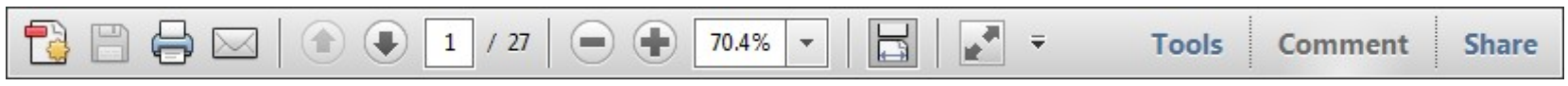
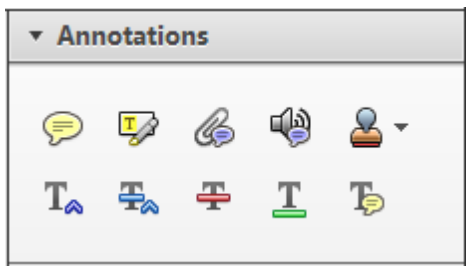
USING e-ANNOTATION TOOLS FOR ELECTRONIC PROOF CORRECTION

Once you have Acrobat Reader open on your computer, click on the Comment tab at the right of the toolbar:



This will open up a panel down the right side of the document. The majority of tools you will use for annotating your proof will be in the Annotations section, pictured opposite. We've picked out some of these tools below:

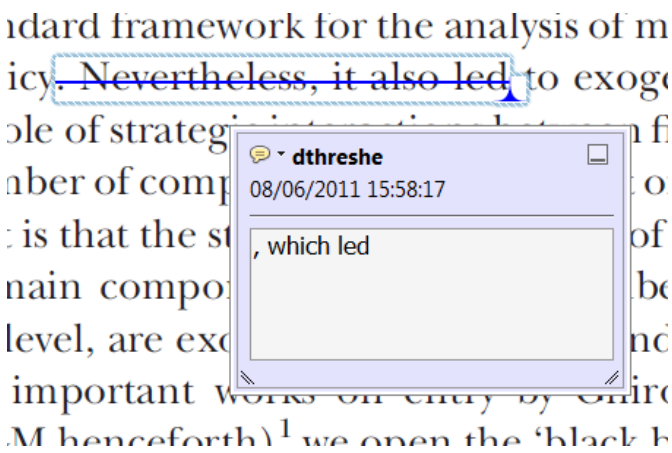


1. Replace (Ins) Tool – for replacing text.

Strikes a line through text and opens up a text box where replacement text can be entered.

How to use it

- Highlight a word or sentence.
- Click on the Replace (Ins) icon in the Annotations section.
- Type the replacement text into the blue box that appears.

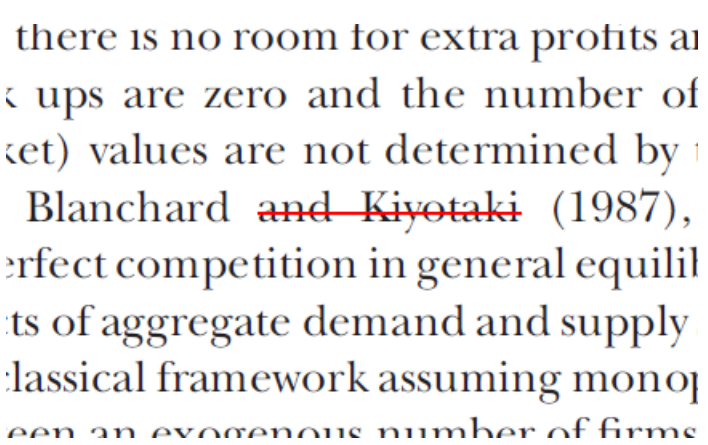


2. Strikethrough (Del) Tool – for deleting text.

Strikes a red line through text that is to be deleted.

How to use it

- Highlight a word or sentence.
- Click on the Strikethrough (Del) icon in the Annotations section.

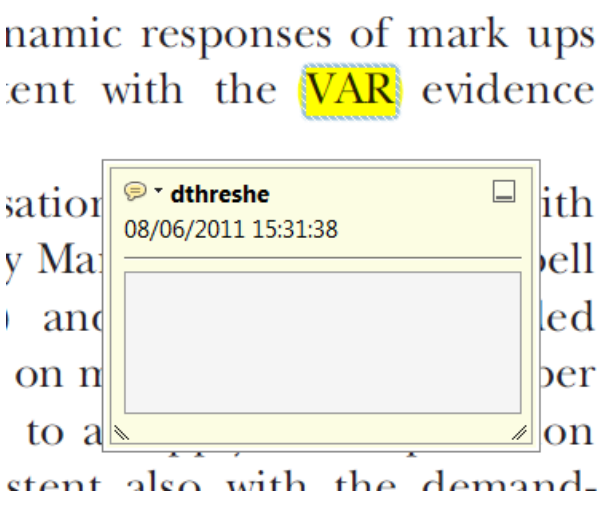


3. Add note to text Tool – for highlighting a section to be changed to bold or italic.

Highlights text in yellow and opens up a text box where comments can be entered.

How to use it

- Highlight the relevant section of text.
- Click on the Add note to text icon in the Annotations section.
- Type instruction on what should be changed regarding the text into the yellow box that appears.

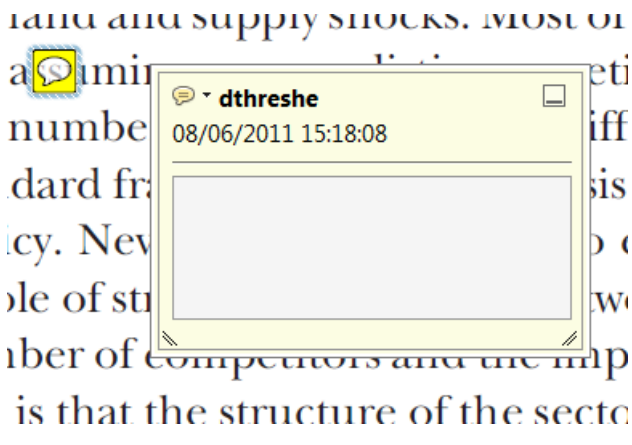


4. Add sticky note Tool – for making notes at specific points in the text.

Marks a point in the proof where a comment needs to be highlighted.

How to use it

- Click on the Add sticky note icon in the Annotations section.
- Click at the point in the proof where the comment should be inserted.
- Type the comment into the yellow box that appears.

