Original Article

Media Neuroscience on a Shoestring

Examining Electrocortical Responses to Visual Stimuli Via Mobile EEG

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Abstract: Event-related potentials (ERPs) capture neural responses to media stimuli with a split-second resolution, opening the door to examining how attention modulates the reception process. However, the relatively high cost and difficulty of incorporating ERP methods have prevented broader adoption. This study tested the potential of a new mobile, relatively easy-to-mount, and highly affordable device for electroencephalography (EEG) measurement – the Muse EEG system – combined with a free, open-source platform for ERP recording and analysis. Specifically, we compared ERPs with affective visual stimuli – representative of the kind of engaging content that pervades modern social media. Our results confirm that the Muse system provides robust visual ERPs, highly reliable across two samples. Although there was no difference between ERPs to moderately positive and neutral stimuli in the expected time windows (200–300 ms, 400–600 ms), an exploratory analysis provided some evidence for differential processing of positive versus neutral images at the right temporal sensor site (TP10). Additionally, a compliance-gaining manipulation in participant instructions significantly improved data quality. These results support the use of the Muse EEG system in large-scale studies examining brain responses to screen media. They also suggest an easy social influence tactic that can enhance data quality as communication neuroscience is scaled up. The availability of a mobile EEG system for 250 USD makes it possible to incorporate neuroimaging into various communication paradigms beyond visual communication.

Keywords: event-related potentials, EEG, attention, emotion

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Recent studies have demonstrated the potential of neural measures to elucidate reception mechanisms, which represent the critical link between media content and media effects (Falk et al., 2015; Huskey et al., 2020; Schmälzle & Grall, 2020a; Weber et al., 2008). However, while neural measures come with many desirable properties, several roadblocks impede their wider adoption (Schmälzle & Meshi, 2020). In particular, the high cost for equipment limits accessibility, and the slow pace with which data are recorded from individuals makes it difficult to acquire large samples.

Here we examine a new approach to overcome these roadblocks via a low-cost, mobile, and comparatively easy-to-mount device for electroencephalography (EEG) measurement. Specifically, we validate the device in the context of an event-related potential (ERP) study of brain responses to affective images, such as the kind of messages shared on popular social media platforms like Instagram. Moreover, the experimental and analytic pipeline is openly available to encourage reproducibility efforts and facilitate adoption (https://github.com/nomcomm/MediaNeuroscienceOnAShoestring_JMP).

We begin by reviewing relevant ERP research on motivated attention. Next, we discuss barriers to using ERP methods in media psychology and present a new system that enables neuroscience studies to be conducted at low cost but with high potential for scalability. We then describe an ERP study to test the system. Moreover, we introduce a compliance-gaining manipulation for the instructions given to participants to optimize data quality in large-scale studies.

The Potential of ERPs for Examining Rapid Brain Responses to Media

ERPs are measures derived from human EEG, which records real-time changes in the brain's electrical activity

