# In search for the most optimal EEG method: A practical evaluation of a water-based electrode EEG system.

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Project Repository: https://osf.io/kubv5/

## Abstract

The study assessed a new mobile electroencephalography (EEG) system with water-based electrodes for its applicability in time-frequency and event related potential research. It was compared to a standard gel-based wired system. EEG was recorded on two occasions as participants completed the flanker task, first with the gel-based system followed by the water-based system. Technical and practical considerations for the application of the new water-based system are reported based on the participant and experimenter experiences. Empirical comparisons focused on EEG data noise levels, frequency power across four bands including theta, alpha, low beta and high beta and P300 and ERN event related potential components. The water-based system registered more noise compared to the gel-based system which resulted in increased loss of data during artefact rejection. Signal to noise ratio was significantly lower for the water-based system in the parietal channels which impacted the observed parietal beta power. It also led to a shift in topography of the maximal P300 activity from parietal to frontal regions. It is also evident, that the water-based system may be prone to slow drift noise which may affect the reliability and consistency of low frequency band analyses. Considerations for the use of this specific system for time-frequency and event related potentials are discussed.

## 1. Introduction

Brain activity measured using electroencephalography (EEG) allows for a close investigation of electrical signals in the frequency and time domains. It is a common method used in psychological, behavioural, cognitive, and clinical research due to its affordability and ease of use. The standard state of the art EEG equipment involves a swim-cap like device with inserted electrodes. The connection between the scalp and the electrode is normally bridged with electrolyte gel. The signal is recorded through electrode wires connected to a computer. Technological advancements aim to improve the useability of EEG systems through new electrode types and wireless EEG signal recording.

The available electrode types used for EEG recordings are wet electrodes (gel -, water -, saline-based) and dry electrodes. The gold standard gel-based electrodes require a time-consuming preparation process for each participant which includes skin abrasion, gel application and impedance checks. The setup time depends on the number of included electrodes and researcher experience but typically varies between the average of 30 to 70 minutes (Kam et al., 2019; Oliveira, Schlink, Hairston, König, & Ferris, 2016). After the recording, the gel remains in participants' hair and needs to be washed out and the electrodes require cleaning. Such preparation process means that only trained researchers or clinicians can apply the system. It cannot be used independently by participants or patients at home which could be beneficial especially for clinical research and observation of neurological patients (Hinrichs et al., 2020; Jochumsen, Knoche, Kjaer, Dinesen, & Kidmose, 2020; Radüntz, 2018). The lengthy preparation process and skin abrasion are also not suitable for participants with sensory sensitivities, attention difficulties and restlessness which are often observed in neurodevelopmental conditions such as autism spectrum disorder (ASD) or attention deficit hyperactivity disorder (ASD) and may be problematic for young children. In this context, researchers prefer the use of systems that do not require skin abrasion such as

EEG nets though they are still generally gel- or saline-based (DiStefano, Dickinson, Baker, & Jeste, 2019; Pierce et al., 2021).

As an alternative to the wet gel-based electrodes, there is a number of available dry electrode EEG systems. They do not require any wet substance to be applied at the scalp for signal recording. The preparation procedure is much shorter as skin abrasion is needed and participants do not need to wash their hair after the procedure. Therefore, these systems could potentially be used by participants independently without the presence of a trained researcher and could be more suitable for use with patients and clinical populations (Hinrichs et al., 2020; Kam et al., 2019; Pinegger, Wriessnegger, Faller, & Müller-Putz, 2016). It is however important to evaluate the quality of data that can be obtained with these new sensors in comparison to the standard gel-based systems. Equipment precision is especially important if these new electrodes are to be recommended for use in clinical research or practice as patient data tend to be generally more variable and contain higher levels of noise (Puce & Hämäläinen, 2017). Unfortunately, dry electrodes have been shown to be more susceptible to environmental noise which is likely caused by the lack of gel or a substance that could bridge the scalp-electrode connection and keep the electrodes close to the skin throughout the recording (Mathewson, Harrison, & Kizuk, 2017; Pinegger et al., 2016). In a number of methodological comparisons, EEG recordings from dry electrode systems had a higher number of artefacts in the recorded signal (Hinrichs et al., 2020; Oliveira, Schlink, Hairston, König, & Ferris, 2016), higher pre-stimulus noise levels (Hinrichs et al., 2020; Mathewson et al., 2017) and lower signal-to-noise ratio (Radüntz, 2018) than standard gel-based electrode recordings. In addition, two studies reported lower participant comfort ratings for dry compared to wet EEG electrode systems due to the pressure from electrodes' metal pins (Kam et al., 2019; Oliveira et al., 2016). These are quite significant disadvantages of the dry electrode EEG systems and researchers may feel it more appropriate to continue using the

standard gel-based systems to ensure high data quality especially in research concerning clinical populations.

Water-based electrode EEG systems are a promising new development which may potentially improve on the disadvantages of the gel-based electrodes and mitigate the risks of low data quality observed in dry-electrode recordings. The electrodes are built with plastic casings and paper or felt inserts soaked in tap water. Scalp-to-electrode connection is supported with the use of water which may help to sustain high quality signal recordings. No metal parts of the electrodes come into direct contact with the skin, there is no need for skin preparation or washing hair and the procedure is generally less time consuming in comparison to the gel-based electrode systems. The quality of EEG recordings using water-based electrodes have only been evaluated in the context of brain computer interface (BCI) designs (Jochumsen et al., 2020; Pinegger et al., 2016) and the results are promising. The noise levels during a short circuit recording expressed as the root mean square values were the lowest in a water-based compared to gel-based and dry electrode systems (Pinegger et al., 2016) and the signal to noise ratio was comparable between water- and gel- based systems (Jochumsen et al., 2020). In addition, participant satisfaction was the highest for water- compared to gel-based and dry systems (Pinegger et al., 2016). It is therefore plausible to assume that the water-based system may potentially be more efficient than the gold standard gel-based EEG systems yielding results of comparable quality with reduced preparation time and higher participant comfort. Moreover, the available water-based EEG systems allow for mobile wireless recordings of the EEG signals. This creates an opportunity to obtain EEG recordings in a wider range of contexts outside of the lab including everyday life situations, at home recordings, motor and sports research (Hinrichs et al., 2020; Oliveira et al., 2016; Radüntz, 2018). Unsurprisingly, these systems are already being used for cognitive research,

for example on visuospatial working memory (Hazarika & Dasgupta, 2018) and attention processes (Raj, Hazarika, & Hazra, 2020).

To our knowledge, there are currently no empirical studies investigating the suitability of the new mobile water-based EEG electrode systems for application in psychological, behavioural and cognitive research. In the current study, we applied evaluation methods and suggested benchmarking comparisons previously used in research investigating signal quality and noise levels, frequency and event-related potential (ERP) analyses in dry electrode systems (Hinrichs et al., 2020; Kam et al., 2019; Mathewson et al., 2017; Oliveira et al., 2016; Radüntz, 2018). The main aim of the study was to evaluate the quality of signal obtained with the water-based electrode EEG systems and to find out whether they can be easily used in research protocols instead of the gold-standard gel-based electrodes. We also aimed to understand potential drawbacks and best methodological practices for the use of such systems. Therefore, we provide practical advice alongside the obtained results for researchers who might want to consider using these systems in the future. Project materials including the Mobita setup protocol, data and analysis log can be found in the study's online repository (https://osf.io/kubv5/; Topor, Opitz, & Dean 2021).

## 2. Method

### 2.1. Participants

The study consisted of two phases. Phase one was completed as part of a procedure for an earlier study which used a gel-based EEG system (Topor, Opitz, & Leonard, 2021). During phase one, 46 participants were recruited during both the pilot and the final stage of the study using the University of Surrey's research volunteer system and through word of mouth. All participants were given an opportunity to win one of two £50 prize vouchers. In addition, those who were in their first or second year of the undergraduate Psychology course

also received lab tokens which are part of their course requirement. Participants were screened and excluded for diagnoses of psychiatric, neurological or neurodevelopmental disorders.

In phase two, the same participants were contacted and invited to participate again with the aim of completing the same computer task as before, but with the new water-based EEG system. Participants were contacted one by one, in no particular order, and recruitment stopped when the 10$^{th}$ participant agreed to complete the study. A-priori power analysis was not conducted for this study. Previously, similar technical evaluations of EEG systems also relied on small samples of eight to nine participants (Mathewson et al., 2017; Oliveira et al., 2016; Pinegger et al., 2016), and they were able to detect significant differences between the devices used. Using a within-subject design helps to preserve power in studies with small sample sizes (Charness, Gneezy, & Kuhn, 2012). The time between participation at phase one and phase two ranged from seven to twelve months. Participants were not offered any additional incentives for participating in phase two. In the final sample there were no individuals who won the £50 prize in phase one. No additional demographic or health checks were carried out at phase two.

The final sample consisted of 10 participants who completed both phase one and two. We attempted to ensure a gender balance within the sample and as a result, we recruited five males and five females with the mean age of 26.5 years old, in the range of 22-38, at phase one testing. The study was designed to investigate the effect of device type on data quality and user experience. The study complied with ethical regulations at the University of Surrey.

## 2.2 Materials and Equipment

### 2.2.1 EEG systems.

#### *2.2.1.1 Phase One, gel-based EasyCap.*

The EEG recordings at phase one were acquired using the EasyCap gel-based setup (EasyCap system kit, Brain Products, from now on referred to as EasyCap) with 32 Ag/AgCl sintered electrodes in a 10/20 system with electrodes at sites Fp1, Fp2, Fz, F3, F4, F7, F8, FC1, FC2, FC5, FC6, Cz, C3, C4, T7, T8, CP1, CP2, CP5, CP6, TP9, TP10, Pz, P3, P4, P7, P8, POz, O1 and O2. The ground electrode was located within the cap at position AFz. The electrooculographic signal was recorded from the left side (vertical, VEOG) and above (horizontal, HEOG) the left eye using electrodes outside of the cap. The reference electrodes were also attached outside of the cap, located on the mastoids and recorded implicitly (i.e. not as separate channels) using the 32-channel input box. Data were recorded in DC mode using Brain Vision Recorder V1.2 (Brain Products, 2012) at 500Hz with amplifier input impedance at 10GΩ and electrode impedance kept below 5kΩ. There was a high cut-off online filter implemented at 250 Hz.

