CORTICAL SOURCE ANALYSIS OF EARLY EMOTION AND FEATURE-BASED VISUAL PERCEPTION

By

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(Under the Direction of Dean Sabatinelli)

ABSTRACT

A widely used paradigm to understand human cortical activity associated with perception, attention, and emotion involves displaying scenes that depict realistic content while recording with electroencephalography (EEG) or magnetoencephalography (MEG). This paradigm has led to many scientific advances, and the approach is increasingly used in clinical settings. However, previous research found the early posterior negativity (EPN) primarily used as a measure of emotional arousal, was more strongly affected by nudist couple scenes than emotional content such as erotica and mutilated body content. The available evidence suggested that this may have occurred because the previously used EPN window may encompass activity more sensitive to the perception of bodies known as the N170. The extent of spatial and content-modulation differences between 130 – 200 ms versus 200 – 300 ms after scene onset was not well captured by the EEG system used in previous studies. To address this, the same scenes were presented using complementary high-density EEG and MEG with L2-Minimum-Norm-Estimation. The results suggested that both components are spatially similar, but they vary in their sensitivities to different content. While both periods were sensitive to bodies and emotion, the N170 was more affected by the emotional neutral nudist couples while the EPN is more sensitive to the other emotional categories. Additionally, pupil diameter suggested that the evoked physiological arousal of nudist content did not explain the strong N170 and EPN modulatory effects. The results were also found to be consistent between participants recruited from the University of Georgia in the United States of America and the University of Münster, Germany. This research also featured two mostly separate auxiliary aims. A well-studied, although inconsistently found, effect suggests that the N170 is larger when evoked by pictures of faces of a different race than the participant's own. This was one of the first studies to recruit a meaningfully large sample of Black participants to address this topic and found no differences based on the participant's identified race. In the last auxiliary aim, a within-participant manipulation of the scene presentation speed did not meaningfully change the relevant emotion-related scene evoked potentials and fields.

INDEX WORDS: EEG, MEG, Source-analysis, Perception, Attention, Emotion

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Page

CHAPTER 1

INTRODUCTION

Research on event-related potentials and fields (ERPFs) evoked by emotional scenes has enhanced our understanding of human emotional perception and is an essential tool in affective neuroscience. The general paradigm involves the use of either electroencephalography (EEG) or magnetoencephalography (MEG) to record brain activity in the response to naturalistic scenes. Decades of research have demonstrated that several ERPFs are reliably modulated by scenes that depict emotional relative to neutral content (Schupp et al., 2006). The emotional modulation of these ERPFs strongly correlates with self-reports of emotional arousal and appears to be a reliable measure even for individual participants (Schupp et al., 2020, Schupp et al., 2023). Research suggests that this emotional modulation occurs because these components reflect obligatory attention toward content that is motivationally relevant; a phenomenon aptly termed motivated attention (Lang et al., 1997; Bradley, 2009). Otherwise stated, these ERPFs seem to index emotion because emotional scenes reliably draw attention or some other kind of elaborative processing. Further research on these ERPFs is important because these measures are widely employed to understand emotional processing and to study psychiatric disorders (Abdelmageed et al., 2020; Trotti et al., 2020, 2021, 2023; Bartolomeo et al., 2020; Versace et al., 2012). Here, we scrutinize some of the most well-established ERPFs to further define the mechanisms of emotional perception which may increase the utility of these measures as basic and clinical research tools.

The basic visual attributes of a scene, in addition to its emotional qualities, can modulate some early- and mid-latency ERPFs. Thus, best practices in scene paradigms involve selecting scenes that balance basic low-level visual features, such as brightness and complexity, as well as presenting many different scenes for each category of interest. By averaging the ERPFs from many balanced scenes together, the modulation that remains can be inferred to be associated with the emotional aspects of the scenes. Overall, this appears to be effective approach because standardized sets of scenes such as the

IAPS (Lang et al., 1997) have been shown to reliably elicit emotional effects over a variety of countries and cultures (Lang et al., 2007; Bradley et al., 2022).

Beyond low-level visual features, there is a growing appreciation for how specific scene contents can modulate ERPFs, and what these effects may mean for our understanding of emotional perception. Some content specific ERPFs are well-known and studied. One highly specific component is the N170 that is defined as a sharp negative deflection peaking at 170 ms in response to pictures of faces (Bentin et al., 1996, Eimer, 2000; Peelen et al., 2007, Rossion et al., 2007). Relatedly, a similar component can also be evoked by pictures of bodies on blank backgrounds (Stekelenburg et al., 2004; Thierry et al., 2006). However, even ERPFs that have been primarily associated with general emotional arousal can also be influenced by specific scene content, independent of rated arousal. The two most well studied of these ERPFs are the early posterior negativity (EPN; Junghöfer et al., 2001) and the late positive potential (LPP; Cacioppo et al., 1994). Studies have found that motivationally relevant content (erotica, mutilation, and threatening situations) elicit greater EPN and LPP amplitudes when compared to exciting or victorious sports moments, despite these scenes receiving high ratings of emotional arousal (Weinberg et al., 2010; Farkas et al., 2020, 2023). This seems to indicate that content that has more direct motivational relevance (i.e., sexual opportunity or danger) will impact ERPFs more than would be predicted by arousal ratings alone.