https://doi.org/10.1027/1864-1105/a000348

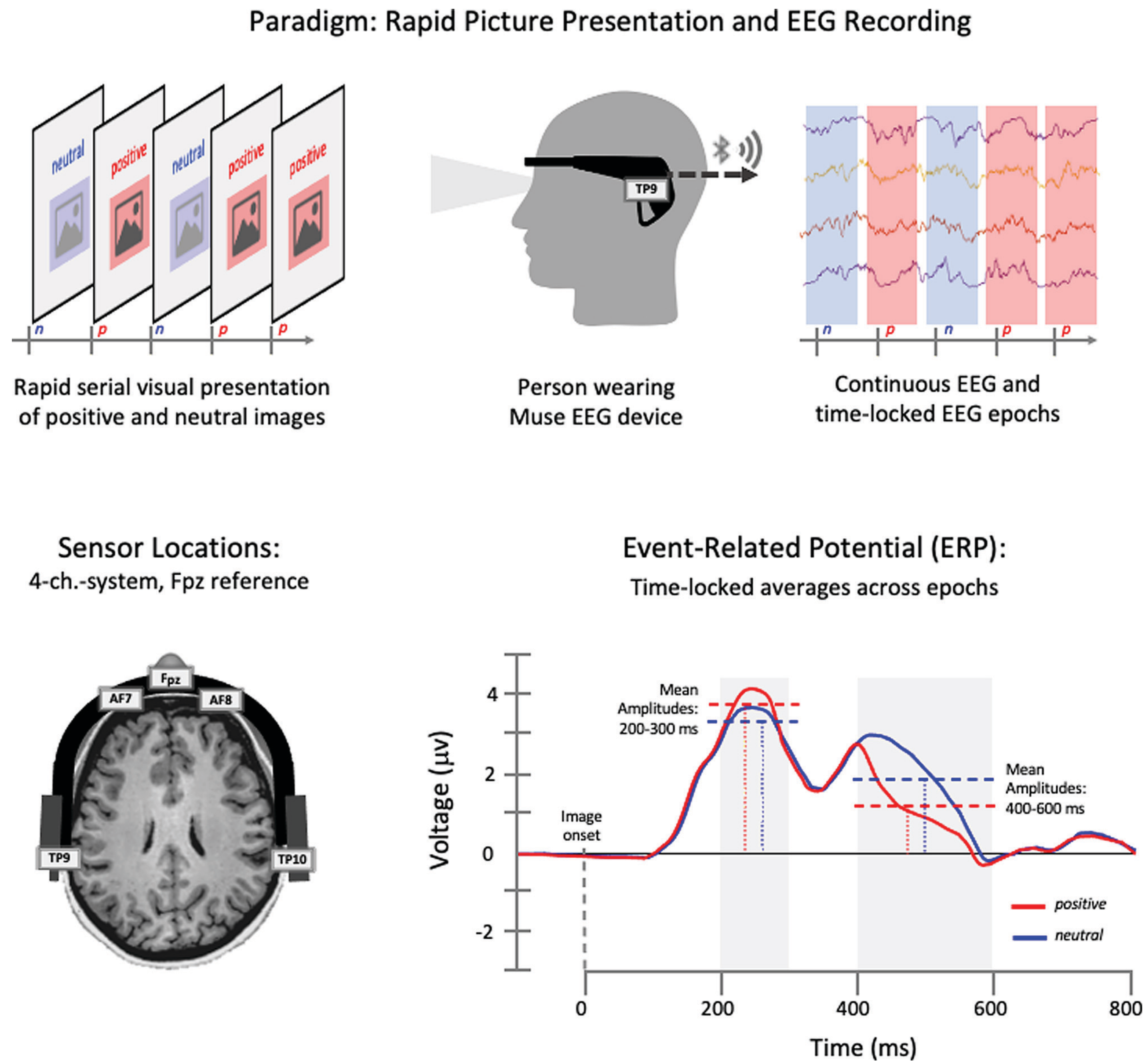

Figure 1. Illustration of the visual message paradigm with mobile EEG recording. Top row: Participants view a stream of emotional and neutral IAPS images while the Muse device records continuous EEG data. Triggers marking image onset and image type (mildly positive vs. neutral) are sent and integrated with the four-channel EEG recordings for subsequent analysis of event-related brain potentials (ERP). Bottom row: Locations of EEG sensors on the Muse device and illustration of idealized ERP waveforms at one sensor and mean amplitude measurements in selected time windows. EEG = electroencephalography. IAPS = International Affective Picture System.

from sensors placed on the head (Luck, 2005). By averaging epochs around experimental events (e.g., the 1,000 ms following stimulus onset), one can derive the ERP. This general procedure is illustrated in Figure 1. Depending on the paradigm, the ERP waveforms contain specific components characterized by the features amplitude, polarity, latency, and topography (Luck, 2005).

ERPs have a long history and are still among the most widely used methods for examining cognitive processes through a neurophysiological lens (Biasiucci et al., 2019; Cacioppo et al., 2007; Rugg & Coles, 1995; Schmälzle & Grall, 2020b). Specific ERP components are associated with higher cognitive and affective computations, such as expectancy or affective evaluation (Cacioppo et al., 1993; Schupp et al., 2004). Because ERPs are directly related to electrical neural activity, which can be measured instantaneously, the method enables researchers to precisely interrogate the timing of internal mental events.

ERP Studies of Motivated Attention

The degree of attention a stimulus attracts is a crucial variable in media psychology and communication more broadly, as this will affect subsequent outcomes (McGuire et al., 2001). Indeed, attention has long played a major role in theories of message processing and persuasion, such as the AMIE (activation model of information exposure), LC4MP (limited capacity model of motivated mediated message processing), or the ELM (elaboration likelihood model) (Donohew et al., 1980; Lang, 2009; Petty & Cacioppo, 1986). With this in mind, researchers would benefit from methods capable of parsing reception processes without interruption or interference, and neural measures are prime candidates for this task. However, while a few early studies used EEG to explore attention to messages (Reeves et al., 1985; Thorson, 1990), the use of EEG in media psychology has remained limited (Morey, 2018).

Within cognitive neuroscience, however, attention has been intensely studied and the exquisite temporal resolution of ERPs yielded many insights into the operations of selective attention (Chun et al., 2011; Luck et al., 2000; Nobre & Kastner, 2014). Within this context, the work on motivated attention is particularly relevant from a media psychology perspective (Lang, 2009; Lang et al., 2013). In brief, motivated attention refers to a form of selective attention commanded by motivationally relevant stimuli, such as affective images or words that speak to motivational variables based on evolutionary significance or intrinsic personal relevance (Bradley, 2009; Lang et al., 1997). Motivational influences, such as evolutionary significant stimuli (e.g., food, sex, and danger), have been shown to powerfully steer attention to stimuli and modulate ERP responses (Ferrari et al., 2011; Hillyard & Anllo-Vento, 1998; Junghöfer et al., 2010; Schupp et al., 2004, 2014).

Several ERP components are reliably associated with motivational influences on attention, particularly in studies of affective vision (Schupp et al., 1997, 2003, 2004). For the sake of the present study, we limit the discussion here to the two most prominent ERP components associated with motivated attention: the early posterior negativity (EPN) and the late positive potential (LPP; Schupp et al., 2006). The EPN and LPP are different components, both assessed by subtracting ERPs in response to emotionally arousing images from ERPs toward neutral images. The EPN emerges as relative negativity over occipitotemporal sites between approximately 200–300 ms after stimulus onset, and the LPP emerges as a centroparietal positivity between approximately 400–600 ms. Functionally, the EPN is linked to an early tagging for prioritized processing, while the LPP is linked to the ignition of higher-order cell assemblies related to conscious access and relevance evaluation (Schupp et al., 2006).

Low-Cost, Mobile EEG Devices for Conducting Neuroscience Studies

Neural measures in general hold promise for media psychology because they make it possible to study the brain's response to screen media on a moment-to-moment basis, without interruption or overt questioning. ERP methods are very well-suited to uncover the split-second response to affective images, which are extremely common in modern media (e.g., images of disasters in newspaper websites, affective content on Instagram, etc.). Unfortunately, there are three key barriers when it comes to incorporating neuroscience methods into communication and media research (Schmälzle & Meshi, 2020).