Recordings were performed in an electrically shielded room. Participants stayed seated throughout the preparation of the system and for the duration of the recording. Each individual's head circumference was measured with tape to select the right EEG cap size (52, 54, 56 or 58 cm available). The electrodes were kept fitted within the cap for all participants and there was no need to remove them between the sessions. Such prepared caps were then fitted on the head and the position of the electrodes was adjusted. The external electrooculographic and reference electrodes were placed on the skin using electrode stickers. Using a cotton bud, participant hair was gently moved from under the electrodes. We also applied an alcohol solution on the skin and the scalp directly through the whole in the electrodes (see figure 1 for the illustration of electrodes). This was followed by the application of the electrolyte gel directly at electrode locations. In the case of noisy channels, it was possible to improve the signal quality by reapplying the gel and securing the electrode

closer to the scalp. The preparation of each participant for recording lasted from 30 minutes to one hour.

The electrode cables were gathered at the back of the participant's head in a tight net and plugged in an input box connected to Brainamp MR Plus amplifier (Brainamp MR Plus; Brain Products). The EEG signal was recorded directly to a laptop that the amplifier was connected to using an USB adapter. The same USB adapter received the stimulus-response digital event markers from the stimulus computer via its parallel port. This setup enabled each stimulus and response category to have a unique signal at the parallel port translated to a unique marker value within Brain Vision Recorder alongside the EEG signal recording.

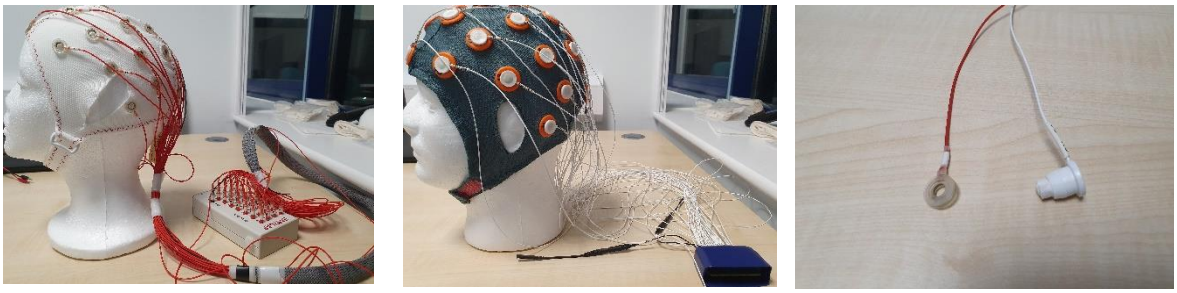


*Figure 1*. Two types of EEG recording setups and electrodes used in the current study. **A.** EasyCap setup. **B.** Mobita setup. **C**. A gel-based EasyCap electrode. **D**. A water-based Mobita electrode.

***2.2.1.2 Phase two, water-based Mobita*.** During phase two, EEG data were acquired using the Mobita water-based setup (Mobita – W – 32 EEG, Biopac Systems, Inc.; from now on referred to as Mobita) with 32 electrodes in a Mobita-32EEG-CAP-A ConfiCap (Biopac Systems, Inc.). The cap has fixed electrode positions that follow the 10/20 system. It is similar to the EasyCap cap, though includes Fpz and Oz channels instead of TP9 and TP10. In contrast to EasyCap, the ground electrode was not located within the cap but secured with

a sticker in the middle of the forehead. It was not possible to add any additional electrodes to the setup. Therefore, the electrooculographic signal was extracted from already existing channels (Fp1 for VEOG and F7 for HEOG). The reference electrodes were located on the mastoids within the cap, and they were recorded as separate channels. The data were recorded in DC mode using the Acqknowledge software (Acqknowledge 5.0.3, Biopac Systems, Inc., 2018) at 1000Hz. The Mobita system does not allow for the measurement of electrode impedance. It has been argued that electrode impedance may have little influence over data quality if amplifier input impedance is high (Ferree, Luu, Russell, & Tucker, 2001). Mobita's input impedance was comparable to that of EasyCap amplifier (10GΩ) so we felt it necessary to monitor possible noise interference for consistency between the two systems. Therefore, live spectral power was visually inspected for each electrode to assess whether any power spikes occurred at 50Hz. Online filters were not applied. Table 1 displays a summary of technical differences between the two systems.

All Mobita electrodes were manually prepared before each recording. This included rolling small pieces of absorbent paper (supplied by Biopac Systems, Inc.) and inserting them into the plastic electrode casing. They were then placed in a jug of tap water shortly before participant arrival. The electrodes could not be pre-fitted in the cap as it would prevent the adjustment of electrodes and moving of the hair because there are no holes in the electrodes (see Figure 1). Thus, during system preparation, participants were seated and had an empty cap placed on their head. One adjustable size (medium: 54-58cm) was used for all participants, with holes (grommets) to put the electrodes into. The instruction manual for the Mobita system does not indicate what type of skin preparation should be performed before using Mobita (Biopac Systems, Inc. 2019). We decided to apply the same alcohol solution we used in the EasyCap recording in the areas with exposed skin (forehead and mastoids) to remove the natural oiliness which could prevent good conductance for the water-based

electrodes. However, alcohol makes the skin dry which may prevent the water from soaking in and creating a connective bridge between the skin and the electrode (BIOPAC Systems, Inc. 2016), so we did not apply it anywhere else. The hair was gently moved with a cotton bud to expose the scalp in the empty grommets where the wet electrodes were inserted subsequently. If a spike was observed at 50Hz whilst checking the live spectral power, the electrode was removed, and the hair was moved again to expose the scalp more and improve the electrode to scalp contact. In one case, due to very noisy signal across a number of electrodes, we tied a bandage around the participant's head to ensure that the electrodes stay close to the scalp and to prevent them from being dislocated by hair movement. Lastly, the Mobita amplifier (Mobita-W-32EEG, Biopac Systems Inc.) was placed in a sleeve and attached to participants' right arm with a strap. The preparation procedure required 15 minutes prior to participant arrival and between 15 and 30 minutes in the presence of the participant (30-45 minutes preparation in total). Recordings were performed in an unshielded room as the system has been designed to be mobile and suitable for use in a wide range of environments and contexts.

The electrodes rested loosely at the participant's back and were attached to the amplifier placed on the arm. They were not taped or gathered as they are relatively short. The amplifier wirelessly transferred the recorded EEG signal through a Wi-Fi antenna attached to a laptop via a USB port. However, it was not possible to set up the wireless transmission of stimulus-response event markers from the stimulus computer. The stimulus computer was linked via its parallel port to the Digital I/O (37 pin) port of an STP100C module (isolated digital interface) attached to the MP160 Biopac device (MP160WS, Biopac Systems, Inc.) which allowed for the digital signal to be recorded using Acqknowledge. However, the EEG data stream from the Mobita amplifier and the stimulus-response event marker data stream from MP160 could not be integrated into one recording pane in Acknowledge (version 5.0.3).

It was also not possible for two separate recording panes to start recording at the same time point to ensure that marker data can be accurately synchronised with the EEG data (the "Linked acquisition" option within acknowledge was not available for Mobita recordings at the time of this study). To solve this, a bespoke setup was made, whereby the stimulus-response event markers were sent via a wired connection to the Mobita amplifier to integrate into the recording at source. The integrated (EEG & event marker) data was then transferred wirelessly to the recording laptop as described before. Further details on this setup can be found in the supplementary file. One shortfall of this solution was that the digital signal value was limited to 1 or 0 and it was not possible to digitally label the markers to reflect the type of event (type of stimulus and responses).

Table 1. *A summary of technical differences between the EasyCap and Mobita EEG systems.*

| | **EasyCap** | **Mobita** |
|---|---|---|
| **Non-Overlapping Channels** | TP9, TP10 | FPz, Oz |
| **Ground Electrode Location** | AFz | Middle of the forehead |
| **Reference Electrodes' Location** | Mastoid, external to the cap | Mastoid, within the cap |
| **Reference Recording Mode** | Linked Mastoids (Implicit) | Common Average Reference |
| **Electrooculographic Electrodes** | Separate HEOG and VEOG | Fp1, F7 |
| **Electrode Impedance** | <5kΩ | Not available |
| **Online Filter** | 250Hz | None |
| **Sampling Rate** | 500Hz | 1000Hz |
| **EEG Cap Size** | Based on the head size | One adjustable size |
| **Total Preparation Time** | 30-60 min | 30-45 min |
| **Recording Room** | Shielded | Unshielded |

### 2.2.2 Cognitive task.

The participants completed an arrow version of the flanker task (Eriksen & Eriksen, 1974) whilst the EEG data was acquired. This is a commonly used task in the study of attentional and error-control processes in the brain and thus suitable for ERP research investigating stimulus- and response- locked components such as P300 and error-related negativity (ERN; Pratt, Willoughby, & Swick, 2011; Rietdijk, Franken, & Thurik, 2014). The task was presented using E-Prime software version 3 (Psychology Software Tools, 2012). For a detailed description of the task, see Topor et al. (2021). Each trial consisted of 7 arrowheads presented at the centre of the screen. The target stimulus was the middle arrowhead and participant's task was to detect whether it was pointing left or right and respond using the computer keyboard (letter "C" for left and letter "M" for right). Three distractor arrowheads on each side of the target changed direction depending on the trial condition. If they pointed in the same direction as the target the condition was congruent. If in the opposite direction, it was incongruent. In the neutral condition the distractor arrowheads were replaced with the letter "v". Each trial was proceeded by a fixation cross. Maximum response time in each trial was 600ms and between-trial intervals were jittered in duration (400-1600ms) to increase the likelihood of erroneous responses. One participant who initially participated in the study during its piloting completed 750 trials whilst all remaining participants completed 600 trials (200 per condition) with the task taking approximately 20 minutes.

### 2.2.3 Researcher and participant experience.

The differences between the two systems in terms of participant experience was not systematically recorded. The observations were noted and used for the preparation of standard operating procedures and future study protocols. They therefore remain anecdotal in nature though provide significant practical information that should be considered by

researchers planning to use Mobita in the future. Notes taken during the recording with both systems can be accessed from the demographic data available in the project repository (https://osf.io/kubv5/; Topor, Opitz, & Dean 2021).

## 2.3 Data Analyses

### 2.3.1 Data import and digital marker positions.

Offline analysis of the EEG data from both systems was performed using BrainVision Analyzer 2 (Brain Products, 2012). EasyCap data were recorded in a format compatible with BrainVision. Digital event markers were integrated and correctly numbered to reflect different event types (congruent, incongruent and neutral conditions). Correct and incorrect responses were marked using participant response data extracted from Eprime and a Perl script that was previously prepared and used with the task.