However, there are also differences in how specific content affects the EPN versus the LPP. In two recent studies we found that scenes of nudist couples rated as unarousing evoked greater EPN amplitudes than erotica, this pattern was best explained by a combination of self-reported scene features including the amount of body exposure and upright posture in a scene, independent of rated scene arousal (Farkas et al., 2020, 2023). The LPP however, was not modulated by body orientation, and was clearly sensitive to rated scene arousal. These findings may suggest that clearly depicted visual features commonly associated with motivational relevance have an early advantage seen in the EPN, whereas the LPP reflects a more complete measure of arousal once the scenes are fully resolved by complete perceptual processing. However, an alternative explanation is that the current EPN conceptualization and recording procedures encompasses partially distinct activity related to the mere recognition of body parts such as the N170 noted above. Understanding if either or both explanations are true may improve the utility of these ERPFs. Researchers could construct a richer understanding of each participant by integrating the initial responses of the EPN with the arousal linked to the LPP amplitude. If exposed bodies can elicit partially distinct activity that confounds the EPN, experimental designs and recording guidelines could be tailored to better account for the emotion-related modulation of interest.

In our previous two studies, we were unable to investigate three open questions necessary for a more rigorous interpretation of emotion-modulated ERPFs: 1) how distinct are the N170 and EPN spatially and in scene content modulation, 2) do nudist scenes evoke more arousal than self-reports suggest, and 3) how similar will the results be at different research sites? In the previous studies, a 64-channel system may have been inadequately dense to resolve the scalp topography or cortical source estimates of early ERPF activity. The second question addresses the possibility that participants may not be willing or able to accurately assess their evoked arousal to scenes of nudist couples, thus biasing our prior interpretation that emotion is not playing a role during the EPN time window (Farkas et al., 2023). Lastly, both prior ERP studies were conducted at the University of Georgia with the same experimental methods and sample population. It would be prudent to replicate the findings at a different research site, as well as informative to assess if the results are similar at the sites or not.

To address these outstanding questions, data were collected at multiple sites with additional complementary methods to estimate neuronal source activity and to measure physiological arousal. To better understand the sources of the relevant ERPFs, high-density EEG was paired with MEG. To better understand evoked emotional arousal, pupil diameter in response to scenes was recorded. The data were recorded at the University of Münster, Germany and at the University of Georgia in the United States of America. In Münster, college students (N = 37) were recruited for simultaneously recorded 57-channel EEG, 270-channel MEG, and pupil-diameter. These participants viewed the same scenes used in the previous two studies (Farkas et al., 2020, 2023). In Georgia, two samples were recruited. The first sample viewed the scenes in a 140-channel MEG system (N = 42), while the second group viewed the scenes in a

128-channel EEG system (N = 68). This scene set used most of the same scene categories as the previous studies, but the less relevant animal scenes were replaced with pictures of faces. This was done to help to contextualize the EPN results by evoking a standard N170 response which has been heavily studied in the ERPF and source analysis literature.

Beyond our main research questions, there are two auxiliary aims of this study that could have meaningful implications for other lines of research. The first centers on research from the field of social neuroscience that suggests viewing a face of someone of a different race or ethnicity evokes a larger N170 response (Herrmann et al., 2007; Stahl et al., 2008; Walker et al., 2008; Caharel et al., 2011; Wiese et al., 2018). However, this effect has not been found in other similar studies (Caldara et al., 2003; Caldara et al., 2004; Ito et al., 2004), and one study found a larger effect when participants viewed faces that matched their own racial identity (Ito et al., 2005). A particularly noticeable issue in this research has been the lack of Black identifying participants. While faces of Black people are commonly used in these studies, in our review of over 40 articles published investigating this effect, none recruited a group of Black participants. In EEG research, Black participants have been historically and systematically excluded mostly due to differences in hair (Louis et al., 2022; Choy et al., 2022; Bradford et al., 2022; Parker et al., 2022). In our experience, useable EEG can be recorded from people with different hair types in most cases with appropriate training and tailored procedures. Additionally, MEG data collection is not affected by hair type, so there should be no concerns about data quality.

Based on this information, the present research contributes to this face processing literature by purposively sampling additional Black participants and presenting pictures of White and Black male faces that have been balanced for low-level visual features. From UGA, we recruited 21 White and 21 Black women for the MEG sample. For the EEG sample, we recruited 22 White women, 22 Black women, and 24 participants that did not identify as either. The choice of recruiting only women and using male faces was for two reasons. The first is because of practicality, as there are fewer Black men in the Psychology research pool to recruit for the study, and we did not have the resources to recruit from the local community. For the face scenes, holding the gender of the participants and face scenes constant (Female participants and Male face stimuli) reduces the number of possible contrasts. This data may also allow for future analyses, not conducted here, for a better understanding of emotion and body part effects in participants that have different lived experiences. The two previous studies featured convenience samples of University of Georgia college students whom the majority of which identified as White. The homogeneity of the samples could lead to less generalizable results for numerous reasons that are difficult to predict, as scholarly work has documented in numerous social science findings (Henrich et al., 2010). This is also true for neuroscience research, with one relevant example being the effect of cultural differences on object-based attention (Chiao et al., 2010). While these samples are likely not large enough for a robust between-sample comparisons of general emotion reactivity, each individual group has a sample size typically for published ERPF work which is incredibly rare for Black participants. So present data should act as a meaningful contribution to the scientific literature for each subgroup.