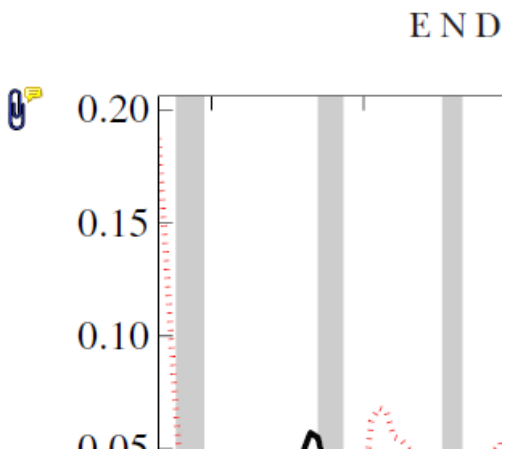


5. Attach File Tool – for inserting large amounts of text or replacement figures.

Inserts an icon linking to the attached file in the appropriate pace in the text.

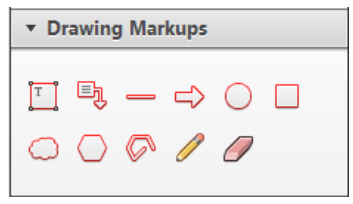
How to use it

- Click on the Attach File icon in the Annotations section.
- Click on the proof to where you'd like the attached file to be linked.
- Select the file to be attached from your computer or network.
- Select the colour and type of icon that will appear in the proof. Click OK.



6. Drawing Markups Tools – for drawing shapes, lines and freeform annotations on proofs and commenting on these marks.

Allows shapes, lines and freeform annotations to be drawn on proofs and for comment to be made on these marks.



How to use it

- Click on one of the shapes in the Drawing Markups section.
- Click on the proof at the relevant point and draw the selected shape with the cursor.
- To add a comment to the drawn shape, move the cursor over the shape until an arrowhead appears.
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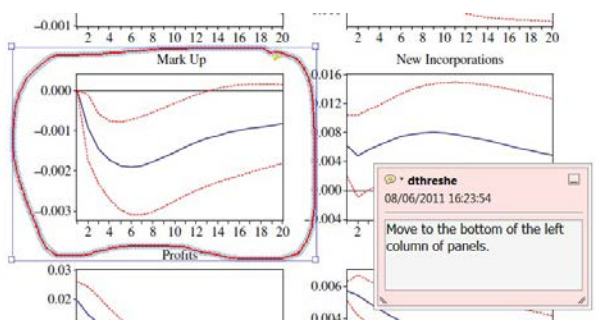

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High and dry? Comparing active dry EEG electrodes to active and passive wet electrodes

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Abstract

Dry electrodes are becoming popular for both lab-based and consumer-level electrophysiological-recording technologies because they better afford the ability to move traditional lab-based research into the real world. It is unclear, however, how dry electrodes compare in data quality to traditional electrodes. The current study compared three EEG electrode types: (a) passive-wet electrodes with no onboard amplification, (b) actively amplified, wet electrodes with moderate impedance levels, and low impedance levels, and (c) active-dry electrodes with very high impedance. Participants completed a classic P3 auditory oddball task to elicit characteristic EEG signatures and event-related potentials (ERPs). Across the three electrode types, we compared single-trial noise, average ERPs, scalp topographies, ERP noise, and ERP statistical power as a function of number of trials. We extended past work showing active electrodes' insensitivity to moderate levels of interelectrode impedance when compared to passive electrodes in the same amplifier. Importantly, the new dry electrode system could reliably measure EEG spectra and ERP components comparable to traditional electrode types. As expected, however, dry active electrodes with very high interelectrode impedance exhibited marked increases in single-trial and average noise levels, which decreased statistical power, requiring more trials to detect significant effects. This power decrease must be considered as a trade-off with the ease of application and long-term use. The current results help set constraints on experimental design with novel dry electrodes, and provide important evidence needed to measure brain activity in novel settings and situations.

Descriptors: •••

Laboratory-based research has dominated cognitive neuroscience because of tightly controlled environments and tasks, as well as limitations of neuroimaging technologies. Advances in the ability to record in and manipulate both real and virtual environments have directed proposals to study the human brain behaving in its natural habitat (e.g., Debener, Minow, Emkes, Gandras, & Vos, 2012; Tarr & Warren, 2002). The portability of electrophysiological recording equipment has improved due to advances in technology and manufacturing processes, including hardware miniaturization (Lovelace, Witt, & Beyette, 2013), active-electrode amplification (Metting Van Rijn, Kuiper, Dankers, & Grimbergen, 1996), dry-electrode technologies (Taheri, Knight, & Smith, 1994; Zander et al., 2011; Xu et al., 2014; Yang et al., 2014), and flexible electronics (Kim et al., 2011; Xu et al., 2014; Yang et al., 2014). Active electrodes are on-electrode circuit boards that actively amplify voltage at the electrode (Meeting Van Rijn et al., 1996; Kappenman & Luck, 2010), allowing for lower input impedance to the amplifier. Dry electrodes interface with the skin with no bridging electrolyte gel, and use mechanical force to push the electrode against the skin (Taheri, Knight, & Smith, 1994). The current article will focus on the use of active electrode amplification and dry electrode technologies, testing the effectiveness of active-dry electrodes to measure lab-quality EEG and event-related potential (ERP) signals in ideal settings. Information about the noise levels and statistical power of active-dry electrode systems will help define the limits and constraints of this new technology, educating experimental design as cognitive neuroscience moves outside the lab using these novel technologies.

The statistical power of EEG and ERP recordings is largely influenced by the amount of nonneural noise, both physiological and environmental (Luck, 2014). Physiological noise includes eye movements, muscle activity, cardiovascular activity, skin potentials, and physical displacement of the electrodes due to movement (Gratton, Donchin, & Coles, 1983; Jung et al., 2000; Kappenman & Luck, 2010; Keil et al., 2014). Physiological noise is unavoidable and must be dealt with using restrictions in movement or signal processing techniques. Environmental noise includes line noise from the local AC power in the recording environment, any electrical equipment in the room, and cell phone and other radio frequency signals (Luck, 2014). Environmental noise can be mitigated in other ways. Amplifiers often include common mode noise

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rejection to remove any artifactual signal common to multiple electrodes, eliminating noise picked up by the leads between the scalp and amplifier.