Data recorded with Mobita was exported to .EDF format (Kemp, Värri, Rosa, Nielsen, & Gade, 1992) and imported to BrainVision Analyzer for comparison with the EasyCap data. Digital event markers were labelled as stimulus (0 to 1 in digital channel) or response (1 to 0 in digital channel) within the Acqknowledge software and then exported as .csv file. In R Studio (RStudio Team, 2020), task relevant data recorded with Eprime were used alongside the Acqknowledge markers to label the type of condition and correct/incorrect responses. These details were then imported to BrainVision Analyzer as event markers.

For a detailed description of the preparation of digital markers for the bespoke digital signal transfer used in this study, see the supplementary material. One particularly significant difficulty observed during this process concerned the fact that some data was lost in the Mobita recording. The number of markers was not consistent between the Eprime logfile and the Mobita markers extracted from Acqknowledge. These inconsistencies were found in 3 out of 10 participants due to two types of signal drops. One type of signal loss was caused by the

loss of Wi-Fi connection during which the cognitive task and the Acknowledge recording continued but no EEG data were obtained (all channels were flat). This led to very minor data losses of a few trials at each instance. The second type of signal drop led to the freezing of the Acknowledge software and termination of the EEG recording for one participant. The cause of this is unknown. The recording was re-started within around one minute whilst the cognitive task continued on the stimulus computer. Acqknowledge does not record the duration of recording termination in such situations, and this had to be determined manually by comparing the timings recorded by Acqknowledge and Eprime and determining the temporal location of the gap. Data loss in this case included 68.09 seconds of data (40 consecutive trials).

#### 2.3.2 Pre-processing.

For pre-processing, only channels overlapping between the two systems were selected. In EasyCap, TP9 and TP10 and in Mobita, Fpz and Oz were excluded. Data were visually inspected for channels with no or extreme activity. No channels were interpolated for EasyCap. In Mobita, channels were interpolated in two recordings (one channel in the first case and two channels in the second case). In addition, during the inspection of the Mobita data, the mastoid reference channels were observed to be extremely noisy or flat in three recordings. Therefore, all EEG recordings from both systems were re-referenced to the average activity of the subset of overlapping channels (for EasyCap, this included the initial implicit reference). Subsequently, the following filters were applied: 0.1 Hz high-pass, 50Hz low-pass and 50Hz notch filter with threshold selection designed to avoid ERP distortion and ensure the most optimal signal to noise levels based on best practice recommendations and previous EEG system comparisons (Tanner, Morgan-Short, & Luck, 2015; Tanner, Norton, Morgan-Short, & Luck, 2016). Data were then re-sampled to 512 Hz for both systems. Before artefact cleaning, all non-task data were removed. This included the start and the end of the

recordings as well as breaks between the blocks leaving only task-related block segments for further analysis.

Ocular correction independent component analysis was used with default BrainVision Analyzer settings (p.279, Brain Products GmbH, 2019) to automatically detect components around blinks. Channels used to train the algorithm were HEOG and VEOG in EasyCap and Fp1 and F7 in Mobita. Component rejection was semi-automatic where one researcher (MT) inspected each ICA component and confirmed its removal/retainment. There were no significant differences between the number of components removed in EasyCap (*Median* = 2.5, *IQR*= 1) and Mobita (*Median* = 2.5, *IQR*=3; *V*=7.5, *p*=.59). Data were epoched into two types including stimulus-locked epochs for frequency and P300 analyses and response-locked epochs with correct and incorrect responses for ERN analyses. Stimulus-locked epochs for frequency and P300 analyses were selected at -200ms to 500ms respective to stimulus onset. Response-locked epochs for the ERN analysis were selected at -150ms and 200ms respective to response onset. Automatic artefact rejection was performed on all epochs using the default settings of BrainVision Analyzer excluding trials with activity below 0.5µV for a duration of 50ms, amplitude values falling outside of the -200µV and 200µV range, absolute amplitude difference above 200µV in any interval of 200ms and lastly, voltage steps of more than 50µV per millisecond.

**2.3.3 Noise Measurements.**

To assess potential noise in raw data, the fast Fourier transform was applied to unfiltered data that were re-referenced, re-sampled and segmented to task-related blocks without any ocular correction or artefact rejection. 0.1-2Hz and 49-51Hz power values were then extracted for further analysis to understand the potential of slow drift interference (de Cheveigné & Arzounian, 2018) and line noise interference (Leske & Dalal, 2019).

Levels of noise were also assessed in the fully pre-processed stimulus-locked data. First, the above comparison of power at 0.1-2Hz and 49-51Hz was applied for comparison of noise after pre-processing. The stimulus-locked data allowed for further noise evaluations. The proportion of rejected artefactual stimulus-locked trials was calculated for comparison between the two systems. In addition, signal to noise ratio (SNR) and the root mean square (RMS) values were calculated from a subset of electrodes which excluded those located at the edges of the cap which are particularly prone to noise. The remaining subset therefore included F3, Fz, F4, FC5, FC1, FC2, FC6, C3, Cz, C4, CP5, CP1, CP2, CP6, P3, Pz, P4. SNR and RMS metrics are common in studies comparing different types of EEG equipment (Kam et al., 2019; Mathewson et al., 2017; Oliveira et al., 2016). SNR was calculated from averaged, stimulus-locked trials using the formula embedded within the BrainVision Analyzer software (p. 402, Brain Products GmbH, 2019) which estimates the average signal power as squared absolute values of the average data across all data points and all frequency bins whilst noise power is estimated as the biased variance of the data across all segments. The values were extracted for all electrodes included in the specified subset and then averaged for each participant. RMS values were determined with BrainVision Analyzer's RMS function which calculated the root from the average of the squares of the individual values (p. 210, Brain Products GmbH, 2019) within the stimulus-locked epochs' baseline period of -200 to -100ms prior to stimulus onset.

#### 2.3.4 Time-Frequency Measurements.

For time-frequency analyses of task-related brain activity, the fast Fourier transform was applied to the pre-processed stimulus-locked epochs. Power was extracted from the same subset of electrodes used in the SNR and RMS analyses (see previous section). The data were analysed for four frequency bands including theta (4-8Hz), alpha (8-14Hz), low Beta (14-24Hz) and high beta (24-30Hz). For the comparison of power activity within these bands, we

followed the method used by Kam et al. (2019) whereby 5 electrodes with maximum activity were identified per system and power was averaged across the overlapping channels. For theta and alpha, electrodes with the most positive power were selected (theta Fz, F4, FC1, FC2, alpha Fz, Pz, P4) due to expected engagement of cognitive control and attentional processes. For low and high beta, electrodes with the least positive power were selected (low beta CP1, CP2, Pz, high beta CP1, CP2, Pz, P4) as motor-related beta desynchronisation was expected (Doyle, Yarrow, & Brown, 2005).

**2.3.5 Event-Related Potential Measurements.**

For ERP analyses, baseline correction was applied to all fully pre-processed epochs. The baseline window was located at -200ms and -100ms prior to stimulus onset for stimulus-locked P300 epochs and at -150ms to -100ms for response-locked ERN epochs following best practice recommendations by Alday (2019). Subsequently, the number of included epochs for each type (stimulus-locked, response-locked correct, response-locked incorrect) was matched for each participant across the two systems. The selection of trials for matching was based on the order of occurrence. EEG activity was then averaged across trials. One participant was identified to only have 5 trials with incorrect responses available for ERN analyses. This is below the recommended value of at least six trials (Olvet & Hajcak, 2009) so this case was removed from all ERN analyses. Mean amplitude for the P300 component was extracted for a 300 to 500ms interval at Pz and for the ERN component for a 0 to 100ms at Cz which is suitable for flanker task analyses (Klawohn, Santopetro, Meyer, & Hajcak, 2020; Rietdijk, Franken, & Thurik, 2014). To investigate the characteristics of the ERPs further, peak amplitude and latency were calculated. ERN and P300 peaks were semi-automatically identified in BrainVision Analyzer.

### 2.3.6 Statistical Analyses.

All dependent variables were tested using the Wilcoxon test to assess central tendency differences and Fligner-Killeen test to assess homogeneity of variance between the two systems. The dependent variables were divided into the following groups for the purpose of controlling the familywise error: average power values at 0.1-2Hz and 49-51Hz before and after pre-processing; proportion of artefactual stimulus-locked trials; stimulus-locked noise level metrics including SNR and RMS; averaged power for four frequency bands (theta, alpha, low beta, high beta); mean amplitude, peak amplitude and peak latency for P300 and ERN. Bonferroni correction was applied accordingly.

In addition to tests of difference, averaged power for each frequency as well as the mean amplitude values for P300 and ERN were correlated between the two systems using Kendall's Tau correlation. These analyses were also adjusted using the Bonferroni correction.

***2.3.6.1 Exploratory analyses.*** Due to observed P300 and ERN topographical differences between the two systems, we decided to explore whether SNR values might differ between the two systems in terms of electrode locations. We therefore divided the SNR electrode subset into three general regions: Frontal (Fp1, F2p, F7, F3, Fz, F4, F8), Central (FC5, FC1, FC2, FC6, C3, Cz, C4, CP5, CP1, CP2, CP6) and Posterior (P7, P3, Pz, P4, P8, O1, O2). We calculated the average SNR values for these regions for each participant and each system and compared these values using the Wilcoxon and Fligner-Killeen tests. Bonferroni correction was applied.

***2.3.6.2 Power Analysis.*** The data presented had some significant differences between the EEG setups, but also a number of potentially practically informative non-significant differences with large effect sizes. This could be due to small sample size, the large number of statistical tests and the resulting Bonferroni correction for multiple comparisons. To help in the interpretation of these potentially informative effects, we decided to run a post-hoc

power analysis on the smallest large effect size obtained. Post-hoc power analyses are discouraged due to their reliance on effect sizes achieved with a limited sample as it is not possible to estimate whether these effect sizes reflect the true population effects (Lakens, 2021). However, considering the methodological focus of the current study and the practical importance of differences between the two systems, it is important to understand the current study's statistical sensitivity to detect the effects of interest. The power calculation was conducted with G*Power (Faul, Erdfelder, Lang, & Buchner, 2007) using the results of the 0.1-2Hz raw data power comparison between EasyCap and Mobita where a non-significant large effect size was found ($r$=.53). The analysis yielded power of 21.7% (calculation output https://osf.io/fdmzx/). This therefore reflects very small chances for obtaining statistically significant results, even for large effect sizes of interest with the current sample and with the given number of tests and comparisons. To aid the interpretation of the results, we deemed all results with large effect sizes as practically informative regardless of whether the p-values reached the desired 0.05 threshold.