The last aim of this study regards the impact of scene presentation timing on emotion related ERPFs. Generally, MEG recordings can be more susceptible to noise and so the duration between scenes is often shortened to allow for additional trials. It is unclear how this could affect the modulation of the ERPFs of interest. To address this question, participants in the Georgia EEG sample viewed the scenes in two counter-balanced blocks in which the inter-trial interval (ITI) between scene presentations was altered. In one block, the scenes were presented once each with an average ITI of 4.5 seconds in line with our previous EEG studies. In the second block, the scenes were presented twice with a shorter average ITI of 1.5 seconds, the same duration as the MEG study. Prior studies suggest that reliable emotion modulation can occur regardless of the ITI duration. Reasonable arguments can be made for which durations best balance participant comfort, experimental efficiency, and lead to the largest effect sizes. This ITI manipulation may help to further understand the tradeoff of different paradigm timing for scene evoked ERPFs.

From this study we expected to replicate previous findings while forming a fuller understanding of early and late occurring ERPFs. In a more specific summary, we had five total research aims for the present work: RA1) the primary goal of comparing the N170 and EPN with EEG, MEG, and source-estimation, RA2) assessing nudist couple scene evoked arousal with pupil diameter, RA3) comparing body exposure and emotional scenes ERPFs effects between the research sites, RA4) an auxiliary aim of looking at race effects of the N170, and lastly RA5) the methodological aim of understanding if presentation speed affects the relevant ERPFs. For RA1 we hypothesized that the added temporal and spatial accuracy of high-density EEG and MEG would reveal partially distinct sources between 130 to 300 ms after scene onset. We expected there to be a quantifiable spatial difference over the scalp as well as different cortical sources as found with an L2-Minimum-Norm-Estimation method (L2-MNE). For RA2, we expected the measure of pupil diameter would show that nudist couples are more arousing than self-reports suggest. However, we did not expect nudist content to elicit more pupil dilation than erotic content, suggesting erotic content is more arousing and clearly exposed bodies are still the best predictor of ERPF activity between 130-300 ms. For RA3, we hypothesized the general pattern of effects of emotion and body exposure on ERPFs would be similar between the two research sites. In RA4, we did not expect N170 amplitudes to be larger for participants viewing faces of a different racial identity than their own as the literature is inconsistent with some effects possibly influenced by specific task demands and low-level visual features. Lastly, for RA5 we speculated that longer ITI would heighten the overall mean differences between emotional and neutral ERPF amplitudes, and this effect would be particularly pronounced for the LPP. The reason being that a more relaxed pace would allow for more conscious or top-down influences on these emotion-related components. These research aims were addressed with Hierarchical Gaussian Process Model (a type of multi-level Bayesian analysis) because this statistical tool is well suited for estimating the effects of the multi-faceted design of the proposed study, as detailed in the literature review.

CHAPTER 2

LITERATURE REVIEW

2.1 Electroencephalography and magnetoencephalography

Electroencephalography (EEG) and magnetoencephalography (MEG) are methods that noninvasively measure the electromagnetic activity of the brain. The first EEG records were published by Dr. Hans Berger in 1929 after decades of work (Berger, 1929; Collura, 1993; La Vaque,1999). In 14 follow up papers, which were translated to English by Gloor (1969), Berger made seminal contributions to various aspects of EEG research still being used and developed today. This includes the use of Fourier analysis as well as documenting changes in EEG recordings under general anesthetics, during sleep, and from neurological conditions such as epilepsy. Although initially met with skepticism that electrical measures of brain activity were possible without invasive surgery, mass adoption began once his work was first replicated by Adrian and Matthews in 1934 (Adrian et al., 1934; Collura, 1993; La Vaque,1999). Once it was understood that measuring the electrical signals of the brain was possible, research teams began to investigate how the magnetic component (MEG signals) of these currents could be recorded. This was first accomplished at MIT by Dr. David Cohen with copper induction coil (1968), and then more successfully in 1972 with a superconducting quantum interference device (SQUID) similar to the sensors that are used today (Cohen, 1968; 1972). Although MEG was invented before fMRI, it remains a rarer scientific tool with most of its use in research having come in the last 30 years because of necessary technological innovations (Baillet, 2017).

Recording brain activity with EEG and MEG is only possible because of the convenient shape and orientation of cortical glutamate neurons. As described by Hansen et al. (2010), pyramidal glutamate neurons in Lamina II, III, and V are primary generators of EEG signals and make up 75% of neocortical cells. They are also the only neurons which are predominantly vertical shape and are orientated perpendicular to the surface of the cortex with apical dendrites reaching into the top layer of Lamina I.

