+ and EPOCX, which is user configured)

asked to switch their browser to full screen mode to minimize any disturbances from other computer applications.

Participants then began the experiment and were presented with a 3-s audio-visual countdown after which a fixation cross appeared in the middle of the screen. Participants were instructed to keep their eyes open during this time. The Eyes Open condition lasted 2 min. Next, participants were instructed to close their eyes until they heard a tone, which signaled the end of the trial. The Eyes Closed condition also lasted 2 min. The conditions were not counter-balanced and participants always completed Eyes Open first.

2.7. Data processing and analysis

Participant data were first downsampled to 128 Hz (if needed) and re-referenced to the interquartile mean of all the channels. The data were then high-pass filtered at a threshold of 0.5 Hz. The power (in dB scale relative to 1 μV) across the alpha frequency band (8–12 Hz) was computed for each electrode using a Fast Fourier Transform (FFT), using a 4 s epoch length. EEG data was high-pass filtered (0.18 Hz Bessel), mean-centered and a Hanning window was applied. Alpha power was updated at 1-s intervals. EEG power for each 2-min epoch (Eyes Open/Eyes Closed) was averaged for each electrode. Custom scripts in python were used for EEG processing and FFT and have been made openly available (find link to repository under Data Availability).

As differences in sensor numbers, location and technology (See Table 1) may contribute to differences in signal amplitude, we conducted data analysis for INSIGHT and EPOC separately. We performed a paired samples *t*-test and Bayesian *t*-test on the absolute Alpha power between the Eyes Open and Eyes Closed conditions measured at Pz (INSIGHT) and O1, O2 (EPOC). We chose these sites as visual alpha suppression is typically larger at posterior sites (Magosso et al., 2019; Thut et al., 2006; Toscani et al., 2010). To determine the strength of evidence provided by the Bayes Factor calculated in the *t*-test, we used the guidelines reported by Jarosz & Wiley (2014). We also report mean alpha averaged over all electrodes for INSIGHT and EPOC separately. Statistical analysis was undertaken using R (R Core Team, 2021) and all figures are presented using ggplot [17].

3. Results

3.1. Alpha suppression

We observed strong evidence for a difference in alpha power averaged across all channels, between Eyes Open and Eyes Closed conditions for INSIGHT ($t(13) = 4.78$, $p = < .001$, Cohen's $d = 1.28$, $BF_{10} = 94.27$; Fig. 2A) and for EPOC ($t(11) = 4.952$, $p = < .001$, Cohen's $d = 1.43$, $BF_{10} = 81.50$; Fig. 2B). See Fig. 3 for topographic alpha power distributions for INSIGHT (Fig. 3A & B) and EPOC (Fig. 3C & D).

We also observed strong evidence for difference in alpha power between Eyes Open and Eyes Closed conditions at Pz electrode for INSIGHT ($t(13) = 4.95$, $p < .001$, $d = 1.32$, $BF_{10} = 123.29$; Fig. 4A) and at O1 ($t(11) = 4.52$, $p < .001$, $d = 1.31$, $BF_{10} = 45.34$; Fig. 4B) and O2 ($t(11) = 4.74$, $p = < .001$, $d = 1.37$, $BF_{10} = 60.78$; Fig. 4B) for EPOC.

4. Discussion

In this study, we introduced an approach for remote EEG data collection. We demonstrated how an experiment can be built via the EmotivPRO Builder and deployed to home users that own commercial EEG headsets. We observed alpha suppression phenomenon in home users similar to that observed in laboratory settings([16,18,19]), thus demonstrating the feasibility of conducting online EEG studies.

The method described for collecting online EEG data has several strengths in ensuring participants obtain high quality data. The EEG quality gate helps participants achieve high contact quality (low impedance) at each channel and enables them to identify and improve signal quality before they can proceed. However, we note that while 60 unique participants initiated this study on the EmotivLABS website, only 27 completed it. As noted in the results, some participants were unable to pass the EQ gate and some participants abandoned the experiment midway. Home users may require additional training on obtaining high quality EEG data in order to minimize time spent at the EQ gate thereby motivating them to proceed with an experiment.

A particular benefit of online studies is the ability to sample a wider range of demographics than is typically possible with laboratory EEG systems [1]. Our study was able to reach participants in diverse geographical locations with a broad age range and educational backgrounds. However, the gender ratio in our sample was biased towards males. In addition, our sample was composed solely of participants that owned or had access to an EMOTIV EEG system. Though these systems are more affordable than research systems, they still require a non-trivial expenditure to own. Thus our sample was likely biased toward individuals with relatively higher socioeconomic status.