## 3. Results

### 3.1 Participant Experience

During both phases of the study, participants commented on their experience with the EEG systems used. For the fit of the cap, during the EasyCap recording (phase one), common comments referred to the chin strap that felt "scratchy" for some participants. It had to be adjusted throughout the procedure to improve comfort. In comparison, during the Mobita recording, participants also found the cap to be generally comfortable but in some instances the front of the cap put pressure on the forehead which led to moderate discomfort. The Mobita cap has a tightening string which helps to adjust the fit though it is positioned around the face only. We either loosened it up for participants or refrained from using it to improve comfort.

Participants were generally impressed with Mobita due to its shorter preparation time. The preparation procedure that involved participants took up to 30 minutes compared with up to an hour for EasyCap. Some were also relieved that they did not have to wash their hair following the procedure and could quickly go back to their activities after participating in the study. In fact, some participant mentioned that they only agreed to participate again when they were informed that the procedure would be shorter this time and the gel will not be used on their scalp. It is worth noting however, that from the experimenter point of view, the total time taken to prepare each system was not very different as Mobita required extra preparation before participant arrival.

### 3.2 Noise Comparisons

Prior to pre-processing, average power was significantly more variable for Mobita at 0.1-2Hz ($X^2$=8.9, $p$=.022) and 49-51Hz ($X^2$=11.0, $p$=.007) compared to EasyCap but there were no significant differences for central tendency comparisons. However, there was a large effect size for the difference in central tendency at 0.1-2Hz ($r$=.53) indicating that Mobita may be more likely to yield larger power values. Figure 1 displays individual data plots with average power at 0.1-2Hz and 49-51Hz for both systems as well as the overall averaged power spectrum for the raw EEG data.

Following pre-processing, there were no statistically significant differences in central tendency or variance between the two systems. However, at 0.1-2Hz, the Fligner-Killeen $X^2$ value only decreased slightly and the difference in variance is nearing the significant p-value threshold. Figure 2 displays individual data plots with average power at 0.1-2Hz and 49-51Hz for both systems as well as the overall averaged power spectrum for the pre-processed EEG data. Exact statistical results are presented in Table 2.

Table 2. *Median and inter-quartile ranges are displayed for both systems before and after pre-processing for average power at 0.1-2Hz and 49-51Hz to assess potential noise levels. The results of statistical comparisons of the central tendency (Wilcoxon) and variance (Fligner-Killeen) are also presented. Significant differences are marked with an asterisk. Bonferroni correction was used to adjust obtained p-values.*

| | EasyCap Median (IQR) | Mobita Median (IQR) | Central Tendency Wilcoxon *V, p (r)* | Variance Fligner-Killeen $X^2$, *p* |
|---|---|---|---|---|
| **Raw Data** | | | | |
| **0.1-2Hz** | 0.03 (0.42) | 1.31 (2.67) | 11, .84 (.53) | 8.90, .022* |
| **49-51Hz** | -4.76 (0.33) | -5.64 (5.30) | 30, 1.0 (.08) | 11.01, .007* |
| **Pre-processed Data** | | | | |
| **0.1-2Hz** | 5.31 (0.57) | 5.68 (1.61) | 18, 1.0 (.31) | 6.86, .07 |
| **49-51Hz** | -5.06 (0.78) | -5.05(1.16) | 32, 1.0 (.21) | 0.44, 1.0 |

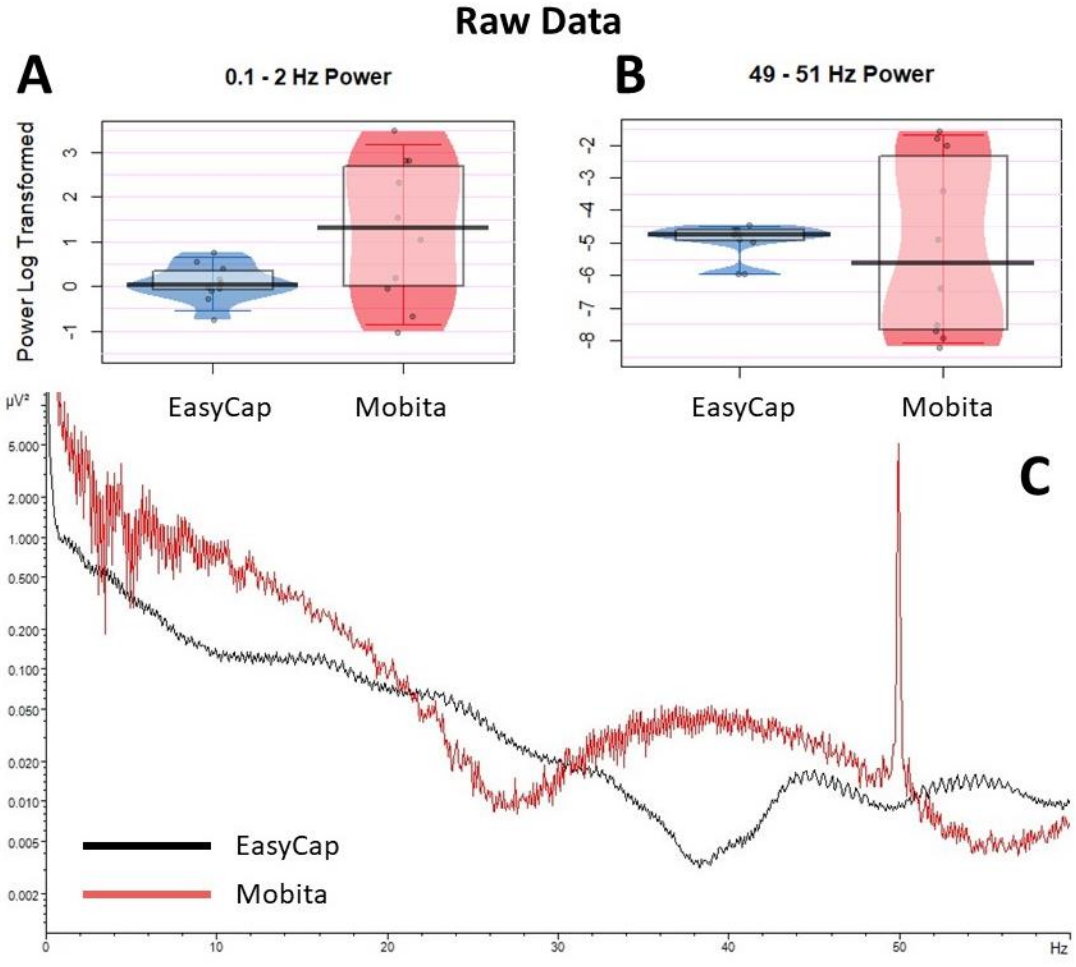

*Figure 2.* Raw data average power prior to pre-processing. Jittered individual data points are plotted for 0.1-2Hz **(A)** and 49-51Hz **(B)** to compare between the EasyCap and Mobita recordings. The vertical bar marks the median and the shaded box reflects the inter-quartile range. **C** Is a representation of log-transformed power spectrum for EasyCap and Mobita.

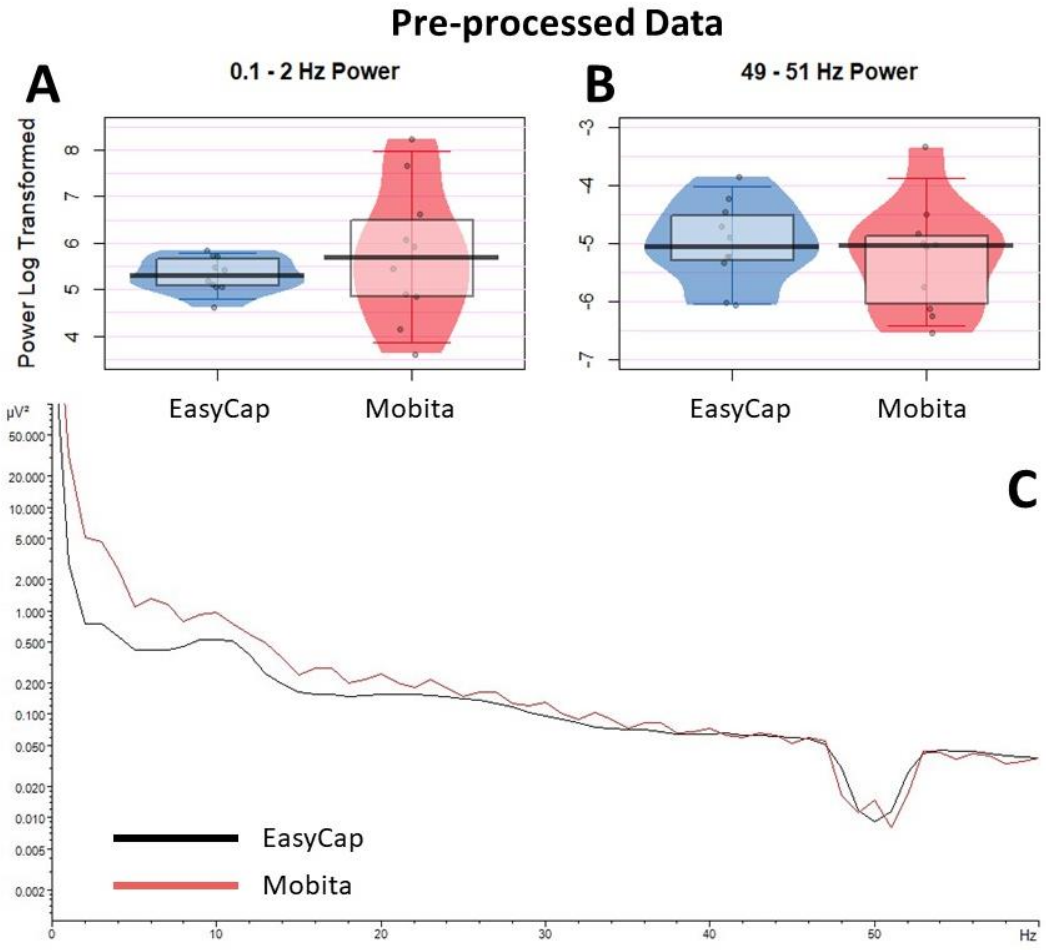


*Figure 3.* Pre-processed data average power. Jittered individual data points are plotted for 0.1-2Hz **(A)** and 49-51Hz **(B)** to compare between the EasyCap and Mobita recordings. The vertical bar marks the median and the shaded box reflects the inter-quartile range. **C** Is a representation of log-transformed power spectrum for EasyCap and Mobita.