This apical section of the dendrite is where excitatory connections from other neurons are made, and account for the majority of the connections made to these pyramidal neurons. When excitatory glutamate is released, positive ions flow into the neuron at the dendrite and out of the neuron's cell body. The relatively far distance between the dendrite and the body of the neuron creates a dipole aimed towards the cortical surface. When thousands of neurons are acted on in synchrony, the collective dipole generates currents and fields strong enough to be recorded at the scalp surface (Niedermeyer et al., 2005; Baillet, 2017). These excitatory connections comprise the majority of recordable signal studied. Newer modeling methods based on substantial a priori assumptions suggest that subtle differences in voltages can reveal activity in rarer inhibitory neurons and connections (David et al., 2006; Kiebel et al., 2008; Neymotin et al., 2020). For this research, it is assumed we will only be interpreting excitatory pyramidal glutamate activity as other contributions make up a small percentage of recordable activity (Hansen et al., 2010).

Although EEG and MEG systems measure the same electromagnetic sources, there are substantial differences between these apparatuses. EEG systems rely on electrodes held in place against the scalp via elastic caps or bands and sometimes with adhesive. Usually, some type of electrolyte solution is needed to complete the connection of the sensor to the scalp. Brain activity is recorded as a voltage in reference to something else which is often another electrode or, for systems that have many electrodes, to an "average reference" which is the average from all available electrodes. EEG systems are relatively inexpensive when compared to other neuroimaging devices with prices in the thousands of dollars for a system that can last for years. EEG is the most widely used neuroimaging method in research and clinical practice. Although it is one of the oldest neuroimaging methods, it still makes up most of the published research compared to other methods (Baillet, 2017). EEG has well-established clinical utilities in the guided treatment of epilepsy (Tatum et al., 2018) and sleep disorders (Berry et al., 2017).

Relative to EEG, MEG systems are larger, more expensive, and rarer. Almost all MEG systems rely on SQUID sensors to measure minuscule magnetic fields. To function, superconducting loops within the SQUID sensors rely on liquid helium to keep them close to absolute zero in temperature. Thus, MEG systems require more substantial engineering and monetary investment. A MEG system is much larger and features a large helmet-like covering which houses the SQUIDs. Usually, an adjustable seat is used to raise seated participants into the device. It is different from MRI in that it does not generate a strong static magnetic field. In fact, any magnetic interference can affect the recordings. Thus, specialized rooms are necessary to exclude background EMF noise. While in many domains MEG is still being validated versus EEG, there is growing evidence it provides superior utility for preoperative seizure assessments (Kharkar et al., 2015; Murakami et al., 2016; Nissen et al., 2016).

EEG and MEG recordings exhibit distinct characteristics because of the physical properties of electromagnetism described in Maxwell's and colleagues work (Maxwell, 1890). This results in various advantages and disadvantages for each method. While EEG is recorded as a voltage compared to a reference, MEG is recorded in the units of Tesla and is reference free. EEG signals are greatest in the same direction of neuron activation dipoles. For MEG, activity appears perpendicular to the source compared to the EEG signal. This is because when current runs from the source (positive pole) to the sink (negative pole), a magnetic field is generated as described by the "right hand rule" formulated in Maxwell's Ampère's circuital law. Also notably, the electrical EEG signal conducts differently through the tissues that surround the brain (e.g., blood vessels, meninges, and skull), and is spatially smoothed via volume conduction, while the fields of MEG move identically through all materials including the air. Theoretically, this means MEG should have superior temporal and spatial accuracy because EEG will spread as the signal conducts to the electrodes differently based on individual differences. However, MEG has its own set of limitations due to how the signal drops off sharply with distance. This results in MEG being less sensitive to sources deeper than 20 mm below the skull (Hansen et al., 2010). While this limits MEG as an effective neuroimaging tool to look at deep cortical sources, it allows for more credible source estimations of surface cortical activity. Another distinction is MEG is weakly sensitive to radial sources oriented toward the SQUIDs, whereas EEG can record tangential and radial sources. Thus, it is occasionally recommended that researchers employ a sparse EEG array during MEG recording to gain a more comprehensive insight into potential radial sources that may not be detected by MEG (Baillet, 2017).

The combination of EEG and MEG recording can have super-additive benefits for source analysis, although high precision is limited by naturally occurring individual differences in cortical structure. It is well known that EEG and MEG have high temporal resolution of cortical activity but poor spatial resolution of the neural sources. This is often contrasted with fMRI that has nearly the opposite limitations. The fMRI method can reliably detect the location of active sources, but most temporal information is coarse. A logical step is to combine the use of EEG or MEG with fMRI recording to make up for the limitations associated with each method. This M/EEG-fMRI fusion usually involves correlating ERPFs with BOLD responses in specific regions of interest (Junghöfer et al., 2017; Sabatinelli et al. 2013) or using multi-variate pattern analysis to find a pattern of time points in M/EEG that correlate with fMRI voxel signal change over trials or experimental conditions (Cichy et al., 2020). While these types of studies have led to many scientific advances, the inherent correlational analysis can lead to mistaken assumptions regarding how the independent signals are related.