Common mode rejection of noise is less effective with high interelectrode impedance due to amplified differences between electrodes (Kappenman & Luck, 2010). Interelectrode impedance represents the opposition to the flow of alternating current between the scalp and the electrode. The wires connecting the electrode to the amplifier act as antennae, allowing additional environment noise to intrude. Interelectrode impedance is lowered through the use of skin abrasion, cleaning, and electrolyte gel to electrically bridge the scalp and the electrode, techniques which can lead to discomfort and consume time. Traditionally, because of fixed low-input impedance to EEG amplifiers, low interelectrode impedance is needed in order to acquire adequate voltage signals from the scalp. Active amplification with circuits built into the electrode itself is used to minimize noise while allowing for higher electrode impedances. Differences in voltage are amplified at the scalp source (Metting Van Rijn et al., 1996), and are thus less sensitive to environmental noise (Kappenman & Luck, 2010; Laszlo, Ruiz-Blondet, Khalifian, Chu, & Jin, 2014).

Even with active amplification, high interelectrode impedance (10–190 kΩ) increases low-frequency noise, and lowers ERP statistical power, as compared to very low interelectrode impedance (<5 kΩ; Kappenman & Luck, 2010). This low-frequency noise is reduced with high-pass filtering, mitigating the decrease in statistical power, but distorting slow ERP components. Directly comparing active and passive amplification in the same system has revealed a slight benefit for passive electrodes at very low interelectrode impedance levels (<5 kΩ), whereas at moderate impedance levels (<50 kΩ), active electrode data had both lower environmental noise and more statistical power given the same number of trials (Laszlo et al., 2014). In theory, active electrode amplification should be even more beneficial with extremely high interelectrode impedance levels (>300 kΩ), without the use of skin preparation or electrolyte gels, as in new dry electrode technologies (Kim et al., 2011; Lopez-Gordo, Sanchez-Morillo, & Valle, 2014; Taheri et al., 1994; Xu et al., 2014; Zander et al., 2011). Increased noise with very high, as opposed to moderate, interelectrode impedance active-electrooculogram (EOG) recordings has been found, especially during times of fast voltage changes (Laszlo et al., 2014). The question, therefore, remains as to what extent this increased noise influences EEG and ERP recording noise and statistical power.

A new system of gold-plated dry electrodes offered by Brain Vision LLC (actiCAP Xpress) provides a novel means of testing the effectiveness of dry EEG electrodes. Dry electrodes remove the need for wet gel by directly contacting the scalp, considerably reducing setup time. In exchange for increased flexibility, the system records greater noise, which is mitigated with active amplification. Dry electrodes offer the promise of long-term continuous recording, and use in aging, infant, and patient populations and applied settings such as sports, driving, classrooms, and marketing. However, it is not yet known empirically how much extra noise the very high interelectrode impedance levels will create, or what the influence of this additional noise will be on EEG and ERP recording. The current study extends the experimental design and analysis strategy of Kappenman and Luck (2010), as well as Laszlo and colleagues (2014) to novel dry EEG electrodes with very high interelectrode impedance. Each participant completed an auditory oddball task with three electrode recording configurations in separate sessions: passive low-impedance wet electrodes (*Passive Wet*; actiCAP Passive; <10 kΩ), Active moderate-impedance wet electrodes (*Active Wet*; actiCAP; <50 kΩ; both using electrolyte gel to lower impedance), or the novel active dry electrodes (*Active Dry*; actiCAP Xpress; >300 kΩ). The power spectra, baseline noise levels, ERP traces and topographies, and P3 statistical significance as a function of the number of trials are compared. The effectiveness of the novel actively amplified dry electrode system is of particular interest in educating the field about the statistical power of these new technologies.

Method

Participants

A total of eight members of the university community participated in the experiment (mean age = 21.52; age range = 19–25; 4 female). Each participant completed an identical session on separate days in each of the three electrode conditions (Active Wet, Passive Wet, Active Dry; order counterbalanced). Participants were all right handed, and all had normal or corrected normal vision and no history of neurological problems. All participants gave informed consent, were compensated at a rate of $10/hr for their time, and the experimental procedures were approved by the internal Research Ethics Board of the University of Alberta.

Materials and Procedure

In each of the three electrode conditions, participants completed an auditory oddball task to measure their P3 response to target tones. A pair of Logitech Z130 speakers played one of two different frequency tones (either 1,500 or 1,000 Hz; sampled at 16,384 Hz; one channel; 16-ms duration; 2-ms linear ramp up and down), with the rare target tone always at 1,500 Hz. The volume of the speakers and sound output was kept constant for every participant and condition. The participant's task was to sit still and fixate a 1° white cross in the center of a black background that stayed constant throughout the auditory task. Whenever the rare tone was heard, participants were to move only the fingers of their right hand (which was rested on the table in front of them), to press the space bar on a keyboard.

Participants were seated 57 cm away from a 1,920 x 1,080 pixel ViewPixx/EEG LED monitor running at 120 Hz with simulated-backlight rastering. Stimuli were presented using a Windows 7 PC running Matlab R2012b with the Psychophysics toolbox (Brainard, 1997). Video output was via an Asus Striker GTX760, and audio was output via an Asus Xonar DSX sound card. Coincident in time with sound onset, 8-bit TTL pulses were sent to the amplifier by a parallel port in the stimulus computer to mark the data for ERP averaging.

In each of the three conditions, each participant completed three blocks of 250 trials for a total of 750 trials in each condition. Each trial had a 1/5 likelihood of being a target trial. Each trial began with a pre-tone interval chosen randomly from a uniform distribution between 500 and 1,000 ms, followed by the tone onset. The next trial began immediately after the tone offset, with participants responding to targets during the following pre-tone interval.

EEG Recording

The three types of electrodes tested were Passive Wet low impedance (actiCAP passive electrodes kept below 10 kΩ), Active Wet moderate impedance (Brain Products actiCAP adjusted for signal quality, estimated <50 kΩ), and Active Dry electrodes with

impedance close to that of human skin (estimated >300 kΩ; actiCAP Xpress, adjusted for signal quality; Brain Products, 2014). For the passive electrodes, interelectrode impedances were measured at the start of each recording session. In the case of the active electrodes, impedance was not measured directly but inferred from data quality per the suggested usage guidelines provided by the manufacturer (Brain Products, 2014). Interelectrode impedance in these active conditions was confirmed in separate recording session using identical setup techniques, measured using an ImpBox (Brain Products).