Artefact rejection rates for Mobita were significantly higher ($V$=1, $p$=.008, $r$=.85) and more variable ($X^2$=6.42, $p$=.023) than for EasyCap. There were no statistically significant differences between the two systems in terms of SNR central tendency or variance. Baseline RMS was significantly more variable for Mobita compared with EasyCap ($X^2$=12.74, $p$=.001) but there was no difference in terms of central tendency. However, all central tendency noise comparisons (artefact rejection, SNR and RMS) between the two systems

obtained large effect sizes indicating a possibility that Mobita recordings may yield lower SNR and higher baseline RMS in comparison to EasyCap. Exact statistical results are reported in Table 3 and individual data plots are presented in Figure 4.

Table 3. *Median and inter-quartile ranges are displayed for both systems for all three measures of noise: percentage of rejected artefactual trials, signal-to-noise ratio, and root mean square. The results of statistical comparisons of the central tendency (Wilcoxon) and variance (Fligner-Killeen) are also presented. Significant differences are marked with an asterisk. Bonferroni correction was used to adjust obtained p-values.*

| | EasyCap | Mobita | Central Tendency Wilcoxon | Variance Fligner-Killeen |
|---|---|---|---|---|
| | Median (IQR) | | *V, p (r)* | $X^2$, *p* |
| **Artefact Rejection %** | 0.58(0.64) | 3.80(12.60) | 1, .008 (.85)* | 6.42, .023* |
| **SNR (µV)** | 0.05(0.05) | 0.04(0.04) | 48, .15 (.66) | 1.67, .76 |
| **RMS (µV)** | 10.80(1.83) | 20.80(12.39) | 5, .08 (.73) | 12.74, .001* |

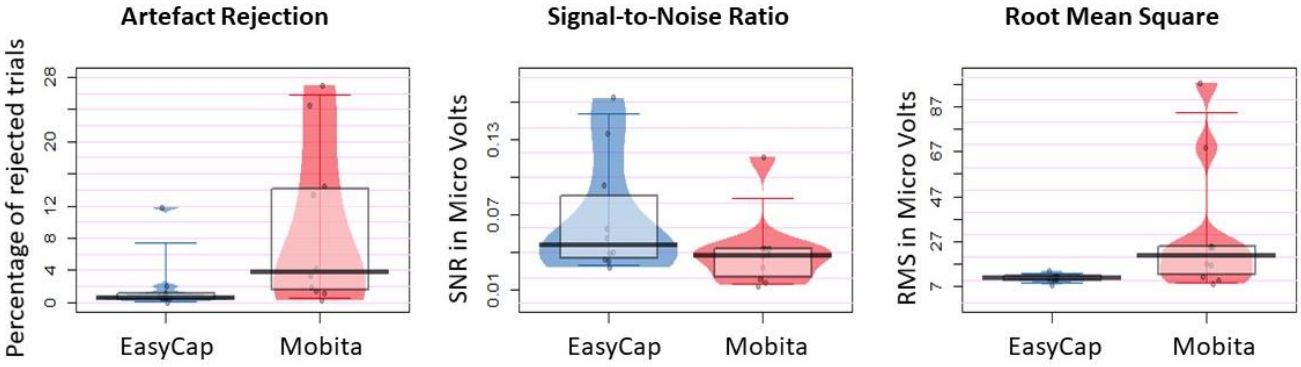


*Figure 4.* Jittered individual data points to reflect average percentage of rejected artefactual trials, signal-to-noise ratio and root mean square to indicate the levels of noise observed in EasyCap and Mobita recordings. The vertical bar marks the median and the shaded box reflects the inter-quartile range.

### 3.3 Frequency Power Comparisons

Frequency power was compared between EasyCap and Mobita across four bands (theta, alpha, low beta and high beta). No statistically significant results were obtained for the tests of difference in central tendency and variance and the correlations were also non-

significant. However, the central tendency differences between the two systems yielded large effect sizes for low and high Beta power values where weaker activity has been recorded with Mobita. In addition, a large correlation was observed between EasyCap and Mobita for the high Beta band. Medians, inter-quartile ranges and exact test results can be found in Table 4. Figure 5 displays topographical power distribution, scatter plots and individual data plots for EasyCap and Mobita across the four frequency bands.

Table 4. *Median and inter-quartile ranges are displayed for both systems for four frequency bands: theta, alpha, low beta and high beta. The results of statistical comparisons of the central tendency (Wilcoxon) and variance (Fligner-Killeen) and the correlations (Kendall's Tau) between the two systems are also displayed. Bonferroni correction was used to adjust obtained p-values.*

| | | | **Central Tendency** | **Variance** | **Correlation** |
|---|---|---|---|---|---|
| | **EasyCap** | **Mobita** | **Wilcoxon** | **Fligner-Killeen** | **Kendall's Tau** |
| | **Median (IQR)** | | ***V, p, r*** | $X^2$***, p*** | **τ, *p*** |
| **Theta** | -0.78(0.59) | 0.10(1.03) | 12, 1.0, .50 | 1.03, 1.0 | .11, 1.0 |
| **Alpha** | -1.15(0.88) | -0.38(1.82) | 18, 1.0, .31 | 1.23, 1.0 | .42, 1.0 |
| **Low Beta** | -2.35(0.67) | -1.65(0.82) | 6, .33, .69 | 1.72, 1.0 | .42, 1.0 |
| **High Beta** | -3.67(0.84) | -3.11(0.67) | 3, .12, .79 | 0.07, 1.0 | .51, .56 |

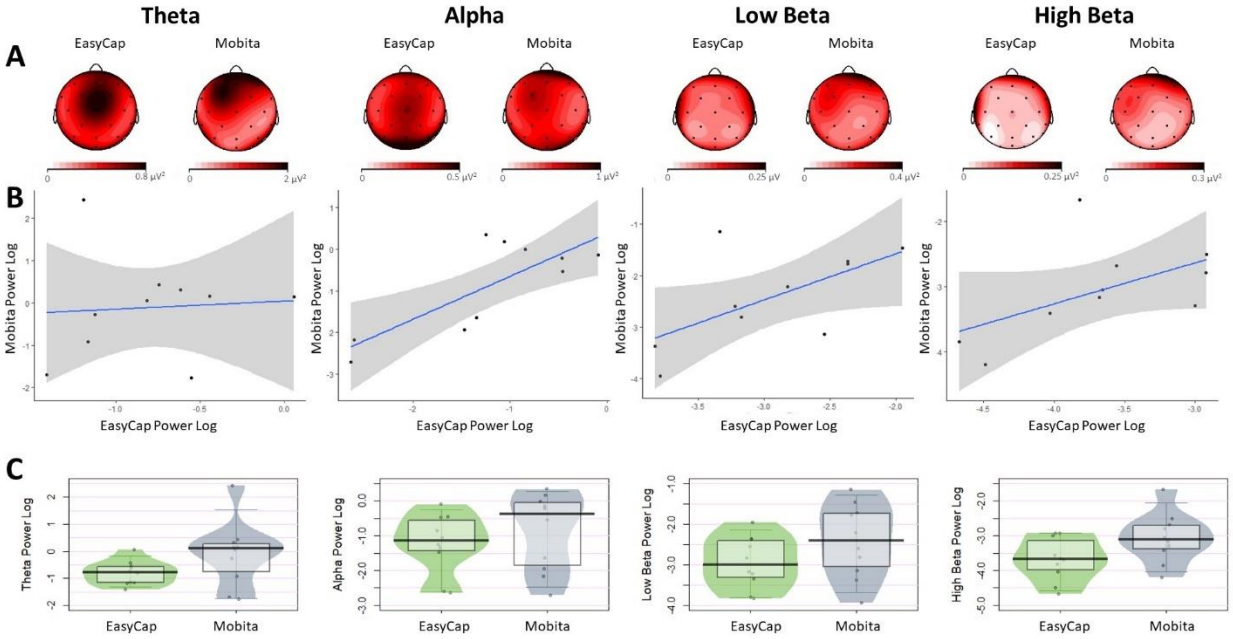


*Figure 5.* **A.** Topographies for all power frequencies are displayed for comparison between the two systems. The topographies have not been normalised and different scales are used for EasyCap and Mobita. **B.** Scatter plots with fitted line of best fit and confidence intervals to visually reflect the relationship between power obtained with the EasyCap and Mobita systems. **C.** Jittered individual data points reflecting average power for each participant recorded with each system. The vertical bar marks the median and the shaded box reflects the inter-quartile range.

## 3.4 Event-Related Potentials Comparisons

### 3.4.1 P300.

No statistically significant differences were found between EasyCap and Mobita for the mean P300 amplitude at 300ms to 500ms in terms of central tendency and variance. All observed effect sizes were small. The correlation between the two systems was also non-significant with a small-medium relationship. In addition, no statistically significant differences in central tendency or variance were identified in P300 peak amplitude or peak latency. Table 5 displays the medians and interquartile ranges observed, as well as exact statistical results. Figure 6 displays the P300 waveforms, topographies, a scatter plot and an individual data plot for comparison of P300 mean amplitude values.