The first barrier is cost: The cost for a standard research EEG system with 64–256 channels lies between 30,000 and 100,000 USD, excluding other costs, such as setting up a lab. While these costs are considerably lower than those for functional magnetic resonance imaging (fMRI), they are high enough to place EEG methodology out of reach of many researchers. The second barrier relates to the ease and speed of data acquisition: Historically, mounting an EEG net on a participant's head required substantial effort and time, and participants could only be measured one at a time. Beyond burdensome setup procedures, another bottleneck is the number of available EEG systems (usually one, due to the cost). As a result, a typical EEG lab will rarely record data from more than two to four participants per day on average. Comparatively, this is far less than other methods can output. The last barrier is the intangibles needed to conduct reliable research with neuroscience methods. Traditionally, those employing neuroimaging underwent thorough training in neuroscience theory, data collection, and analysis.

In sum, the relatively high cost, low speed/scalability of neuroimaging, and the intangible skills and resources needed represent three key barriers that prevent the wider use of ERP methods in media research. Over the past decade, however, several companies made efforts to overcome these barriers. As of 2019, there are now four companies offering EEG devices under 1,000 USD and another nine that offer devices under 25,000 USD (Farnsworth, 2019). By lowering costs, increasing mobility, and improving ease-of-use, these devices make neurophysiological measures more available to other fields.

One specific EEG system that holds promise for use in media research is the Muse device from Interaxon Inc. (SCR_014418). It is a small device with four sensors – AF7, AF8, TP9, and TP10 – and the Fpz electrode to serve as the reference (see Figure 1). The device is low-cost (250 USD), transmits data through a Bluetooth connection, and can be set up within minutes. While it has not been primarily developed for research, its dry electrodes and amplifier specs can be considered adequate for EEG research. Furthermore, with it being designed for commercial purposes, the price and comparative ease-of-use make it one of the most viable EEG devices in its category.

In fact, the potential of the Muse for research has already been tested in prior work (Krigolson et al., 2017, 2021). Results showed that the Muse can detect two standard ERP effects, an oddball and a reward-related component. Krigolson et al. (2017) also compared the Muse ERP results with a research-grade 64-sensor EEG system and demonstrated very similar ERP results after re-referencing the data to a common site. These results are encouraging, but more testing is needed to certify the use of the Muse device in research settings that are of more interest to media psychologists. Moreover, Krigolson and colleagues (2017, 2021) used a custom Matlab-based platform to obtain the data from the Muse, which requires a Matlab license and technical expertise. Recently, an open-source tool has become available that allows EEG data to be recorded more easily (BlueMuse; Kowaleski, 2022), and a suite of open-source EEG paradigms, called "EEG notebooks," has been developed. The EEG notebooks are a collection of classic EEG experiments that combine the popular PsychoPy system (Peirce & MacAskill, 2018) with the Muse device (Griffiths et al., 2020), and they integrate stimulus presentation, data collection, and data analysis within one relatively easy-to-use system. With this setup, it would be possible to conduct ERP studies with a budget of 250 USD and freely available software. Overall, the Muse system and the EEG notebooks show promise as a low-cost and scalable method to examine the reception and processing of media, especially visual images. However, further feasibility testing and validation are necessary.

The Current Study

In this study, we propose to expand the scope of the Muse system into the domain of affective image processing, a common message format in today's social media communication environment (e.g., Instagram, Pinterest). In brief, participants will view images from the International Affective Picture System (IAPS; Lang et al., 2008), which has been used in many ERP studies of selective attention. Thus, this study will not use real social media images, although this would be an obvious next step, but instead employ IAPS images that have been used in hundreds of psychophysiological studies, such that the expected ERP effects are well understood. However, to focus on the kind of content that is more regularly encountered during day-to-day web browsing and social media activities, we selected IAPS images that have either moderately positive or neutral content, excluding highly emotionally evocative IAPS images, such as mutilations and erotica (see Figure 1). Importantly, this builds on work from Krigolson and colleagues (2017, 2021), as our study moves from classic ERP paradigms to naturalistic stimuli that resemble social media messages.

A large body of ERP research on motivated attention has consistently demonstrated that affectively valenced images prompt differential ERP responses (Schupp et al., 2006). Accordingly, we expect a difference between ERPs in response to emotional versus neutral images, particularly in the range of EPN and LPP components. We note, however, that previous ERP findings were established under different conditions. First, as stated earlier, seminal studies employed strong affect manipulations by comparing ERPs toward erotica or mutilations with the ERPs toward neutral images, whereas a comparison of moderately arousing positive versus neutral images is a less impactful manipulation. Second, studies that used high-density systems with 128 and 256 channels (and average reference montages) differ markedly from the Muse's sensor layout with only two frontal and two temporal sensors and a recording reference at location Fpz. Therefore, we can expect that the recorded ERP will differ in terms of waveform shape and topography, although a differential effect between positive arousing and neutral images should still emerge (Luck, 2005). In sum, this study will assess the utility of the Muse device by testing the following hypothesis:

> *Hypothesis 1 (H1)*: There will be a discernible difference (comparable to previously reported findings using high-density EEG systems) between event-related potentials (ERPs) for the positive versus the neutral images.