Thus, the combination of EEG and MEG may be the most effective means to maximize spatial and temporal accuracy for many research questions. Because EEG signals are perpendicular to MEG, simultaneous recording of both methods would provide 2 angles for every cortical dipole. However, this too cannot fully resolve the brain regions active because individual differences in anatomy (such as brain structure, skull thickness, and head shape) can change the angle at which electromagnetic signals are recorded (Hinds et al., 2008; Amunts et al., 2000; Dougherty et al., 2003). This can be alleviated with the addition of structural MRI imaging such that inverse and forward models can be tailored to each brain to better predict the source of simultaneous EEG and MEG recording. However, this type of source analysis is novel and rapidly evolving, while also requiring knowledge and access to EEG, MEG, MRI, and complex mathematical modeling. As a result, a simultaneous joint source estimate of EEG and MEG data alone is currently not recommended (Tadel et al., 2019; Baillet et al., 1999). Current best practices for credible results are to quantitatively combine separate source estimates (Tadel et al., 2019). The present study should benefit in source analysis accuracy from the combination of EEG and MEG because the ERPFs of interest are fairly robust and stable across participants. The quantitative combination of EEG and MEG source analysis results via a Bayesian multi-level model (explained in sections 2.5 and 3.7) should properly weight their influences and account for individual differences.

2.2 Event-related potentials and fields

EEG and MEG can be used to measure neural activity in response to a specific stimulus or task. The activity recorded in this way is fittingly called an event-related potential or field (ERPF). The method of finding ERPFs is powerful because activities related to specific processes are often obscured by constant ongoing brain activity and oscillations. The act of recording isolated ERPFs is predicated on repeating trials time-locked to the events of interest. Given enough trials, consistent activity associated with an event will become more prominent as noise not associated with the task averages out to zero. This method is common practice and the bedrock for much of EEG and MEG literature. There are numerous ERPFs often named for when they are recorded such as the P100 which relates to a positive peak recorded around 100 ms after a visual stimulus. Researchers often interpret the change in the amplitude of these ERPFs to better understand the function of the brain.

The ERPF method relies on assumptions and proper experimental designs for findings to be meaningful. For a given ERPF, the amplitude must be consistent in space and time throughout all the trials otherwise it would be cancelled out during trial averaging. This is true not only within a participant but also between participants. Thus, it is a concern that there may be ERPF signals that do not get reported because only the potentials that do not habituate contribute to the grand average. Another issue is that ERPFs can vary in amplitude not because of the differential impact of experimental conditions, but because of the individual differences in anatomy. For example, differences in the skull or head size could affect the overall amplitude of an ERPF. For these reasons, proper ERPF research designs employ within-participant designs with stimulus trials counterbalanced.

2.3 Relevant ERPFs

The N170 is one of the most well-known and studied ERPFs and has been strongly associated with the perception of faces. It can be recorded as a negative deflection over lateral occipital regions behind the ears starting at 130 ms and quickly dissipating by 200 ms (Eimer, 2000; Peelen et al., 2007, Rossion et al., 2007). The first study to record this potential was Bentin (1996), although it is now recognized that the positive end of the same dipole, known as the vertex positive potential (VPP), was studied earlier (Botzel et al., 1989; Jeffreys, 1989). While the N170 and VPP have been found to have near identical response properties (Joyce et al., 2005), the N170 is more often studied because its location on the scalp is likely closer to the neural sources. Research suggests that the N170 primarily reflects specific configural processing of faces early in the ventral visual stream with the likely strongest contributor being the fusiform face area (Hadjikhani et al., 2010). Here, configural usually means that the face is processed as a single object rather than a series of facial features. This is supported by the quick dissipation of the N170 and inverse effects in which presenting upside-down faces cause the N170 to be delayed and larger in amplitude (Rossion et al., 2000). This is taken to mean that fusiform face area is still processing the upside-down face configurally, but it is slower to recognize the stimulus and it requires more cortical activation.

Research suggests that the N170 can be modulated by emotion and possibly by the race or ethnicity of the face being shown. A meta-analysis suggested that happy, angry, and fearful facial expressions modulate the N170, while disgust and sad expressions may not (Hinojosa et al., 2015). This same study also found that these emotional facial expressions appear to exogenously draw attention based on paradigms in which attention was manipulated. The authors' interpretation was that N170, not only indexes recognition of the structural elements of a face, but also higher-level social information as well. Studies on how race and ethnicity affect the N170 report more mixed results. A number of studies have found that when viewing the face of a different racial identity than oneself, the N170 is larger (Herrmann et al., 2007; Stahl et al., 2008; Walker et al., 2008; Caharel et al., 2011; Wiese et al., 2018). However, a considerable number of other studies do not find this effect (Caldara et al., 2003; Caldara et al., 2004; Ito et al., 2004) or the opposite (Ito et al., 2005). The races and ethnicities across these studies vary widely. Possibly relatedly, behavioral studies have found that people are less accurate in tasks that involve faces that are a different racial identity than their own (Levin, 2000). Considering this, a larger N170 amplitude could reflect increased effort, similar to when a face is presented upside down causing the inverse effect. However, low-level visual features have not always been well balanced in these studies which could explain the N170 effects. Additionally, because emotional expressions are known to affect the N170, perhaps there is a slight emotional modulation indicative of an outgroup effect.