All electrodes were arranged in the same 10–20 positions (Fp2, F3, Fz, F4, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, and Oz). In all three conditions, a ground electrode was used embedded in the cap at position Fpz. Electrolyte gel was applied to this ground electrode in all three conditions. EEG was recorded online referenced to an electrode clipped to the left ear lobe, and offline the data were re-referenced to the arithmetically derived average of the left and right ear lobe electrodes. In both the Passive and Active Wet conditions, Ag/AgCl pin electrodes were used, with SuperVisc electrolyte gel and mild abrasion with the blunted syringe tip used to lower impedances. Gel was applied and interelectrode impedances were lowered to <10 kΩ in the Passive Wet condition, and until data quality appeared good in the Active Wet condition (inferred to be around 50 kΩ in separate sessions; Kappenman & Luck, 2010; Laszlo et al., 2014). In the Passive and Active Wet conditions, electrolyte gel was used to lower the impedance of the electrodes on the ears. The Active Dry electrodes consist of gold-plated metal tips that push through the participant's hair and against his or her scalp. The gold-plated metal tips were physically manipulated, longer tips were changed in, or they had external pressure applied to them (via Pro-wrap) until the data quality was sufficient enough to be recorded. In the Active Dry electrodes, a flatted gold disk electrode was clipped to the ear, with no electrolyte gel.

In addition to the 15 EEG sensors, 2 reference electrodes, and the ground electrode, in all three conditions the vertical and horizontal bipolar EOG was recorded from passive Ag/AgCl easycap disk electrodes affixed above and below the left eye, and 1 cm lateral from the outer canthus of each eye. Electrolyte gel was used to lower the impedance of these EOG electrodes in all three conditions based on visual inspection of the data. These bipolar channels were recorded using the AUX ports of the V-amp amplifier, using a pair of BIP2AUX converters, and a separate ground electrode affixed to the central forehead.

For all three electrode types, EEG was recorded with a V-amp 16-channel amplifier (Brain Products) with identical settings. Data were digitized at 500 Hz with a resolution of 24 bits. Data were filtered with an online bandpass with cutoffs of 0.1 Hz and 30 Hz, along with a notch filter at 60 Hz. These narrow filters were used as recommended in the actiCAP Xpress manual in order to minimize high-frequency noise and low-frequency drifts from the active dry electrodes (Brain Products, 2014). All three conditions took place in a dimly lit sound and radio frequency–attenuated chamber from electromedical instruments, with copper mesh covering the window. The only electrical devices in the chamber were an amplifier, speakers, keyboard, mouse, and monitor. The monitor ran on DC power from outside the chamber, the keyboard and mouse were plugged into USB outside the chamber, and the speakers and amplifier were both powered from outside the chamber. The lights and fan were turned off, and nothing was plugged into the internal power outlets. Any devices transmitting or receiving radio waves (e.g., cell phones) were either turned off or removed from the chamber for the duration of the experiment.

EEG Analysis

Analyses were computed using Matlab R2012b using EEGLAB (Delorme & Makeig, 2004), as well as custom scripts. The timing of the TTL pulse was marked in the recorded EEG data, and used to construct 1,200-ms epochs time locked to the onset of standard and target tones, with the average voltage in the first 200-ms baseline period subtracted from the data for each electrode and trial. To remove artifacts due to amplifier blocking and other nonphysiological factors, any trials in any of the conditions with a voltage difference from baseline larger than +/– 750 μV on any channel (including eyes) were removed from further analysis. A lenient threshold was used in order to keep as many trials as possible for the power analysis, and to allow about equal numbers of rejected trials for each electrode type. At this time, a regression-based eye-movement correct procedure was used to estimate and remove the artifactual variance in the EEG due to blinks as well as horizontal and vertical eye movements (Gratton et al., 1984). After identifying AQ2 blinks with a template-based approach, this technique computes propagation factors as regression coefficients predicting the vertical and horizontal eye channel data from the signals at each electrode. The eyes channel data are then subtracted from each channel, weighted by these propagation factors, removing any variance in the EEG predicted by eye movements. On average, artifact rejection left roughly equal number of trials per participant the Passive Wet (M_{targ} = 152; $range_{targ}$ = 137–166; M_{stand} = 599; $range_{stand}$ = 545–628), Active Wet (M_{targ} = 160; $range_{targ}$ = 143–172; M_{stand} = 586; $range_{stand}$ = 556–613), and the Active Dry conditions (M_{targ} = 158; $range_{targ}$ = 137–181; M_{stand} = 593; $range_{stand}$ = 559–629), from which the remaining analyses are computed. No further filtering was done on the data.

Results

EEG Spectra

The raw data for a representative participant are depicted in Figure 1 A at electrode location Pz. We estimated the noise in the data on F1 individual trials in two ways. First, we computed the average frequency spectra of each EEG epoch, as shown in Figure 1B. For each participant, we randomly selected 545 of their artifact free standard target trials from electrode Pz. For each trial, we computed a Fast Fourier Transform by symmetrically padding the 600 time point epochs with zeros to make a 1,024-point time series for each epoch, providing frequency bins with a resolution of .488 Hz. Because the data are collected with an online 30 Hz low-pass filter, we plot only frequencies up to 30 Hz. Each participant's 545 spectra are then averaged together to compute participant spectra, which were then combined to form grand average spectra plotted in Figure 1B. The shaded regions represent standard error of the mean across participants. Evident from the plot are almost-identical spectra for Passive Wet and Active Wet measurement, and a broad-band power increase for the Active Dry electrodes. All conditions showed both the expected 1/f frequency structure in the data, as well as the typical peak in the alpha frequency range between 8 and 12 Hz (Mathewson et al., 2011).

Single-Trial Noise

To compute a second and related estimate of the noise on single-trial EEG epochs, we randomly selected 300 standard-tone epochs for each participant, and computed the root mean square (RMS) of the baseline period on each trial (De Vos, Gandras, & Debener,