Our next goal, a practical one, is to test whether a compliance-gaining manipulation improves the quality of acquired EEG data. The applied motivation for this goal lies in the fact that EEG data are noisy and that even minor movements create artifact signals that are multiple times larger than the to-be-measured EEG signals (Luck, 2005). It is common to reject approximately one third or a half of the recorded epochs from any given dataset based on violations of artifact-rejection criteria, such as implausible voltage, blinks, or signal drifts. Thus, for the success of neuroscientific studies, it is crucial that participants adhere to the instructions to keep movement during the experiment at a minimum. This can be a big request that participants are unlikely to adhere to correctly and that requires a fair amount of self-regulation.

Therefore, labs take great care in developing instructions, but researchers tend to rely on tacit knowledge and intuitive strategies to instruct their participants. While many labs use standardized procedures, they do not test and optimize them to improve performance. If a simple compliance-gaining request could improve data quality, this could be useful to implement it in all future experiments.

Aside from these practical considerations, there is also much scientific merit in studying the role of instructions as a communication topic (De Houwer et al., 2017). Clearly, the way that instructions are delivered and worded can affect participants' behavior – a simple and ubiquitous real-life instance of persuasion or compliance gaining. The quality of EEG recordings depends on the participants' behavior, such as artifacts due to body motion. In this vein, EEG quality metrics might serve as an objective outcome of a compliance-gaining instruction (Rhodes & Ewoldsen, 2013). In sum, these considerations lead to the second hypothesis:

Hypothesis 2 (H2): Participants who receive an additional compliance-gaining request will exhibit a lower data sample drop percentage compared with participants in a control group.

Method

Participants

A total of 70 undergraduates from a large university in the Midwest US participated in the study. All participants provided written consent to the study procedures, which were approved by the local IRB. All participants had normal or corrected-to-normal vision and participated for course credit. There were two internal subsamples, each comprising 35 participants, allowing for internal split-half comparison. The second subsample performed an additional target-counting task immediately after the image viewing task, which will not be reported here. Furthermore, the 70 participants were randomly assigned to the experimental or control group for the compliance-gaining manipulation.

Applying strict artifact screening criteria to exclude participants whose EEG provided low-quality data (for details, see next section and the online reproducibility package), we excluded 23 participants, leaving a final sample of 47. This number is high even compared with other neuroimaging studies, which typically exclude about 10% of participants for reasons related to data quality. However, we deliberately chose to accept a higher attrition rate because we wanted to let participants mount the EEG devices in a mostly self-directed fashion and thus performed only minimal calibrations or corrections. The motivation behind this decision was that we envision a trend toward the commodification of EEG technology. This will make it possible to conduct neurophysiological studies in settings other than traditional lab environments (Krigolson et al., 2021). Therefore, it was important to test the system under conditions with low experimenter involvement.

Stimulus Material

The positive and neutral images were selected from the IAPS based on their normative ratings of arousal and valence, respectively (Lang et al., 2008). The class of "positive images" comprised 30 pictures selected to be moderately arousing, positively valenced (M_{valence} = 7.01, SD = 0.72; M_{arousal} = 6.14, SD = 0.61, comprising nature and sports scenery), and 30 "neutral images" that are rated as low-arousing and neutral (M_{valence} = 4.9, SD = 0.26; M_{arousal} = 2.55, SD = 0.35, images of household objects). Specifically, the IAPS numbers used were #1560, 1720, 5450, 5460, 5470, 5600, 5621, 5626, 5629, 5700, 5950, 7230, 7270, 7501, 7502, 7570, 8021, 8030, 8080, 8178, 8179, 8185, 8190, 8210, 8211, 8341, 8400, 8475, 8500, and 8501 (positive images), as well as #7000, 7004, 7009, 7010, 7020, 7025, 7030, 7031, 7035, 7038, 7040, 7041, 7050, 7060, 7090, 7100, 7110, 7140, 7150, 7161, 7175, 7185, 7187, 7217, 7224, 7233, 7235, 7490, 7491, and 7705 (neutral images).

Experimental Task

Upon arrival, participants consented to participation and received a verbal description regarding the EEG device and how to put it on. The instruction on how to mount the headset and the experimenter setting up the stimulus took less than 2 min. Participants were told that this study was a simple image-viewing task, which was broken up into two brief 2-min viewing sessions. Upon the completion of the setup, participants in both conditions received the same instruction for viewing session 1: "Please sit still and focus on the middle of the screen." The presentation was controlled by a PsychoPy script (Peirce & MacAskill, 2018), which presented each image for 200 ms with an intertrial interval that varied randomly between 800 and 1,000 ms.

After Session 1, the participants were instructed to relax while the integrity of the signal stream was checked again. The experimental conditions were introduced before the second viewing session, where the instructions were varied by condition. Based on whether participants were in the experimental or control group for the upcoming compliance-gaining test, they received one of two instructions: Participants in the control group received the same instruction as in Session 1. Participants in the experimental group, however, received the instruction: "It is imperative to focus on the middle of the screen. Please relax and limit all body, head, and facial movements. If possible, minimize the amount that you blink while you view another brief presentation. Any movement can affect the signal and we hope to obtain the best results possible during this video." This instruction served as the more intensive request for the experimental group, whereas both groups received the same instruction for Session 1, which served as a baseline. The following session consisted of the same task, that is, a 2-min series of neutral and positively valenced images.

Equipment and ERP Recordings

EEG data were recorded using a Muse device from Interaxon Inc., Toronto, Canada. The Muse has four electrodes, in the 10–20 coordinate system, with locations corresponding to AF7, AF8, TP9, and TP10, and a reference at Fpz. EEG data were sampled at 256 Hz and were streamed via a Bluetooth connection (Kowaleski, 2022) to a Python program (Griffiths et al., 2020), which stored the data.