Table 5. *Median and inter-quartile ranges are displayed for both systems for the measures of P300 mean amplitude at 300ms to 500ms, ERN mean amplitude at 0ms to 100ms, peak amplitude values and peak latency. The results of statistical comparisons of the central tendency (Wilcoxon) and variance (Fligner-Killeen) are displayed for all measures. In addition, the mean amplitude correlation results (Kendall's Tau) are displayed. Bonferroni correction was used to adjust all obtained p-values.*

| | EasyCap | Mobita | Central Tendency Wilcoxon | Variance Fligner-Killeen | Correlation Kendall's Tau |
|---|---|---|---|---|---|
| | Median (IQR) | | *V, p, r* | $X^2$, *p* | τ, *p* |
| **P300** | | | | | |
| **Mean Amplitude (µV)** | 2.40 (1.63) | 1.69 (2.39) | 31, 1.0 (.11) | 1.53, 1.0 | 0.24, 1.0 |
| **Peak Amplitude (µV)** | 2.54 (1.75) | 2.49 (3.22) | 21, 1.0 (.15) | 1.69, 1.0 | |
| **Peak Latency (ms)** | 346 (38) | 343 (67) | 23, 1.0 (.16) | 2.85, 1.0 | |
| **ERN** | | | | | |
| **Mean Amplitude (µV)** | -2.69 (5.46) | -0.89 (1.62) | 1, .11 (.85) | 1.04, 1.0 | .28, 1.0 |
| **Peak Amplitude (µV)** | -3.96 (7.96) | -4.56 (0.98) | 36, 1.0 (.02) | 0.31, 1.0 | |
| **Peak Latency (s)** | 41 (16) | 6 (29) | 13, .20 (.87) | 1.48, 1.0 | |

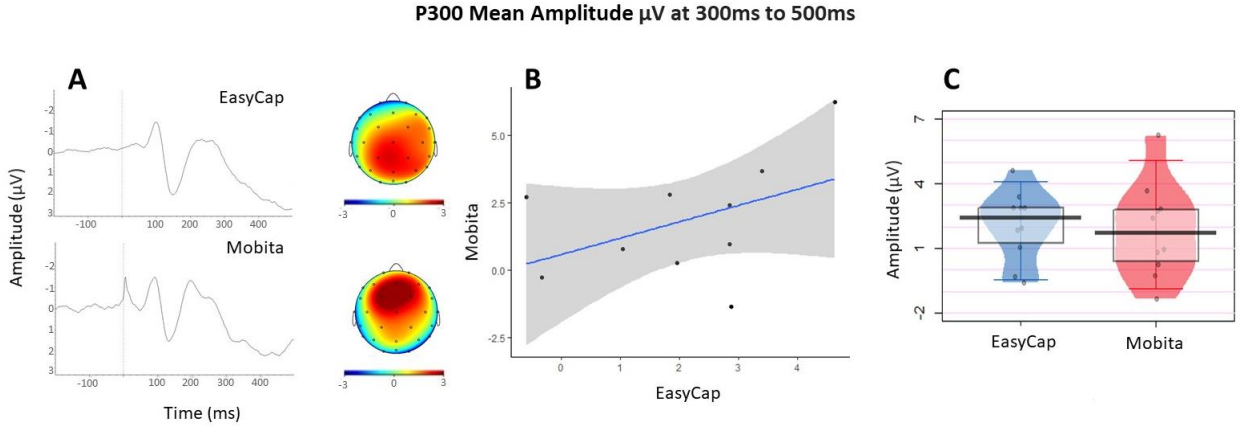


*Figure 6.* **A.** The P300 waveforms and topographies for each system. **B.** Mean amplitude scatter plot with a fitted line of best fit and confidence intervals to visually reflect the relationship between EasyCap and Mobita. **C.** Jittered individual data points reflecting average mean amplitude for each participant recorded with each system. The vertical bar marks the median and the shaded box reflects the inter-quartile range.

### 3.4.2 ERN.

No statistically significant differences were found between EasyCap and Mobita for the mean ERN amplitude at 0ms to 100ms in terms of central tendency and variance. The correlation between the two systems was also non-significant with a small-medium association. In addition, no statistically significant differences in central tendency or variance were identified in ERN peak amplitude or peak latency. However, mean amplitude and peak latency central tendency differences between the two systems yielded large effect sizes. In Figure 6A it is evident that the ERN peak occurs early in Mobita, almost directly at the time of response onset. Table 5 displays the medians and interquartile ranges observed, as well as exact statistical results. Figure 6 displays the P300 waveforms, topographies, a scatter plot and an individual data plot for comparison of ERN mean amplitude values.

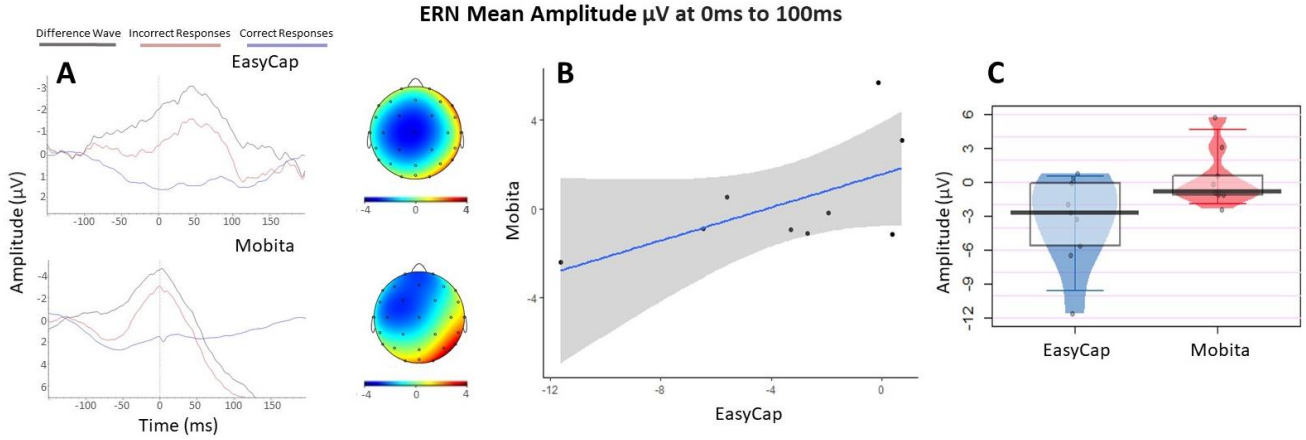


*Figure 7.* **A.** The ERN waveforms and topographies for each system. **B.** Mean amplitude scatter plot with a fitted line of best fit and confidence intervals to visually reflect the relationship between EasyCap and Mobita. **C.** Jittered individual data points reflecting average mean amplitude for each participant recorded with each system. The vertical bar marks the median and the shaded box reflects the inter-quartile range.

### 3.5 Exploratory Analysis

Exploratory analysis focused on the differences in SNR values by electrode locations including frontal, central and posterior. In Figures 6A and 7A, we have observed that the obtained ERP peaks are shifted frontally. The shift is especially prominent for P300. We were therefore interested in finding out whether some electrodes might be particularly susceptible to high noise levels. We found no differences in variance between the two systems. However, all central tendency differences between EasyCap and Mobita yielded large effect sizes with this difference being statistically significant for posterior electrodes ($V$=54, $p$=.04, $r$=.85). Table 6 displays the medians and interquartile ranges observed, as well as exact statistical results. Figure 7 presents the individual data plot for comparison of SNR values across electrode location and between EasyCap and Mobita.

Table 6. *Median and inter-quartile ranges are displayed for both systems for SNR values recorded with frontal, central and posterior electrodes. The results of statistical comparisons of the central tendency (Wilcoxon) and variance (Fligner-Killeen) are provided. Statistically significant results are marked with an asterisk. Bonferroni correction was used to adjust all obtained p-values.*

| SNR(µV) | EasyCap Median (IQR) | Mobita Median (IQR) | Central Tendency Wilcoxon *V, p (r)* | Variance Fligner-Killeen $X^2$, *p* |
|---|---|---|---|---|
| **Frontal Electrodes** | 0.05(0.05) | 0.03(0.02) | 47, .49 (.63) | 0.46, 1.0 |
| **Central Electrodes** | 0.04(0.05) | 0.03(0.02) | 46, .63 (.60) | 0.33, 1.0 |
| **Posterior Electrodes** | 0.07(0.04) | 0.03(0.03) | 54, .04 (.85)* | 0.09, 1.0 |

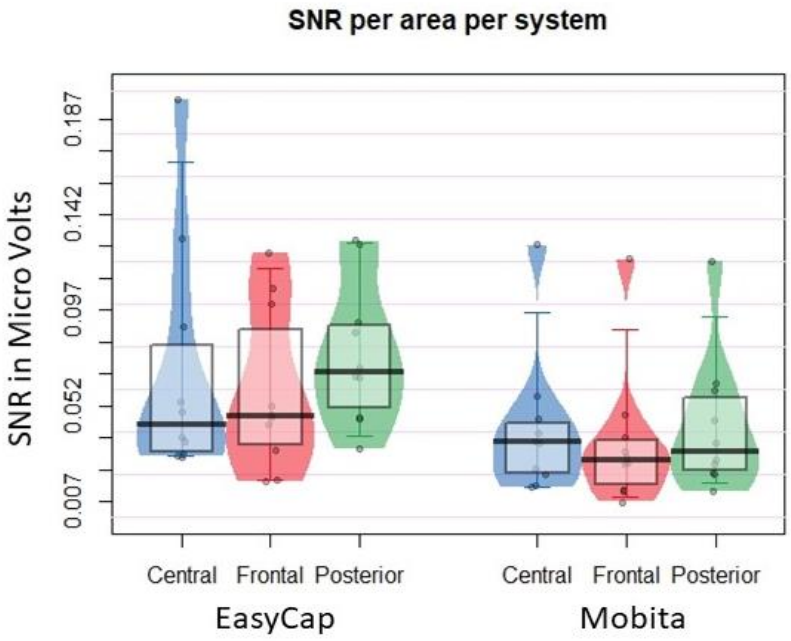


*Figure 8.* Jittered individual data points reflecting average SNR values for each participant presented by electrode location and recording system. The vertical bar marks the median and the shaded box reflects the inter-quartile range.

## 4. Discussion

Mobita is an interesting new EEG system which may be of interest to researchers who want to shorten the EEG preparation time for participants (e.g. children or hyperactive participants), reduce the possibility of sensory discomfort (e.g. for participants with sensory sensitivities) or when considering procedures requiring participants or patients taking their own recordings at home. From our experience, Mobita is currently not suited for a quick and easy application in studies aiming to analyse EEG recordings in time-locked epochs for frequency or ERP comparisons. Researchers considering the use of this system should weigh the potential benefits against technical, practical and data quality disadvantages presented in this study.

### 4.1 Technical and Practical Considerations

Participants in the current study had a generally positive experience when using Mobita and some expressed their preference for Mobita over EasyCap due to the reduced

preparation time and not having to wash their hair. Although, none of the participants had any pre-existing sensory sensitivities, hyperactivity or attention difficulties. It is not clear if Mobita would be more beneficial for participants with such difficulties and how much improvement it could bring overall to the experience of the EEG procedure.