Relevant to the current study, a similar ERP as the N170 can be elicited by bodies. Initial reports suggested that body scenes elicited a smaller amplitude than faces, but if the bodies are unclothed, they evoke a larger amplitude than faces (Hietanen et al., 2011, Hietanen et al., 2014). This "body-N170" peaks around 20 ms later that the N170 at about 190 ms (Thierry et al., 2006). Like faces, bodies also show an inversion effect, even when the bodies are unclothed (Bernard et al., 2019). Surprisingly, in this same study, this inversion effect disappears when perceptually similar bodies are presented in sexually suggestive postures, just as what would be seen for oddly configured objects. While the potential looks similar to the N170 over some sensors, the body-N170 elicits a more widespread negativity over occipital channels particularly when the body is unclothed (Hietanen et al., 2011). Source analyses with both EEG (Thierry et al., 2006) and MEG (Meeren et al., 2013) suggest that different sources are active for the body versus face evoked N170. The signals underlying the N170 appear to include occipital-temporal network including the ventral temporal cortex, whereas the body-sources were localized to the lateral occipital cortex. Notably, fMRI research suggests this is where the "extrastriate body area" is located (Peelen et al., 2007). Specific instructions to attend to a body does not increase the body-N170, although this is also the case for the later occurring ERPFs (Hietanen et al., 2014).

The last two relevant ERPFs for this study are the emotion-modulated early posterior negativity (EPN) and late positive potential (LPP). The EPN is recorded over lateral occipital sensors in EEG and over posterior temporal channels for MEG. The time at which it is recorded varies between research teams but is usually a window between 150 ms to 350 ms after scene onset. It was first reported by

Junghöfer and colleagues (2001) in which rated scene arousal appeared to be the best predictor of its amplitude. Many subsequent studies have replicated this emotional effect for scenes, as well as for faces (Langeslag et al., 2018; Yoon et al., 2016; Herbert et al., 2013; Jaworska et al., 2012; Schupp et al., 2004), words (Schindler et al., 2016; Kissler et al., 2013; Herbert et al., 2008; Kissler et al., 2007), and hand gestures (Flaisch et al., 2009). Similarly, the LPP has also been linked to emotional arousal through scene studies. The LPP was discovered before the EPN (Cacioppo et al., 1994) and has been more well-studied. It appears as a positive slow-wave over centroparietal sensors starting around 350 ms and peaking before 900 ms. Emotional scenes will modulate the potential to be more positive than neutral content with a significant difference that can last for several seconds. The EPN and LPP have been primarily studied in scene presentation paradigms as compared to the N170 and body-N170 studies that typically involve figure-ground cues on blank backgrounds. This subtle distinction has led to somewhat separate lines of research with possibly meaningful distinctions. Scenes are supposed to more closely mimic realistic perception at the cost of scientific control. To counteract this, researchers utilize standardized picture sets such as the IAPS (Lang et al., 1997) and paradigms in which many different scenes are presented for each category of interest. This in theory averages out the effects of low-level visual features. Overall, emotional arousal effects do appear to be larger for scenes over faces for the EPN and LPP (Thom et al., 2014).

Personal preference and disorders of emotion can additionally modulate these ERPFs (Junghöfer et al., 2010; Langeslag et al., 2019; Weinberg et al., 2016). The EPN and LPP both appear to be more sensitive to motivationally relevant content such as erotica and threatening content (Weinberg et al., 2010; Farkas et al., 2020, 2023). Emotional content reliably modulates the EPN and LPP in nearly all participants given enough trials (Schupp et al., 2020, Schupp et al., 2023). This emotional difference also resists habituation, even if only a small number of scenes are repeatedly presented many times (Ferrari et al., 2020; Schupp et al., 2006). The EPN and LPP rarely differ in their pattern of emotional modulation. However, the EPN appears to be more sensitive to simple figure-ground content (Bradley et al., 2007), human content (Löw et al., 2013), and snakes (Van Strien et al., 2014). In our own work, we found that the EPN seems to be especially sensitive to upright, unclothed bodies as compared to the LPP (Farkas et al., 2020, 2023).

Given this collection of results, researchers theorize that the EPN and LPP reflect partially distinct stages of a process of “motivated attention” (Lang et al., 1997; Schupp et al., 2006). This is a form of selective attention in which emotional content exogenously captures attention. It is sometimes stated that this appears to be an “obligatory” process due to the lack of habituation and heightened sensitivity for motivationally relevant content. So, these ERPFs may be better conceptualized as one of many action dispositions that can be physiologically measured and are loosely coupled to self-reports of emotion (Bradley et al., 2007; Bradley, 2009).

2.4 Auxiliary measures of emotion

One of the most common and validated self-reports measures is the use of the Self-Assessment Manikin (SAM; Bradley et al., 1994). This measurement tool was developed to standardize self-reports of valence and arousal in a paradigm that would allow for reliable reports across the world. It involves using a manual that describes the two relevant scenes and how participants should use the scales to report how they feel when presented with an emotional stimulus. Each scale has multiple synonyms for terms commonly associated with pleasant, unpleasant, high arousal, and low arousal. Each scale is usually presented with a manikin representation that depicts the emotional state increasing and decreasing across the scale. Measures from this scale have been shown to have reliable associations with physiological measures such as skin conductance, the EPN, and the LPP.