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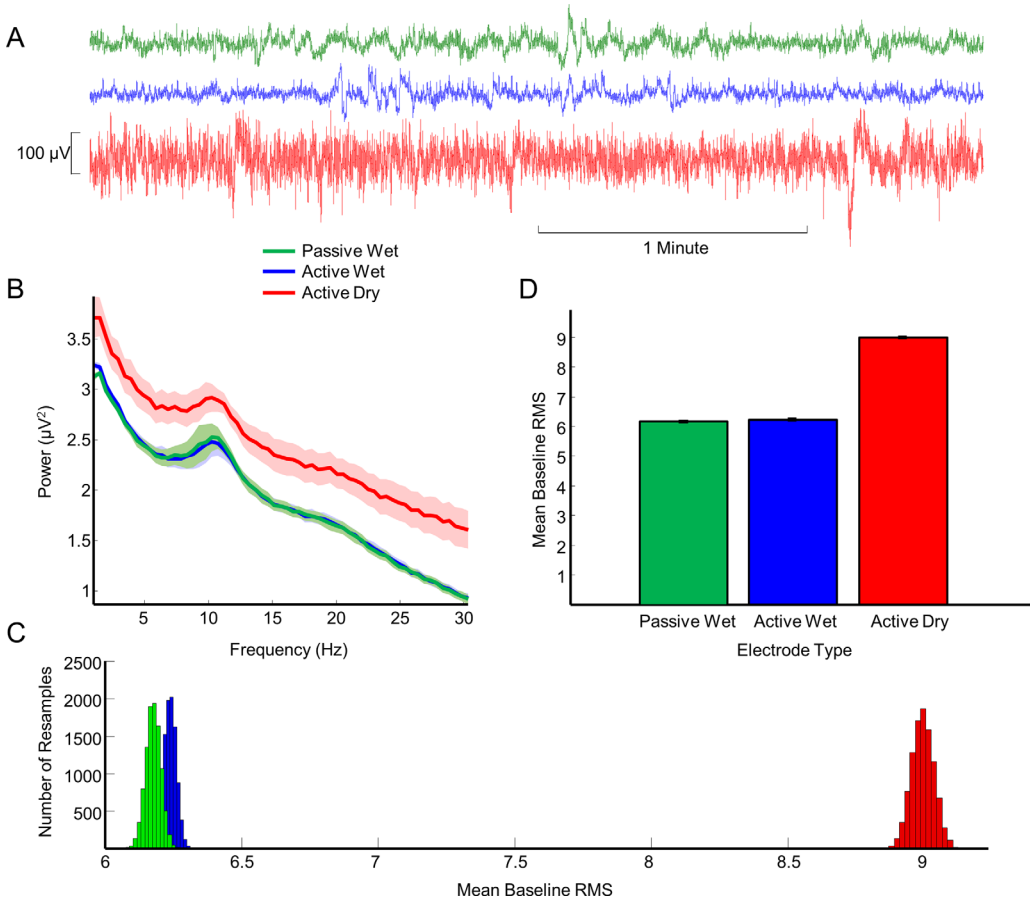

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Figure 1. Single-trial noise levels. a: Raw EEG data (with online bandpass and notch filters) for a number of minutes for a representative subject in each of the three electrode recording conditions, shown at electrode location Pz. b: Single-trial EEG spectra from electrode Pz, computed with zero padded FFTs on 545 standard auditory target trial epochs for each subject, averaged first over trials and then subjects. Shaded regions show the standard error of the mean. c: Histogram of grand average root mean square (RMS) values during the 200-ms baseline period, for 10,000 permutations of 300 random standard target trials. Values are averaged over electrodes for each trial, then over trials, then subjects. d: The mean of the permuted distributions in 1C are shown, with error bars indicating the standard deviation.

2014). We used the 200-ms baseline period (100 time points) prior to the onset of each tone in order to avoid the influence of any evoked ERP activity on the RMS measurement. The RMS is a measure of the average absolute difference of the voltage around the baseline, and is therefore a good estimate of single-trial noise in the EEG data. For each trial, we averaged the RMS values for each EEG electrode, then averaged over trials for each participant, then computed the grand average RMS across participants (as in Laszlo et al., 2014).

To estimate the distribution of RMS in our data for each condition, we employed a permutation test in which a different 300 epochs were selected without replacement for each participant on each of 10,000 permutations (Laszlo et al., 2014). For each of these random selections, and for each electrode condition, we computed and recorded the grand average single-trial RMS. Figure 1C shows a histogram of the grand average single-trial RMS values computed for each permutation. Figure 1D shows a bar graph of the mean and standard deviation of these permuted grand average single-trial RMS distributions. The results show a clear separation between the RMS distributions. The Active Dry system ($M_{RMS\text{-}EEG} = 8.993$; $SD_{RMS\text{-}EEG} = 0.041$) showed clearly larger single-trial noise levels, which was reliable compared to both the Passive Wet ($M_{RMS\text{-}EEG} = 6.176$; $SD_{RMS\text{-}EEG} = 0.028$; $z = 122.472$; $p < .0001$) and Active Wet conditions ($M_{RMS\text{-}EEG} = 6.238$; $SD_{RMS\text{-}EEG} = 0.023$; Wilcoxon rank sum test; $z = 122.472$; $p < .0001$). The Passive Wet had lower single-trial noise than Active Wet ($z = 111.190$; $p < .0001$).

ERP Analysis

Next, we examined noise levels in the trial-averaged ERPs. Figure 2Ashows the grand average ERPs from electrode Pz following standard and target tones, computed using all artifact-free trials for each participant. Evident as expected is the standard P3 oddball difference, with more positive voltage between 250–450 ms following rare target tones compared to frequent standard tones. We used this time window for all further ERP analyses of the P3. The shaded regions show the standard error of the mean at each time point for each tone type, with very similar levels of error in the Passive and Active Wet conditions, and a much larger standard error in the Active Dry condition. F2

Figure 2B shows the topography of this P3-window difference, revealing the classic central posterior scalp distribution for all three electrode conditions. Figure 2C shows the difference waves subtracting each participant's ERP for standard tones from those for target tones. A clear peak at around 380 ms is observed for each electrode condition. The shaded regions represent the within-