The experimental stimuli were presented through PyschoPy (Peirce & MacAskill, 2018), which also sent triggers during the stimulus onset, which were merged into the EEG data stream. The images were presented on a 14″ LCD monitor with full brightness, located approximately 50 cm in front of the participant. The experimental control software was based on the EEG Notebooks system and the modified code for the picture viewing task is available online (https://github.com/nomcomm/MediaNeuroscienceOnAShoestring_JMP).

ERP Analysis

EEG Preprocessing and Artifact Rejection

EEG data were analyzed using the MNE-Python software (Gramfort et al., 2014). The entire analytic pipeline is available online at https://github.com/nomcomm/MediaNeuroscienceOnAShoestring_JMP. In brief, continuous EEG data were filtered and epochs were extracted from 100 ms before the stimulus to 800 ms after the presentation of the stimulus. Given that only the four-channel (AF7, AF8, TP9, TP10) and Fpz-recording reference are available, we did not re-reference the data offline. Rejection of epochs due to artifacts was done based on the MNE automated artifact rejection routines and complemented by visual inspection (Gramfort et al., 2014; Jas et al., 2017).

From the 240 trials that each participant saw over the course of the experiment (some participants received minimally fewer trials due to a small change in the code, but all received well over 200 trials), we applied strict artifact-control criteria to reject artifact-laden epochs (average across participants: 47.6%, SD = 20.5%). After the visual inspection, the Python package *Autoreject* was used, an algorithm that determines the appropriate threshold for epoch rejection (Gramfort et al., 2014; Jas et al., 2017). Moreover, we rejected all the data from 23 participants due to low overall recording quality, leaving a final sample of 47 participants.

ERP Averaging and Statistical Comparison of ERPs Toward Positive and Neutral Images

ERP waveforms were subsequently computed by averaging together clean epochs for positive and neutral images, respectively. These averages were based on approximately 56 epochs per condition (M_{pos} = 59.89, SD = 22.70; M_{neu} = 58.57, SD = 22.91; t-test for dependent samples, *ns*). Finally, the ERPs for positive/neutral images from individual participants were averaged to derive a grand-average ERP for each condition.

To statistically test for differences between the ERPs toward positive and neutral images, we assessed the mean ERP amplitude in the time windows of interest (200–300 ms and 400–600 ms) and compared mean amplitude values for positive and neutral mean ERP amplitudes across participants via paired-sample t-tests.

Results

ERP Results

The ERP results demonstrate that the Muse device was able to capture the millisecond-by-millisecond electrocortical signature evoked during passive picture viewing. As is evident from the grand-averaged ERPs shown in Figure 2, the signal measured at sensors TP9 and TP10 reveals waveforms that are consistent with the ERP literature on visual picture viewing (Luck, 2005; Schupp et al., 2006). These results provide strong evidence that the Muse devices can be used to conduct ERP studies.

Passive Viewing of Positive Versus Neutral Images

To test for ERP differences between positive and neutral images, we calculated average ERP waveforms for each condition and tested for mean amplitude differences in the time windows between 200–300 ms and 400–600 ms, respectively. Importantly, although the EPN and LPP components are typically assessed over occipitotemporal or centroparietal sites, the Muse systems only have two temporal sensors (TP9 and TP10). However, due to the characteristic volume conduction of EEG, effects could still be expressed at these sensor sites (see Figure 2, which shows that there are no differences at frontal sites, but small differences in the grand-average waveforms at temporal sites). Nevertheless, a statistical test showed that these were not statistically significant, neither for the 200–300-ms window – mean amplitude in time window, collapsed over TP9 and TP10: $M_{positive}$ = 2.88 μV, $M_{neutral}$ = 2.97 μV, $t(46) = -0.24$; *ns*; same result when tested separately at each sensor – nor for the 400–600-ms window – $M_{positive}$ = 0.58 μV, $M_{neutral}$ = 0.94 μV,