Another way to measure physiological arousal is with pupil diameter. Autonomic activity is known to increase the size of the pupil to emotional relative to neutral scenes correlating strongly with SAM ratings and skin conductance (Ferrari et al., 2015; Henderson, Bradley, & Lang, 2014; Snowden et al., 2016). However, this measure appears to be more resistant to habituation compared to skin conductance (Bradley et al., 2015). Thus, pupil diameter may also reflect obligatory motivated attention like the EPN and LPP. Pupil diameter is also known to also be modulated by emotional imagery

(Henderson et al., 2018), sounds (Partala et al., 2003), and anticipated shocks (Bitsios et al., 1996; Bitsios et al., 2004). A limitation is that brightness and contrast differences in scenes affect pupil diameter measurements (Bradley et al., 2017). Thus, it is important that scenes are relatively balanced on these low-level visual features, or that this effect is removed in the analysis stage.

2.5 Bayesian multi-level and Hierarchical Gaussian Models

In this study, a Hierarchical Gaussian Model, which is an extension of Bayesian multi-level models, was used to analyze our dependent measures and test hypotheses. This approach is appropriate because it is well suited to make inferences from complex nested designs. More specifically, it can use a technique known as partial pooling in which differences between groups can be appreciated and corrected for, while still contributing to a meaningful overall estimate. This is particularly useful when combining the EEG and MEG derived source analysis results. Additionally, these kinds of models can be flexibly designed to accommodate the structure of the data. Here, we allow the model to learn about the overall correlational structure of channels and estimated dipoles such that we do not have to average similar channels together to increase statistical power. This allows for more powerful spatial inferential statistics when comparing the N170 and EPN time windows.

Bayesian approaches contrast with the traditional frequentist methods in several ways. In Frequentist statistics, there is an assumption that a true value for a population exists and it can be estimated by a sample. This true value can be any statistical parameter, but it is most often the mean of a certain group or the mean difference between two groups. In Bayesian statistics, the value of a parameter is not assumed to be fixed. Instead, the parameter is estimated as a continuous probability distribution describing the likelihood or uncertainty of possible values. This is more in line with how probability is colloquially considered; as the certainty of an outcome in probabilistic terms, and not in comparison to a null hypothesis.

To find this probability distribution of a parameter with observed data (the posterior distribution), a sampling model and prior distributions must be specified. The sampling model states how the data is generated based on one or more unknown parameters. The prior distribution represents the current belief of possible values for the unknown parameter. While the specification of a prior can seem open-ended, uninformative priors can be selected such that the posterior is nearly entirely based on the collected data. Moreover, in multi-level models, adaptive priors can be selected that optimally regularize the model by shrinking overly bold parameter estimates. This creates estimates that maximize prediction accuracy in future data sets as if it were tuned by cross validation. Thus, final estimates do not overfit the data (McElreath, 2020). While Bayesian statistics predated frequentist methods, its viability was only made possible with the availability of modern computing. This is because most Bayesian posteriors cannot be solved using closed-form expressions, but they can be estimated through mass sampling. Algorithms, such as Hamiltonian Monte Carlo or Metropolis-Hastings Monte Carlo, generate a sequence of chained samples that come from the posterior. As the number of samples approaches infinity, the density of these samples is guaranteed to be the same as the posterior.

Bayesian multi-level models feature a concept known as partial pooling which will be an important component of this project's analyses. In this type of model, a separate layer can be used to share information in a process called partial pooling. This gives the model “memory” to better understand the individual observations and the group they are sampled from (McElreath, 2020). For example, in Figure 1 the average ERPF is estimated for each participant from a previous study (Farkas et al., 2023). The black dots indicate the actual mean values of each participant. The red dots indicate the Bayesian estimate of the mean, and the red lines represent the inner 89% of the posterior distribution. From this figure, we can see some of the effects of partial pooling had on our posterior distributions for each participant. First, it leads to a more precise estimate for each participant’s mean than a fixed effects model would, while still allowing for individual variation. Partial pooling also applied “shrinkage” to the most extreme values, shifting participants posteriors inwards toward the overall mean (parameter abar).