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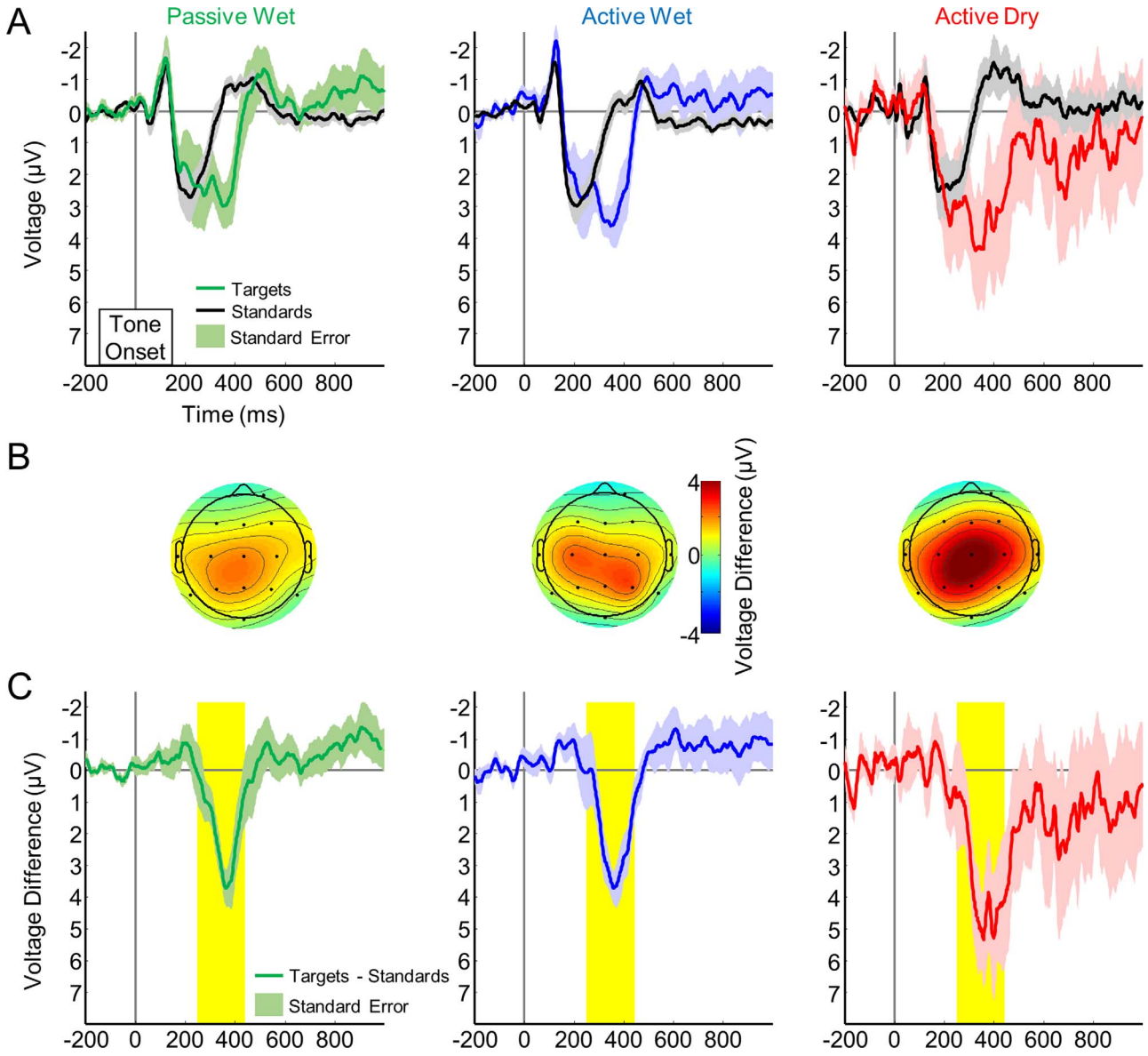

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Figure 2. Grand average event-related potentials (ERPs). a: Grand average ERPs computed at electrode Pz with all artifact-free trials, corrected for eye movements, for both target (color) and standard (black) tones. Shaded regions represent the standard error of the mean and positive is plotted down. b: Scalp topographies of the grand average ERP difference between target and standard tones in the P3 window from 250–450 ms after the tone (indicated in yellow in 2C). Eye channels and reference electrodes are not included in this topography (Target-Standard). c: Difference wave ERPs for each of the electrode conditions, with shaded regions showing the within-subject standard error of the mean of this difference, having removed the differences between subjects (Loftus & Masson, 1994). Yellow regions show the window used for P3 analysis and topographic plotting.

participant standard error of the mean, because within-participant variation has been removed due to the subtraction. This error estimate is therefore equivalent to that used in the *t* test of this difference against zero (Loftus & Masson, 1994). It is again clear that the within-subject standard error is larger for the Active Dry electrodes, and roughly the same for the Passive and Active Wet conditions. A simple *t* test comparing this difference to zero at electrode Pz in the window from 250–450 ms revealed a significant P3 effect for the Passive Wet ($M_{diff} = 1.887$; $SD_{diff} = 1.323$; $t(7) = 4.032$; $p = .0025$), Active Wet ($M_{diff} = 2.078$; $SD_{diff} = 1.221$; $t(7) = 4.813$; $p = .00097$), and Active Dry conditions ($M_{diff} = 3.538$; $SD_{diff} = 4.086$; $t(7) = 2.449$; $p = .0221$).

To quantify the level of noise in the participant average ERPs, we again employed a permutation test of the RMS values in the baseline period. This analysis provides information complementary with the single-trial RMS analysis presented above, in that here we estimate the amount of phase-locked EEG noise in the data that does not average out over trial with respect to the tone onset. In this ERP version, for each of the 10,000 permutations, we averaged the 300 standard trials that were randomly selected without replacement from the larger pool of that participant's artifact free trials in each condition. We then computed the RMS of the resultant 100 time points of ERP baseline. We averaged these RMS values over EEG electrodes, and then computed a grand average across participants. Figure 3Ashows a histogram of the grand average RMS values computed in each of the 10,000 permutations in each condition. Figure 3B shows a bar graph of these same data, with the error bars indicating the standard deviation of the distribution

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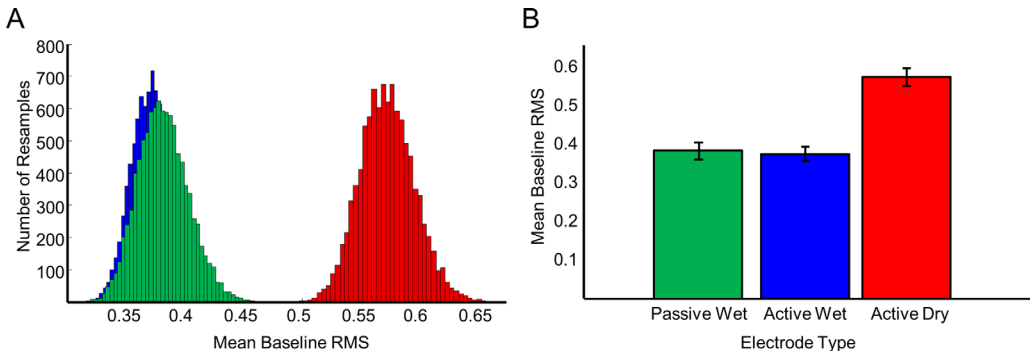

Figure 3. ERP baseline noise. a: Histogram of RMS values of the ERP baseline, computed using 10,000 randomly permuted selections of 300 standard target trials. For each permutation, data are averaged over trials and the RMS of the baseline period is computed. b: The mean of each of these permuted distributions is plotted, error bars represent the standard deviation of the permuted distribution.

of permutation means. The Active Dry system ($M_{RMS\text{-}ERP} = 0.573$; $SD_{RMS\text{-}ERP} = 0.023$) had a higher RMS value compared with both the Passive Wet ($M_{RMS\text{-}ERP} = 0.382$; $SD_{RMS\text{-}ERP} = 0.022$; $z = 122.471$; $p < .0001$) and the Active Wet conditions ($M_{RMS\text{-}ERP} = 0.374$; $SD_{RMS\text{-}ERP} = 0.019$; $z = 122.471$; $p < .0001$). Passive Wet showed reliably larger ERP noise compared to Active Wet electrodes ($z = 27.56$, $p < .0001$).