Although the sample in the current study was potentially biased and limited in number, these factors are unlikely to affect a robust and well-documented phenomena like alpha suppression. In the future, low-cost EEG systems are likely to proliferate thereby increasing the available participant pool resulting in increased sample diversity and shortened data collection times.

Note that EmotivLABS supports both local and online experiment deployment. Researchers can recruit and compensate participants locally using the researcher's own EMOTIV equipment, which can supplement the participant pool in order to obtain any available demographic mix, independent of the participants' ability to afford EEG equipment.

The method introduced in this study showed the feasibility of conducting resting state tasks and frequency domain analysis. We did not investigate event-related potential (ERP) experiments in this study, which require accurate timestamping to enable ERP component analysis. However, it is currently possible to integrate PsychoPy with EmotivPRO Builder to deliver ERP stimuli and obtain accurate timestamps. Future online ERP studies should be conducted to determine the reliability and accuracy of such data.

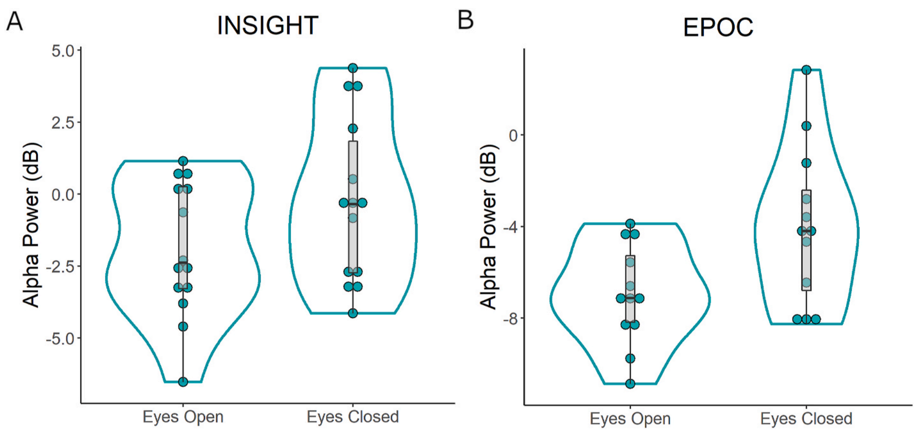


Fig. 2. Alpha suppression (between Eyes Open and Eyes Closed) conditions can be observed in the global mean (i.e., alpha power averaged over all electrodes) for A) INSIGHT and B) EPOC headsets. Violin plots show a density curve (blue outline) with each dot representing an individual participant. Boxplots show median and interquartile ranges and min and max values. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

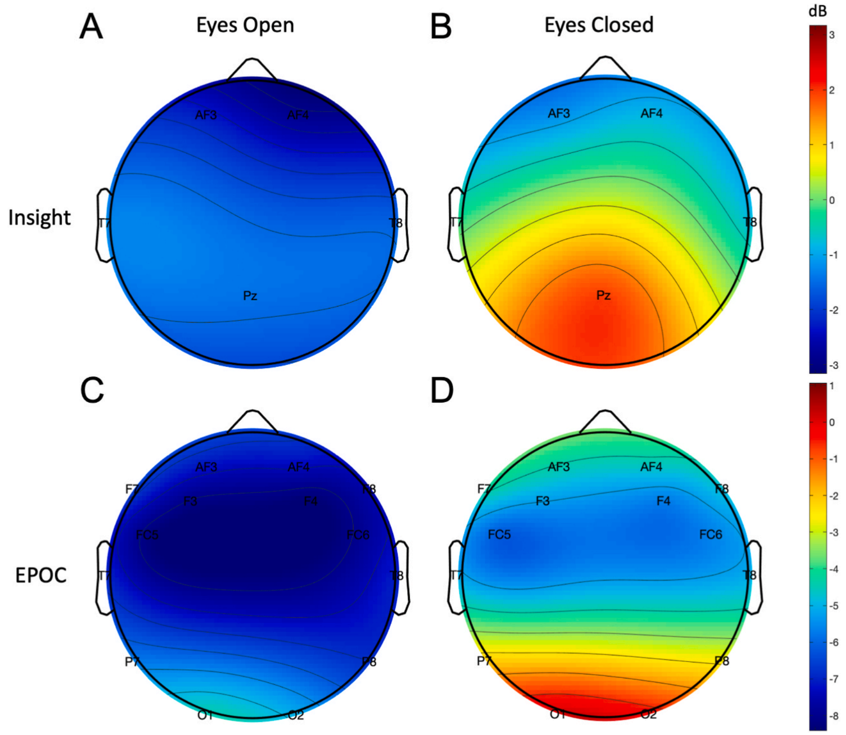


Fig. 3. Topographical alpha power distributions measured by Insight (A and B) and EPOC (C and D) in the Eyes Open (left column) and Eyes Closed (right column) conditions.