From the researcher point of view however, the EasyCap system was more optimal in terms of the technical and practical application whilst the Mobita system required more adaptations and time-consuming solutions at all stages – set-up, recording and analysis. At set-up, it required a bespoke solution in order to allow for it to record synchronised digital and EEG signals for time-locked analyses. This is despite the setup being marketed as being able to record ERP EEG with no modifications solutions that were alternative to the original expectations. It is not a straightforward process to set up Mobita and may require technicians or engineer assistance. At recording, the Mobita cap was not well fitted for some participants as one adjustable size was used instead of selecting the best cap based on individual head size like in the case of EasyCap. The absence of gel made it more challenging to secure the electrodes in one place and prevent them from being dislocated by hair. In addition, the unavailability of an electrode impedance measure meant that the researcher could not easily check and compare signal quality across the cap. Therefore, this increased the chances for Mobita EEG recordings to register more noise than EasyCap. Mobita was also susceptible to signal drop and recording termination which led to loss of data. At analysis, the digital marker signal for cognitive task events (stimuli and responses) had to be extracted from Acqknowledge and labelled (condition and response type) externally as the signal value was limited to numbers 0 and 1 whilst during the EasyCap recording the digital signal was mostly already labelled into different types. This was especially challenging for instances when the EEG and digital signal drops occurred as the gaps had to be manually detected and the markers were then realigned. Though this could be mitigated by choosing an option to record

the signal directly to the logger attached to participants' arms instead of transferring the data wirelessly to the computer for recording. See the recommendation section below.

### 4.2 Data noise

Mobita demonstrated more variance in registered noise at 0.1-2Hz and 49-51Hz compared to EasyCap. No other statistically significant differences were seen in raw or pre-processed data. A large effect size was observed in central tendency comparison of power at 0.1-2Hz in raw data between the two systems which indicates a larger drift in Mobita compared to EasyCap. Following pre-processing, power at 49-51Hz became visually comparable with EasyCap (Figure 2). However, this was not the case for power at 0.1-2Hz and numerically power variance at only reduced slightly and the statistical comparison remained close to significance (Table 2, Figure 3A). This indicates the possibility that EEG data recorded with Mobita may be disadvantaged by slow drifts even after pre-processing. These drifts may be caused by poor electrode-to-skin contact and may mask slow cortical activity in studies looking at low frequencies or distort ERP components (de Cheveigné & Arzounian, 2018). In addition, we observed statistically significant central tendency and variance differences in the artefact rejection rate between the systems indicating that more noise remained in Mobita recordings compared to EasyCap following data pre-processing leading to further data loss. The SNR values were not significantly different between the two systems though a large difference between the two systems was detected with Mobita obtaining lower SNR values compared to EasyCap. The SNR values were then exploratively compared between the two systems by channel location (frontal, central, posterior). For all three comparisons, Mobita had lower SNR values with large effect sizes and statistical significance was reached for posterior electrodes. The RMS values were significantly more variable for Mobita. There was no statistical significance for the central tendency difference although a large effect size was observed for this comparison. Taken together, these findings

indicate that Mobita registers more noise at recording which can be to some extent improved with pre-processing, though the altered artifact rejection rates and exploratory SNR location results suggest that it is likely that the data will still contain higher levels of noise which may distort the EEG results.

### 4.3 EEG Results

Regarding the frequency analyses, there were no statistically significant differences or relationships between the two systems across the frequency bands. However, there was a large effect size detected for the difference between Mobita and EasyCap for the low and high beta frequency bands (Table 4, Figure 5). For these frequencies, we expected to observe motor-related beta desynchronization in the parietal regions reflected with power values that are negative or close to 0. Mobita activity seemed to be more positive than EasyCap activity potentially masking the motor-related beta desynchronisation. This might have been caused by significantly lower SNR in the parietal channels within the Mobita system as evident from the exploratory analysis (Figure 8). In addition, moderate to large $\tau$ correlations were detected between the two systems for alpha and beta frequencies whilst there was no clear pattern of association for theta and the $\tau$ correlation was very small. This could be due to the increase in slow drift noise in Mobita which is observed to be visually more variable in comparison to EasyCap with a trending significance for his difference even after pre-processing (Figure 2A, Table 2). The topographies for all bands are relatively similar based on visual comparisons. For theta and alpha bands, the maximal activity seems to be more shifted towards the frontal areas in Mobita compared to EasyCap. However, these differences are subtle and are unlikely to mislead the interpretation of results.

With regards to the ERP analyses, statistical comparisons were non-significant for P300 with small effect sizes and a small-medium $\tau$ correlation. This suggests that there is no

indication from the current data that Mobita could yield unreliable P300 results. The P300 waveforms seemed visually similar. However, looking at the P300 topographies (Figure 6B), EasyCap recorded maximal P300 activity over parietal regions which is expected in a Flanker task (Klawohn et al., 2020). In contrast, the P300 activity was maximal over the frontal region in Mobita which is unexpected because the same participants were tested with both systems and the topographies should be visually similar. As in the case of low and high beta power, it is possible that the posterior activity was masked by low SNR in parietal and centro-parietal channels which caused the shift of maximal P300 activity more frontally. This is a significant issue for consideration in future research as it may lead to false interpretation of results which may be inconsistent with previous literature and the current understanding of frontal and parietal P300 variants (van Dinteren, Arns, Jongsma, & Kessels, 2014).

For ERN, there were no statistically significant differences between the two systems. The τ correlation was small-medium. However, a large effect size was detected for the central tendency mean amplitude at 0-100ms difference between the two systems with Mobita yielding lower amplitude values compared to EasyCap. This is likely caused by the peak amplitude shift observed in Mobita as the peak amplitude central tendency comparison between the two systems also yielded a large effect size. In addition, by visually inspecting the ERN waveform (Figure 7A), it is evident that the Mobita ERN peak occurs almost at the onset of response. The ERN peak is normally expected at around 50ms post response onset in Flanker tasks (Klawohn et al., 2020; Riesel, Weinberg, Endrass, Meyer, & Hajcak, 2013) which is accurately reflected in the EasyCap waveform. The likely explanation for this latency shift is the bespoke solution for digital marker recording used in Mobita. The P300 peak latency was very similar between the two systems suggesting that stimulus-locked events can be accurately marked with the current system where the digital signal is set from 0 to 1 at stimulus onset. At response onset, the digital signal is set back from 1 to 0 and it seems

that this event is systematically recorded approximately 35ms earlier than the actual response if we directly compare the EasyCap and Mobita peak latency median values (Table 5). This issue may again have adverse consequences in future research and lead to false interpretation of results that will not be consistent with current literature and knowledge about the ERN. Otherwise, visual inspection of the ERN waveforms suggests that the ERN component registered with both systems is rather similar and occurs to be slightly clearer for Mobita than EasyCap. This may be due to practice effects as all Mobita recordings were taken during phase two of the study. The topographies are also visually similar with slight frontal shift observed in Mobita but this is unlikely to lead to false interpretation.

### 4.5 Limitations

One limitation of the current study is the small sample size and thus low power of the study. However, considering the aims and the practical nature of the study, even results that are statistically non-significant but have large effect sizes can be informative and facilitate the interpretation of the data. They will help researchers to understand the quality of the data they are likely to record as well as the consequences it could have on the analysis outcomes. Subsequently, this will help to develop best practice solutions for those who decide to use this system in the future.

Another limitation of the study is that in case of Mobita, it was the first time that the system was used to collect and analyse EEG data at the School of Psychology at the University of Surrey. The EasyCap system has been used numerous times and best practices have already been established over the years. It is therefore possible that data recorded with EasyCap was of better quality because the researchers were able to use it more confidently. It is possible that with the development of best-practice solutions as well as further practice in

the use of the Mobita system, the recorded data will be of higher quality. The current study is an important step in the development of these best practice solutions.

Lastly, authors have not conducted any formal recordings of the objective experiences at data acquisition for participants nor themselves. The experiences were retrieved from lab notes and memory. However, all described experiences illustrate difficulties which have led to certain practical adaptations or methodological considerations for the future as detailed in the section below. Therefore, the subjective nature of these experiences presents a case-scenario of a real-life application of this new system.

### 4.6 Recommendations for future research

Due to Mobita's issues with noise and difficult set up for time-locked analyses which may produce misleading results, researchers should carefully consider the use of this new system. Based on the results presented in this study, we provide a set of general recommendations to avoid technical difficulties and false conclusions from the data. For more specific explanations regarding the assessment of electrode noise prior to recording, the bespoke solution on digital event markers and event markers labelling, see the supplementary file.

Firstly, to avoid *data loss* due to signal drops, we recommend that researchers record EEG signal directly to the logger strapped to participant's arm instead of sending the data wirelessly to a recording computer. If an a system error occurs leading to termination within Acqknowledge, researchers would not be able to monitor the data on the computer screen as the recording would remain in the logger mode only. They should therefore assess signal quality on the recording computer prior to the start of the recording. They may also decide to alter the design of the study and take more than one recording during a single procedure to allow breaks for the assessment of data quality. This would be especially beneficial for long

procedures as the water-based electrodes may become dry after some time which could lead to further increase in noise levels. Data loss can be prevented further by aiming to recruit larger samples and collect data for more trials in studies using Mobita compared to the state-of-the-art gel-based systems. This will also help to preserve power of the EEG analyses considering that more noise can be expected in Mobita data.

For studies focused on low-frequency effects and ERPs, researchers may want to consider robust solutions for detrending data in order to prevent the slow drifts from distorting or masking the effects of interest. For response-locked ERPs, such as ERN, researchers should take a careful approach to avoid the latency shift as observed in the current study. One solution is to synchronise the Mobita EEG recording with the stimulus presentation software at the point of the first stimulus onset and use event timing values from the stimulus recording software output rather than the Mobita EEG digital signal.

In order to improve the cap fit, researchers may consider using a bandage, or another type of an elastic band around the cap to put a slight additional pressure where needed and keep the electrodes in one place.

### 4.7 Conclusions

Mobita is an attractive EEG system that could potentially reduce participant involvement time and discomfort. However, using Mobita will require a number of adaptations that are not needed when using the state-of-the-art gel-based system. If researchers do not carefully consider the impact of different types of noise that is likely to interfere with their Mobita EEG data, they may be at risk of drawing wrong conclusions from time-frequency and ERP results.

# 5. Author Notes

## 5.1 Author Contributions

The following contributions are specified following the CRediT taxonomy.