ERP Power

Given the evidence for increased single-trial and trial-averaged noise in the active dry electrode system, and the slightly lower levels of noise for passive as compared with active electrodes at low impedances, one might expect that active dry electrodes will provide lower statistical power. To test this prediction explicitly, we used another permutation procedure in which we varied the number of trials contributing to the ERP average while keeping the 4:1 ratio of standard to target trials. Trial numbers were varied from 4 standards and 1 target trial, by 20 standard trials, up to 540 standard and 135 target trials, separately for each of the three electrode conditions. For each number of trials, 10,000 permutations were randomly selected from the total pool without replacement.

For each permutation, the selected single trials were averaged to create participant ERPs separately for target and standard tones. The difference between target and standard tones was then computed at electrode Pz between 250 and 450 ms, and these participant average ERP differences were compared to a null distribution with a standard t test (df = 7, one-tailed, $\alpha = .05$). Figure 4plots the F4 proportion of the 10,000 permutations in which the t statistic passed the significance threshold, as a function of the number of samples in each permutation. It is evident from this plot that the P3 data from both the Passive and Active Wet conditions reached significance on 80% of permutations (80% power dashed line) with fewer trials (35 target/140 standard trials) than did the Active Dry electrode conditions (125 target/500 standard trials).

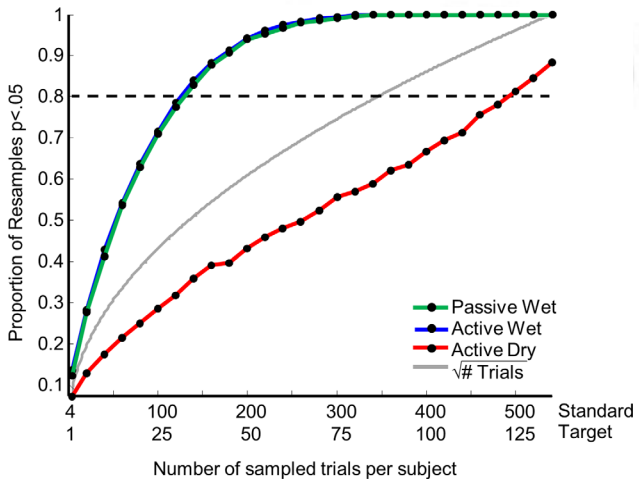

Figure 4. ERP power analysis. The results of a permutation test in which the number of trials selected on each of 10,000 permutations is varied between 5 and 625, while keeping the 4:1 ratio of standard to target trials. For each permutation of each number of trials, the randomly selected trials are averaged to compute subject ERPs. The difference in the P3 window between target and standard trials is computed, and compared with a one-tailed t test across subjects against a null difference ($\alpha = .05$). Plotted are the proportions of the 10,000 permutations for each trial number in which an uncorrected significant difference obtained, for each of the three electrode configurations (Passive and Active Wet are overlapping). The dashed line at .8 indicates the threshold to achieve 80% power at finding an effect when one is present. The gray line indicates the square root of the number of standard trials, but scaled on the vertical axis to range between 0 and 1 by dividing by the square root of the maximum number of standard trials.

Discussion

We directly examined the effectiveness of a new dry-electrode system at recording laboratory-quality EEG and ERP data, comparing it with two other commonly used testing configurations. The results confirm previous research showing increased noise levels at very high interelectrode impedance (Laszlo et al., 2014). Visual inspection of the raw data themselves, as well as comparison of the single-trial EEG spectra and RMS values demonstrated a larger amount of noise which was present even with the active amplification of the voltage at the electrode. Therefore, active electrodes are sensitive to very high levels of interelectrode impedance (unprepared skin). Regardless, they still afforded the ability to measure classic EEG and ERP signatures.

The dry active electrodes measured a reliable 1/f EEG spectra, with the expected peak in the alpha range (Mathewson et al., 2011), which closely matched that observed in the lower impedance conditions with and without active amplification. Of note is a broad-band increase in power, which may indicate frequency-aspecific boosts in noise picked up by the active dry electrodes (i.e., a large noise floor), ruling out biological noise or environment line noise. It may also be the case that there are some calibration

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differences between the electrodes, although the calibration settings are likely not electrode specific. The different materials comprising the Active Dry (Au platting; Brain Products, 2014) and the Passive and Active Wet electrodes (Ag/AgCl) may also play a role in this difference (Tallgren, Vanhatalo, Kaila, & Voipio, 2005).

Further, the ERPs plotted in Figure 2A reveal that the Active Dry electrodes afford the ability to measure laboratory-quality ERP waveforms and scalp topographies, albeit with slightly increased baseline and ERP noise levels. Nonetheless, reliable differences between target and standard tones were observed over posterior-central scalp locations with a latency of around 400 ms. This timing and topography were very similar to those recorded in the same participants using more traditional active and passive electrode technologies in the same amplifier. A consideration of the noise present in the averaged ERP waveforms for standard tones for each participant revealed increased noise even in these trial-averaged data for the Active Dry electrode system, also evident in the size of the within-participant standard error bars in Figure 2C.

Importantly, we also considered analyses very similar to those computed in Kappenman and Luck, (2010) and by Laszlo and colleagues (2014) in which we used a resampling procedure to estimate the number of trials necessary to achieve a certain level of statistical power. This procedure can be used to estimate the number of trials necessary to reliably find a statistically significant effect when one is present, and is proportional to the signal-to-noise level of the data. The analysis confirmed the finding of Laszlo and colleagues (2014) that almost identical numbers of trials were needed to reach a given proportion of significant tests with a low-impedance wet passive system and a moderate-impedance active electrode system (around 25 target tones and 100 standards). Crucially, Active Dry electrodes, with their increased broadband noise, have poorer statistical power. The current results indicate that at a given level of statistical power, the Active Dry electrodes would require around five times the number of trials as the Passive and Active Wet electrodes, holding all else constant.

The present study utilized a high degree of online filtering at recording in order to maximize our ability to find EEG and ERP effects with the Active Dry electrode system. In fact, our high-pass filter eliminated the low-frequency skin potentials observed by Kappenman and Luck (2010) to be particularly problematic at high humidity and temperature. We did not measure or manipulate the temperature or humidity in our recording chamber; however, our lab's location and the local climate are optimal in terms of dryness and cool temperature. Further research with the dry electrode system in more humid and hot environments will be needed. We used a notch filter and a low-pass filter to remove the influence of any high-frequency muscle activity, as well as environmental line noise, therefore limiting our ability to directly compare the level of noise at these frequencies.