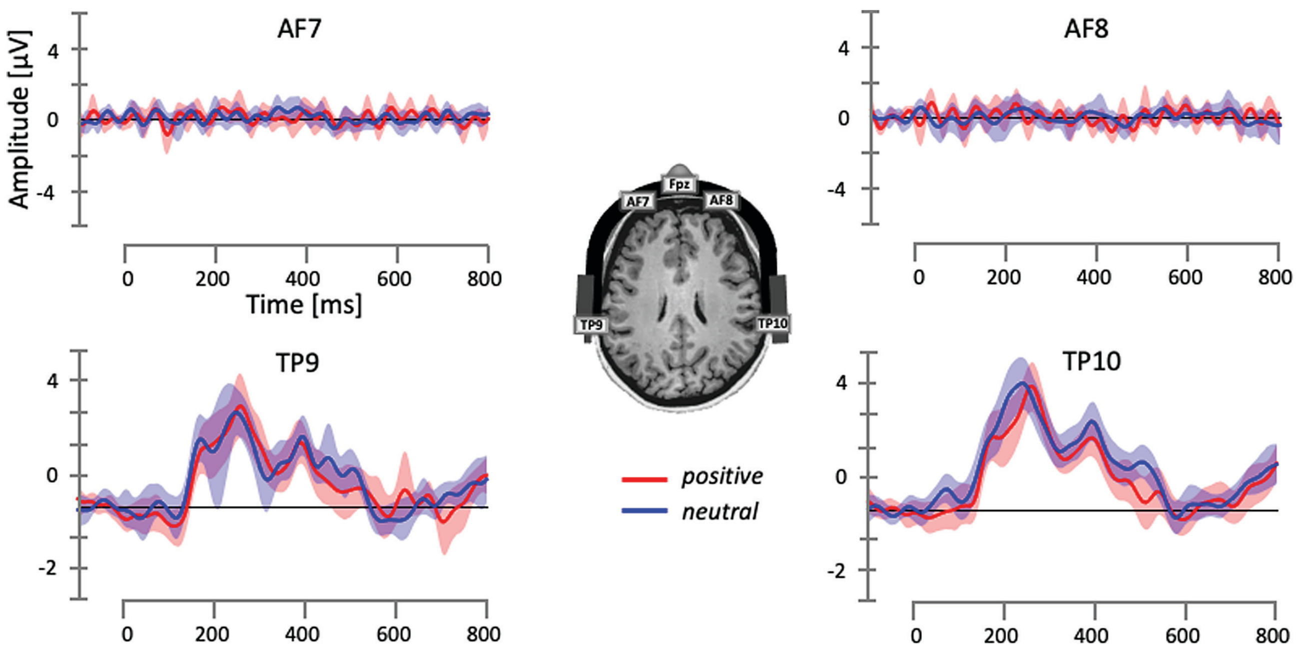

Figure 2. Grand-average ERP waveforms for positive and neutral images. The schematic illustration in the middle shows the approximate location of the sensors in the Muse device. Note that due to volume conduction, a sensor picks up more than the immediate activity from the brain region over which it is placed. The reference is located between AF7 and AF8 at Fpz. Shaded areas around the waveforms represent 95% confidence intervals as these are grand-average ERPs, that is, averages across individuals. ERP = event-related potential.

$t(46) = -1.08$; $p = .29$). A post hoc power/sensitivity analysis (see Electronic Supplementary Material, ESM 1) revealed that with an α level of .05, $1 - \beta = 0.8$ (0.95), and a sample size of 47, the study is powered to detect an effect size of $dz = 0.37$ (0.49).

Although these results do not support our first hypothesis, inspection of Figure 2 shows some evidence for an amplitude difference in the LPP range at TP10 (i.e., approximately 500–550 ms). We assessed this effect in an exploratory follow-up analysis by submitting the average amplitude in the 500–550-ms window to a paired-sample *t*-test. This analysis revealed a significant difference between ERPs to positive and neutral images at the right temporal sensor (TP10) – $M_{\text{positive}} = 0.4$ µV, $M_{\text{neutral}} = 1.23$ µV, $t(46) = -2.38$; $p = .02$ – with positive images prompting relatively lower amplitudes, but no significant difference at the corresponding left sensor (TP9) – $M_{\text{positive}} = 0.49$ µV, $M_{\text{neutral}} = 0.7$ µV, $t(46) = -0.5$; $p = .61$. Of note, the differential pattern in this is compatible with the signature of the LPP, which is traditionally observed as a relative positivity at centroparietal sites and thus should prompt a polarity-inverted negative difference over inferior temporal regions.

Influence of Compliance Instructions on Data Quality

Our second hypothesis was that the compliance-gaining manipulation would improve signal quality. We reasoned that the additional instruction that the experimental group received would lead to a decrease in the sample drop rate in the EEG data, which serves as an implicit measure of compliance-gaining success. To quantify this, we analyzed the sample drop percentage-rates for each session separately for the control and experimental groups. This analysis revealed that the average sample drop rate for the first session of the control group ($M = 51.15$, $SD = 17.38$) was similar to the first session of the experimental group, $M = 47.5$, $SD = 22.59$; $t(45) = 0.61$, *ns*. Importantly, for the second session, the control group had a mean drop rate of 54.13 ($SD = 18.86$), whereas the experimental group (i.e., with added instructions) had a mean drop rate of 35.04 ($SD = 16.35$), which proved to be significantly lower, $t(45) = 3.71$, $p < .001$. Furthermore, the experimental group showed a significantly improved drop rate from Session 1 (before the request) to Session 2 (after the request), $t(23) = 3.13$, $p < .01$. The control group, however, showed no change in drop rate, $t(22) = -0.75$, *ns*. These results are illustrated in Figure 3. The results support our second hypothesis, demonstrating that the additional instructions to gain compliance resulted in better signal quality, as seen in a significantly lower sample drop rate.

Discussion

This study tested a novel, affordable, and mobile EEG device for media research by performing an ERP experiment with affective IAPS images. The results demonstrate

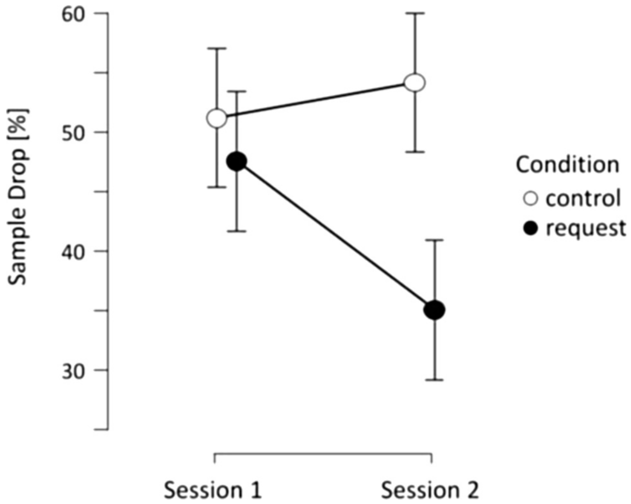

Figure 3. Effect of added instructions on data quality. The experimental group, which received an additional request to comply with EEG instructions, shows a lower sample drop rate in Session 2 compared to the control group that did not receive this request. The drop rates of both groups are not significantly different at baseline (Session 1). The error bars represent the 95% confidence interval.

that the Muse EEG device can assess robust ERPs to visual messages. Although the difference between moderately positive and neutral images was not found in the 200–300-ms and 400–600-ms time windows, an exploratory analysis revealed a significant difference at the TP10 sensor between 500 and 550 ms. Additionally, we tested the effect of a compliance-gaining instruction to improve data quality, finding that it improved the quality of recorded EEG.