MT: conceptualisation, data curation, formal analysis, investigation, methodology, project administration, visualisation, writing – original draft, writing – review and editing.

BO: conceptualisation, supervision, verification, writing – review and editing.

PD: conceptualisation, analysis, methodology, supervision, verification, writing – review and editing.

All authors contributed to the article and approved the submitted version.

## 5.2 Conflict of Interest

The study was funded as part of a PhD stiped at the University of Surrey. No other funding was used to conduct this project. The authors declare no conflict of interest.

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## 5.4 Data Availability

All data, code, analysis outputs and supplementary materials for this project are deposited in an open-access repository which can be found at (https://osf.io/kubv5/; Topor, Opitz, & Dean 2021).

## 6. References

Alday, P. M. (2019). How much baseline correction do we need in ERP research? Extended GLM model can replace baseline correction while lifting its limits. *Psychophysiology*, *56*(12), e13451. https://doi.org/10.1111/psyp.13451

Biopac Systemc, Inc. (2019). *Mobita® User Manual.* Accessed: 11/03/2021. Retrieved from: https://www.biopac.com/wp-content/uploads/Doc85.pdf

Biopac Systems, Inc. (2016). *How should I prepare electrode sites?* Accessed: 11/03/2021. Retrieved from: https://www.biopac.com/knowledge-base/how-should-i-prepare-electrode-sites/

Brain Products. Brainamp Mr Plus. Gilching, DE.

Brain Producs. Easycap System Kit. Stans, CH.

Brain Porducts GmbH. (2019). *BrainVision Analyzer | User Manual Software Version 2.2.0.*

Biopac Systems, Inc. Mobita-W-32EEG. Oldenzaal. NL.

Biopac Systems, Inc. MB-32EEG-CAP-A ConfCap, CA, US.

Biopac Systems, Inc. (2018). Acqknowledge 5.0.3. CA, US.

Biopac Systems, Inc. MP160WS. CA, US.

Brain Products. (2012). BrainVision Recorder & Analyzer 2.1.1. Gilching, DE.

Charness, G., Gneezy, U., & Kuhn, M. A. (2012). Experimental methods: Between-subject and within-subject design. *Journal of economic behavior & organization*, *81*(1), 1–8. https://doi.org/10.1016/j.jebo.2011.08.009

de Cheveigné, A., & Arzounian, D. (2018). Robust detrending, rereferencing, outlier detection, and inpainting for multichannel data. *Neuroimage*, *172*, 903–912. https://doi.org/10.1016/j.neuroimage.2018.01.035

DiStefano, C., Dickinson, A., Baker, E., & Jeste, S. S. (2019). EEG Data Collection in Children with ASD: The Role of State in Data Quality and Spectral Power. *Research in autism spectrum disorders*, *57*, 132–144. https://doi.org/10.1016/j.rasd.2018.10.001

Doyle, L. M. F., Yarrow, K., & Brown, P. (2005). Lateralization of event-related beta desynchronization in the EEG during pre-cued reaction time tasks. *Clinical Neurophysiology*, *116*(8), 1879–1888. https://doi.org/10.1016/j.clinph.2005.03.017

Eriksen, B. A., & Eriksen, C. W. (1974). Effects of noise letters upon the identification of a target letter in a nonsearch task. *Perception & Psychophysics*, *16*(1), 143–149. https://doi.org/10.3758/BF03203267

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior research methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Ferree, T. C., Luu, P., Russell, G. S., & Tucker, D. M. (2001). Scalp electrode impedance, infection risk, and EEG data quality. *Clinical Neurophysiology*, *112*(3), 536–544. https://doi.org/10.1016/S1388-2457(00)00533-2

Hazarika, J., & Dasgupta, R. (2018). Neural correlates of action video game experience in a visuospatial working memory task. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-018-3713-9

Hinrichs, H., Scholz, M., Baum, A. K., Kam, J. W. Y., Knight, R. T., & Heinze, H.-J. (2020). Comparison between a wireless dry electrode EEG system with a conventional wired wet electrode EEG system for clinical applications. *Scientific Reports*, *10*(1), 5218. https://doi.org/10.1038/s41598-020-62154-0

Jochumsen, M., Knoche, H., Kjaer, T. W., Dinesen, B., & Kidmose, P. (2020). EEG Headset Evaluation for Detection of Single-Trial Movement Intention for Brain-Computer Interfaces. *Sensors (Basel, Switzerland)*, *20*(10). https://doi.org/10.3390/s20102804

Kam, J. W. Y., Griffin, S., Shen, A., Patel, S., Hinrichs, H., Heinze, H.-J., … Knight, R. T. (2019). Systematic comparison between a wireless EEG system with dry electrodes and a wired EEG system with wet electrodes. *Neuroimage*, *184*, 119–129. https://doi.org/10.1016/j.neuroimage.2018.09.012

Kemp, B., Värri, A., Rosa, A. C., Nielsen, K. D., & Gade, J. (1992). A simple format for exchange of digitized polygraphic recordings. *Electroencephalography and Clinical Neurophysiology*, *82*(5), 391–393. https://doi.org/10.1016/0013-4694(92)90009-7

Klawohn, J., Santopetro, N. J., Meyer, A., & Hajcak, G. (2020). Reduced P300 in depression: Evidence from a flanker task and impact on ERN, CRN, and Pe. *Psychophysiology*, *57*(4), e13520. https://doi.org/10.1111/psyp.13520

Lakens, D. (2021). Sample Size Justification. https://doi.org/10.31234/osf.io/9d3yf

Leske, S., & Dalal, S. S. (2019). Reducing power line noise in EEG and MEG data via spectrum interpolation. *Neuroimage*, *189*, 763–776. https://doi.org/10.1016/j.neuroimage.2019.01.026

Mathewson, K. E., Harrison, T. J. L., & Kizuk, S. A. D. (2017). High and dry? Comparing active dry EEG electrodes to active and passive wet electrodes. *Psychophysiology*, *54*(1), 74–82. https://doi.org/10.1111/psyp.12536

Oliveira, A. S., Schlink, B. R., Hairston, W. D., König, P., & Ferris, D. P. (2016). Proposing Metrics for Benchmarking Novel EEG Technologies Towards Real-World Measurements. *Frontiers in Human Neuroscience*, *10*, 188. https://doi.org/10.3389/fnhum.2016.00188

Olvet, D. M., & Hajcak, G. (2009). The stability of error-related brain activity with increasing trials. *Psychophysiology*, *46*(5), 957–961. https://doi.org/10.1111/j.1469-8986.2009.00848.x

Pierce, S., Kadlaskar, G., Edmondson, D. A., McNally Keehn, R., Dydak, U., & Keehn, B. (2021). Associations between sensory processing and electrophysiological and neurochemical measures in children with ASD: an EEG-MRS study. *Journal of neurodevelopmental disorders*, *13*(1), 5. https://doi.org/10.1186/s11689-020-09351-0

Pinegger, A., Wriessnegger, S. C., Faller, J., & Müller-Putz, G. R. (2016). Evaluation of Different EEG Acquisition Systems Concerning Their Suitability for Building a Brain-Computer Interface: Case Studies. *Frontiers in Neuroscience*, *10*, 441. https://doi.org/10.3389/fnins.2016.00441

Pratt, N., Willoughby, A., & Swick, D. (2011). Effects of working memory load on visual selective attention: behavioral and electrophysiological evidence. *Frontiers in Human Neuroscience*, *5*, 57. https://doi.org/10.3389/fnhum.2011.00057

Puce, A., & Hämäläinen, M. S. (2017). A review of issues related to data acquisition and analysis in EEG/MEG studies. *Brain sciences*, *7*(6). https://doi.org/10.3390/brainsci7060058

Psychology Software Tools, Inc. (2012). E-Prime 2.0. Pittsburgh, PA.

Radüntz, T. (2018). Signal quality evaluation of emerging EEG devices. *Frontiers in physiology*, *9*, 98. https://doi.org/10.3389/fphys.2018.00098

Raj, V., Hazarika, J., & Hazra, R. (2020). Feature selection for attention demanding task induced EEG detection. In *2020 IEEE Applied Signal Processing Conference (ASPCON)* (pp. 11–15). IEEE. https://doi.org/10.1109/ASPCON49795.2020.9276710

Riesel, A., Weinberg, A., Endrass, T., Meyer, A., & Hajcak, G. (2013). The ERN is the ERN is the ERN? Convergent validity of error-related brain activity across different tasks. *Biological Psychology*, *93*(3), 377–385. https://doi.org/10.1016/j.biopsycho.2013.04.007

Rietdijk, W. J. R., Franken, I. H. A., & Thurik, A. R. (2014). Internal consistency of event-related potentials associated with cognitive control: N2/P3 and ERN/Pe. *Plos One*, *9*(7), e102672. https://doi.org/10.1371/journal.pone.0102672

RStudio Team. (2020). *RStudio: Integrated Development for R. RStudio*. PBC, Boston, MA. URL: http://www.rstudio.com/

Tanner, D., Morgan-Short, K., & Luck, S. J. (2015). How inappropriate high-pass filters can produce artifactual effects and incorrect conclusions in ERP studies of language and cognition. *Psychophysiology*, *52*(8), 997–1009. https://doi.org/10.1111/psyp.12437

Tanner, D., Norton, J. J. S., Morgan-Short, K., & Luck, S. J. (2016). On high-pass filter artifacts (they're real) and baseline correction (it's a good idea) in ERP/ERMF

analysis. *Journal of Neuroscience Methods*, *266*, 166–170. https://doi.org/10.1016/j.jneumeth.2016.01.002

Topor, M., Opitz, B., & Dean, P. (2021). *In search for the most optimal EEG method: A practical evaluation of a water-based electrode EEG system.* https://osf.io/kubv5/ https://doi.org/10.17605/OSF.IO/KUBV5

Topor, M., Opitz, B., & Leonard, H. C. (2021). Error-Related Cognitive Control and Behavioral Adaptation Mechanisms in the Context of Motor Functioning and Anxiety. *Frontiers in Human Neuroscience*, *15*, 615616. https://doi.org/10.3389/fnhum.2021.615616

van Dinteren, R., Arns, M., Jongsma, M. L. A., & Kessels, R. P. C. (2014). Combined frontal and parietal P300 amplitudes indicate compensated cognitive processing across the lifespan. *Frontiers in aging neuroscience*, *6*, 294. https://doi.org/10.3389/fnagi.2014.00294