Past comparison of active to passive electrode amplification systems has revealed that the speed of voltage changes seems to influence the noise in the recorded data nonlinearly (Laszlo et al., 2014). The authors proposed that the slow *slew rate* of the active amplification system (the rate of change of the output voltage of the amplifier), led to increased noise observed during periods of EEG and EOG measurement in which large fast changes in voltage were observed. We did not specifically test this hypothesis, or the influence of even higher interelectrode impedance on this relationship between voltage slope and noise. However, a visual inspection of Figure 2C seems to indicate that during periods of the ERP with steep slopes, the active electrode system does not exhibit greatly increased levels of within-participant noise (compare within-participant error bars in left to middle column). Further research will be needed to elucidate the relationship between amplifier slew rate and measurement noise.

Evidence that traditional EEG and ERP measures can be replicated with a dry electrode system are promising. It does appear, however, that the benefits in convenience and flexibility may be offset by a fivefold increase in trials needed to achieve comparable levels of power. One thing to note is that we were conservative in our comparison; because the goal was to directly compare the new system to existing technologies, we did not take all possible steps to lower noise in the Active Dry data. For example, the actiCAP Xpress manual indicates that electrode gel can be used for the reference electrodes in order to minimize noise in the data (Brain Products, 2014). We did do this for the ground electrode in order to better compare with the other techniques, but we let the reference electrodes on the ear lobes have the same preparation and interelectrode impedance as the other scalp electrodes they were being compared with (as done in Kappenman & Luck, 2010). Although extensive preparation would detract from the benefits of using the system, further increases in statistical power would be possible by using reference electrodes with lower interelectrode impedance. Further, differences in impedance between the active electrode and the reference can introduce additional environmental noise due to capacitive coupling (Ferree, Luu, Russell, & Tucker, 2001), which must be considered. Future research should work toward achieving an optimal balance between skin preparation and convenience.

Another consideration when interpreting the decrease in statistical power with Active Dry electrodes is that our particular task and comparison involved comparing conditions with different numbers of trials (four standards for every one target). The smaller number of target trials may have added additional variance to our comparison of the significance of the P3 effect as a function of the number of total trials. It will be important to consider also tasks and ERP comparisons in which there are equal numbers of trials in each condition in future research into the use of these new electrode systems. Interestingly, Figure 2B indicates that the Active Dry electrodes may have produced a more defined P3 topography than the other electrode systems, a result that should be further investigated using denser electrode montages, a pair of components with distinct scalp topography (e.g., P3a and P3b), and factor analysis techniques to test how well these distinct components get separated using different electrode types.

One of the major benefits of the dry electrode system is the ease and speed of application. While we did not formally compare the setup times among the three techniques, the dry electrode system was clearly faster. This time savings can be an important benefit for experiments with infants, elderly, and patients in hospital settings. We add a caveat that setup was particularly time consuming for individuals with very thick hair. Characteristics of the target population such as hair thickness must therefore also be considered. The dry system also affords decreased delay between successive recording sessions, with less time washing and drying the electrodes between each session. This can be an important improvement for high-throughput scenarios such as classroom, marketing, and equipment demos. Traditionally abrasive agents and minor scratching are used, which can both be very invasive for the participant, and can lead to red marks and discomfort (Luck, 2014). Furthermore, these abrasive techniques, normally used to remove dead skin cells and oils from the skin and thus lower interelectrode impedance, both have the possibility of transmitting blood and bio fluid–borne pathogens (Putnam, Johnson, & Roth, 1992). It is, therefore, advantageous to have a dry electrode system that is

capable of recording experimental quality data with neither of these limitations. The lack of electrode gel in dry systems may also be particularly advantageous during extended recording when impedance may change due to water evaporation.

One additional issue with dry electrode systems is that data quality is greatly enhanced when mechanical pressure between the electrode and skin surface is present. For example, the actiCAP Xpress system utilizes the elasticity of the head cap as well as the thin electrodes protruding into the cap to apply mechanical forces pushing the electrodes against the head. This pressure can be somewhat uncomfortable for long periods of time, and can lead to headaches. Further, uniform pressure across the scalp is required, which is difficult over temporal lobes. New methods and materials of electrodes are therefore needed to address these issues (e.g., Fiedler et al., 2015). Further research is also needed on the susceptibility of active and dry electrode systems to movement artifacts during seated tasks, as well as more naturalistic behavior. We have developed advanced technologies in wireless health monitoring and data transmission which afford new opportunities for continuous, unobtrusive monitoring of electrical and optical activity in the body (Jang et al., 2014; Xu et al., 2014). Flexible electrode systems are often used dry with no skin preparation or electrolyte gel, and achieve the required levels of mechanical pressure via van der Waals forces holding the device against the head (Kim et al., 2011; Xu et al., 2014). Other portable EEG systems are being developed with head-mounted amplifiers and wet electrodes (e.g., Debener et al., 2012; De Vos et al., 2014), with electrodes increasingly placed in novel and unobtrusive locations (e.g., Bleichner et al., 2015). The ability for these systems to continuously monitor electrophysiological activity for extended periods of time rests on the use of stable dry electrodes. Additional research is needed to directly compare these technologies using the same statistical and experimental design as in the current article.

As we move these technologies outside of the lab, similar methods will need to be utilized in order to test the power of ERP and EEG measures in these new settings. The current experiment recorded data inside a radio-frequency–shielded chamber with optimal control of electrical noise, and further research is needed into the levels of noise present with dry and active electrodes in less-controlled environments. Active Wet electrodes, for instance, should perform much better than passive electrodes in increasingly noisy environments. Higher input impedance in current passive systems also should allow for the faster setup times associated with using higher interelectrode impedance without active amplification (e.g., Ferree et al., 2001), which needs to be further investigated (but see Laszlo et al., 2014). Work is currently under way in our lab to test these same EEG and ERP measures on similar tasks during physical activities such as standing, walking, bike riding, and driving. Other potential issues that must be considered when selecting electrodes for a given application is the time needed for preparation and cleanup (which can change based on if electrodes are loose vs. embedded), the wiring of the electrode leads (ribbon cable vs. loose), and the weight of the electrodes (active circuitry adds weight).

In summary, we have shown the effectiveness of a novel dry electrode system available to the research community. It was observed that compared to wet electrodes, the dry (and therefore very high-impedance) electrodes recorded increased broad-band noise that obscured the single-participant ERP data and led to decreased statistical power. More trials were needed to achieve the same probability of observing a significant effect when one was present. However, with traditional lab techniques and paradigms, these new electrodes were nonetheless able to reliably measure classic EEG and ERP signatures, and therefore provide an important tool available for the electrophysiology and cognitive neuroscience community to utilize for new experimental techniques.

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