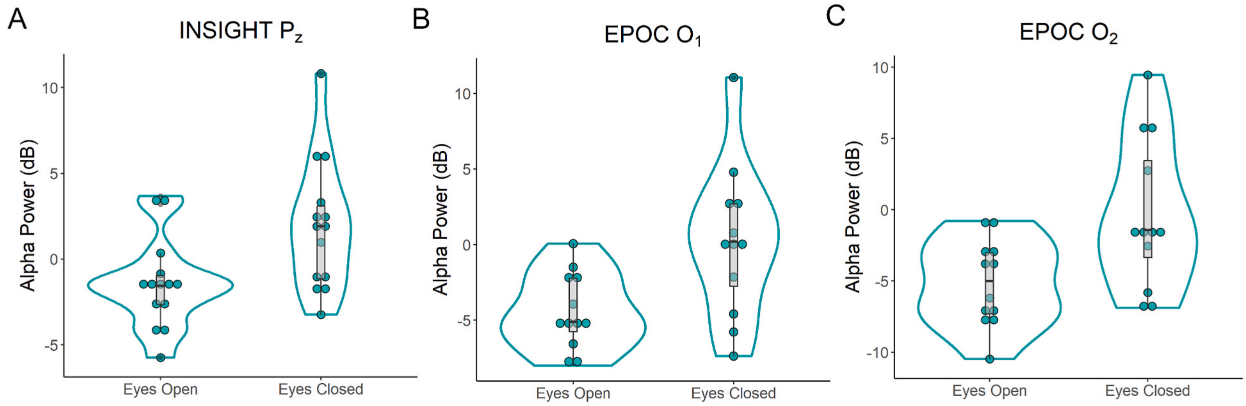


Fig. 4. Alpha suppression (between Eyes Open and Eyes Closed) conditions can be observed at posterior electrodes Pz of INSIGHT(A), O1 of EPOC (B), and O2 of EPOC (C). Violin plots show a density curve (blue outline) with each dot representing an individual participant. Boxplots show median and interquartile ranges and min and max values. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

This feasibility study involved very simple tasks with clear instructions. However, a limitation for conducting online EEG data collection is that of conducting complex tasks. It has been demonstrated that as task complexity increases, participants have difficulty in understanding task instructions online compared to lab as they do not have the opportunity to clarify [4]. This is a difficulty relevant to all online data collection platforms but may be overcome with significant pilot testing online, revision of experiment instructions and guidelines, as well as using video-conferencing to provide specific instructions and guidance to participants.

While the online platform gives as much direction as possible for placement of electrodes, there may still be differences in where sensors are placed on the participant's head. In laboratory settings this is avoided by having trained researchers conduct the EEG setup. However, more instruction and training may be required for home users. In addition, head sizes differ. Whereas this is typically catered for in a lab environment by having different sized caps available, EMOTIV systems are available in a single size only. As such, they may not always conform to maintain exact 10–20 placement over the complete range of head sizes and shapes. Thus, sensor placement may vary by a small degree from participant to participant and we could not ensure precise sensor placement. However, the EMOTIV systems have flexible arms that have been designed to accommodate the heads of participants from small adolescents to large adults. Thus, any deviances from exact 10–20 specifications were likely to be very small.

Finally, in Fig. 3 we provided a topographic alpha power distribution. These calculations were not used for any statistical inference and were provided for illustrative purposes only. However, we still note that the difference between Insight and EPOC with respect to their quantity and positioning of electrodes severely limits the comparison between and interpretability within the two systems. Thus, researchers should exercise caution when drawing any conclusions from them.

5. Conclusions

In this paper, we demonstrated the potential for obtaining high quality EEG data via an online platform that allows researchers to export raw data in.csv and.edf format. The benefits of such a platform are notable when considering current concerns with sampling diversity and public health. By leveraging a user base that is familiar with EEG systems and online platforms, researchers may be able to conduct global EEG studies in a manner that has not been possible.

Data availability

Raw EEG data for all 26 participants and preprocessing, analysis and visualization scripts have been made openly available via OSF here: https://osf.io/9bvgh/?view_only=70744f62157c46d5bd731480db1873df.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Williams, King, Mackellar, Randeniya, and McCormick are employed by Emotiv. At the time of conception and data collection for this study, Williams and Badcock were supported by an industry partnership grant [No. 83673928] between Macquarie University and Emotiv Research Pty Ltd.

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