With our first hypothesis, we predicted a difference in ERPs when participants viewed positively valenced or neutral IAPS images. Testing for this effect in the time windows where this result is typically seen in high-density EEG studies (i.e., between 200–300 and 400–600 ms) did not support this hypothesis. While no significant differences were detected in the a priori defined time windows, follow-up analyses confirmed a significant difference in the reduced time window (500–550 ms) at the right TP10 sensor. Of note, this effect consisted of a relative negativity toward the positive emotional images, which may at first seem incompatible with the notion that ERPs in the 400–600-ms range have been shown to exhibit relative positivities to more emotional images. These differences, however, are normally maximum at centroparietal sites, where the Muse device does not record. The principles of EEG volume conduction, however, predict that these electrocortical differences reverse their polarity over inferior sites, such as TP9/TP10, and thus our observations seem compatible with this literature (another issue being that of the reference electrode, which in our case is at Fpz).

Overall, the Muse device was able to capture robust ERPs during image viewing. This validates the use of this mobile and low-cost device for research, although the predictions for H1 were not supported in its original form. One plausible explanation for this pattern of results might be that positive stimuli came from the middle range of the arousal and valence continuum. In other words, there were no IAPS images depicting explicit erotica, which are rated very high in arousal, in our stimulus sample, but these were deliberately excluded to maintain a focus on visual content that would be encountered on common social media websites. However, this choice made our manipulation of affect considerably less powerful compared to previous studies, where high-arousal content evokes the strongest effects (e.g., Schupp et al., 2004). In sum, although more research with stronger manipulations of emotional image content is needed, our results suggest that the Muse device is a promising tool to make ERP analysis of visual messages more available for media researchers.

The second hypothesis predicted that a compliance-gaining manipulation would result in a lower sample drop percentage compared with participants not receiving this social influence tactic. This hypothesis was supported and the result is promising, as a simple change in instructions could yield better data from a variety of psychophysiological studies. Having a set of optimized instructions is practically relevant. As previously expensive neuroscientific equipment becomes more commodified, this will also lead more inexperienced users, citizen scientists, and early-career researchers to enter this area. Consequently, having standardized best practices (on device use, participant instructions, and analysis pipelines) will aid new researchers to obtain better data and enhance overall reproducibility.

In addition to pointing out a strategy to optimize instructions in pyschophysiological experiments, the approach is also theoretically interesting. EEG quality metrics, such as the sample drop rate (i.e., the fraction of trials that are dropped due to missing quality standards), can be considered an implicit measure (Nosek et al., 2011), allowing us to test how manipulations impact these implicit neural outcomes. Obviously, we selected only one of many possible compliance-gaining strategies here, and future work should expand beyond the specific choice we made in this work (Marwell & Schmitt, 1967).

Broader Implications and Future Research

Overall, this study lays out a viable path to overcome central barriers that plagued the emerging field of media neuroscience: high cost of equipment, limited scalability, and the time-consuming nature of data acquisition. We showed how a study using neurophysiological measures can be conducted on a budget that is comparable to cognitive testing or survey methods. The setup time for this system was less than a couple of minutes and testing one participant took approximately 15 min, including consent. This not only makes the study far more attractive for participants, but it enables media researchers to use neuroimaging methods while avoiding the time sink associated with preparation of high-density EEGs. These developments open the door to swiftly conduct large-scale studies to test the effects of messages in natural environments that people would receive, for instance, a classroom filled with students wearing mobile EEGs and listening to a lecture (Poulsen et al., 2017). Additionally, the Muse is similar to a headband and is very light and comfortable, which improves the participants' user experience and adds to the naturalistic feel of the experiment.

Another important issue is the free availability and open-source nature of procedures. Historically, the cost and proprietary nature of tools presented another significant barrier for adoption. The notebooks from which we developed the current study are available online (Griffiths et al., 2020; https://neurotechx.github.io/eeg-notebooks) and we ourselves provide open-source routines for acquisition and analysis (https://github.com/nomcomm/MediaNeuroscienceOnAShoestring_JMP). Thus, the only barrier that remains if a media researcher wants to adopt these methods is that of acquiring substantive expertise in neurophysiology, including data acquisition, analysis, and interpretation. Given recent developments in the field – via tutorials, workshops, and interest groups – this barrier is continuing to shrink (Floyd & Weber, 2020; Turner et al., 2019; Wilcox et al., 2020). In all, the barriers to start utilizing neuroimaging methods has been greatly reduced through mobile EEG units, such as the Muse.

Based on our encouraging results, future studies may tackle a broader variety of social–cognitive processes using scalable neuroimaging methods. Although, of course, the spatial and temporal resolution of these devices remains below that of fMRI or high-density-EEG, the high scalability and low-cost nature represent a decisive factor that can boost the adoption of neuroimaging methods. One area for which this approach is obviously promising is the study of social-media-sharing decisions (Meshi et al., 2015; Scholz et al., 2019) and the mass appeal and virality of emotional and social content more broadly (Hu et al., 2014; Tong et al., 2020).

The current study focused on the role of visual images for social–emotional processes, but going forward, the benefits of the Muse EEG device and other low-cost EEG systems apply to nonvisual modalities and beyond social-media topics. For instance, similar arguments as we laid out for the impact of emotional and social visual content can be made for spoken and written messages. Indeed, several precursor studies exist in this domain examining the neural reception of buzzwords (Kissler et al., 2007) or clashing moral statements (Van Berkum et al., 2009). This work could likewise be scaled up easily using the strategy proposed here.

Another avenue for research is the study of dynamic media, be it on the order of seconds (YouTube, TikTok) or hours (movies, TV, and radio). In the current study, we focused on ERP methods because they use repeated presentations to increase the signal-to-noise ratio, but future work could employ other EEG analysis methods such as intersubject correlation analysis or entrainment-based methods (Crosse et al., 2016; Lalor et al., 2006; Poulsen et al., 2017; Schmälzle & Grall, 2020a). Additionally, the Muse has shown promise as a medical tool to aid in diagnosing the severity of strokes based on activity in different EEG frequency bands (Wilkinson et al., 2020). Lastly, newer models of the Muse (Muse 2, Muse S) have been fitted with a photoplethysmography sensor, accelerometer, and gyroscope, which all have uses in research and medical settings. As such, we see several promising avenues for future EEG research with the Muse or other mobile devices, including ERP, oscillations, and various other paradigms and analysis approaches.

Limitations

Although the current results are encouraging, several limitations are noteworthy. As discussed earlier, one limitation is that the positive images were not very arousing, which may have precluded more potent effects. Future studies should test the Muse with the same stimuli used in previous studies (Lang et al., 1993; Schupp et al., 2004). Additionally, the study relied on the normative IAPS ratings, and participants were instructed to view all images in a passive stream but were not asked to evaluate the images neither during nor after participating. Although there is no reason to expect that individual ratings would deviate from the carefully collected norms, instructions to evaluate visual content constitutes a different task, which affects processing and thus modulates ERPs.

Another issue to keep in mind is that the low cost of the Muse system does come at a price in terms of data quality and quantity. First, we excluded many participants whose EEG data did not meet quality criteria. Second, across the remaining participants and conditions, the average sample drop rate was almost 50%. This could be due to the four dry sensors on the device and the fact that the device is only loosely mounted – much like glasses. Many EEG units make use of conductive gels or liquid solutions, and EEG sensors are often integrated into elastic nets to ensure a constant force. Although dry EEG sensors considerably speed up data acquisition and are much more comfortable for participants, the signal quality is lower than with conventional gel-based or saline-based EEGs. Lastly, that signal is sent to the recording computer through a Bluetooth connection, which can drop data in the process. These are all noteworthy limitations; they do not override the fact that the system's quality is acceptable for research. We also verified this by comparing the ERP results from subsamples (i.e., between the two sessions and between the two participant groups), demonstrating very high correlations between ERPs (> .9). This demonstrates that the Muse device measures ERPs with precision.

Compounding the quality of data of Muse was the fact that participants self-fitted the EEG headset themselves and that they did not clean or abrase their skin. Additionally, they had never seen or used the device before, and so they fitted it following a brief description. Furthermore, recent work from Wilkinson et al. (2020) shows that connectivity can be improved when sensors are coated in silver chloride and the skin areas have electrolyte gel applied. While it is good to note that data quality can be improved by these procedures, knowing that it is possible for participants to put the device on themselves greatly expands the scalability of EEG studies with the Muse or its use in field studies.

Lastly, we note limitations of the compliance-gaining manipulation. We tested only one condition against a control condition, and this test always came after a baseline instruction. To turn this into a proper instantiation of, for example, a foot-in-the-door manipulation, additional conditions would be needed. Nevertheless, it seems clear that these manipulations could be implemented in future studies, much like A/B testing is regularly performed to optimally steer online user behavior (Kohavi & Longbotham, 2017).

Conclusion

To conclude, incorporating neuroscience in media research has been held back by complicated and expensive methodologies, but advancements in EEG technology have opened the door for researchers to embrace these methods with lower cost and higher scalability potential. The Muse EEG system is a relatively easy-to-use and extremely affordable EEG unit that can provide the temporal resolution needed to study the reception of visual messages. The successful capture of ERPs with the Muse validates the use of the device in future studies.

Electronic Supplementary Material

The electronic supplementary material is available with the online version of the article at https://doi.org/10.1027/1864-1105/a000348

ESM 1. Description of Muse setup and implementation and experimental procedure

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History
Received October 6, 2021
Revision received February 17, 2022
Accepted March 15, 2022
Published online XX, 2022

Acknowledgments
We thank the teams behind the NeurotechX EEG Notebooks, the MNE software, and the developers of BlueMuse for their generous contributions (https://github.com/NeuroTechX/eeg-notebooks). Additionally, we want to thank Clare Grall for help in constructing figures for the Muse.

Publication Ethics
All participants provided written consent to the study procedures, which were approved by the local IRB.

Open Data
The authors are willing to share their data, analytics methods, and study materials with other researchers. Code to reproduce the study and document the analyses is accessible at https://github.com/nomcomm/MediaNeuroscienceOnAShoestring_JMP (Schmälzle, 2022).

Funding
This work was supported by the National Science Foundation (NSF) NSF under Grant CHS-1907807.

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