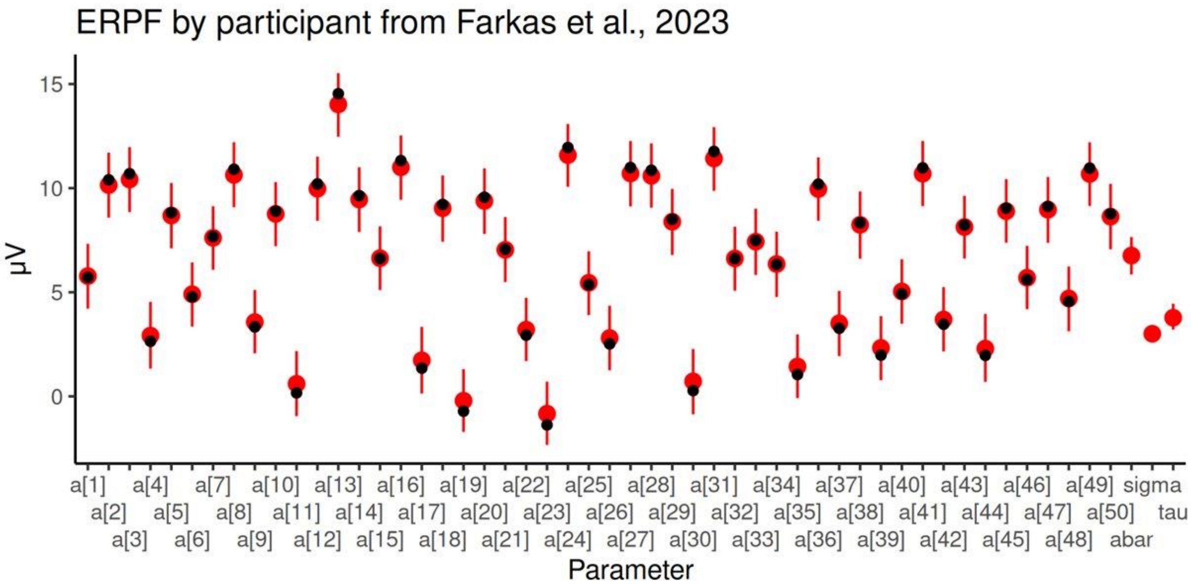

Figure 1. An example of partial pooling in a Bayesian multi-level models. Data is taken from a previous study. Here, a[1] to a[50] represent the posterior estimates for each participant's average ERPF response. The black dots represent their empirically found mean value, while the red dot represents the posterior mean and the inner 89% of the posterior distribution. Note how participants that have more extreme low or high ERPF values have posteriors that are pulled toward the average estimate of abar. This is the result of partial pooling which regularizes the model to be more predictive, as might be a result cross validation. Partial pooling also acts as a multiple comparisons correction, so all posteriors can be directly compared via sampling. The sigma parameter is the estimated variance for the ERPF, while tau is the estimated variance for the higher-level distribution of participants.

This type of model has several beneficial effects. The first is it allows information to be shared among observations to provide a better estimate for each individual. Second, this process regularizes the model, thus preventing overfitting and making it more predictive, as if a cross-validation algorithm had been used. Third, it acts as a more intelligent correction for multiple comparisons. In a frequentist framework, a correction would involve enlarging confidence intervals instead of shrinking estimates toward the mean. Finally, because this is a Bayesian approach, there is no null distribution or p-values;

the red bars represent actual probabilities and can be compared directly with contrasts between posteriors. To perform a contrast between posterior, all matched posterior samples are subtracted to form a new posterior of the difference (example in Figure 2).

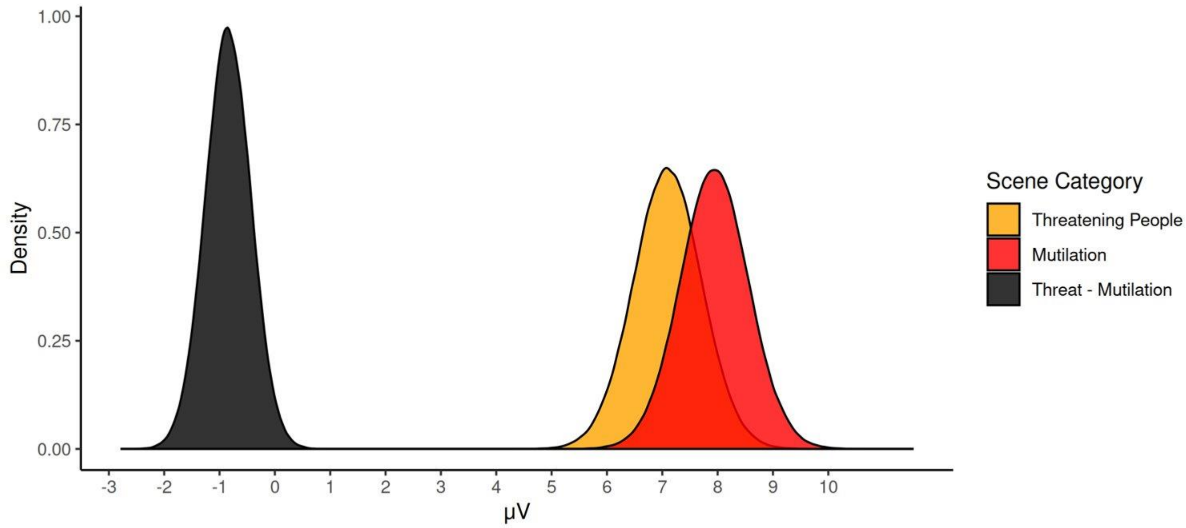

Figure 2. An example of a posterior contrast distribution. To contrast posterior distributions, samples from one posterior are subtracted from another. Here, the posterior difference is meaningful (98% of the contrasted samples are below 0 μV) between mutilation scenes (red) and threatening people content (orange) despite them overlapping considerably. Contrasts between matched samples must be done when comparing posteriors because there could be inherent correlations in the data captured by the sampling process.

This aspect of partial pooling seems ideal for integrating the results of the current study. For example, in this study the separate EEG and MEG results can be combined to better understand the cortical sources. In a frequentist framework, there would likely be a significant interaction between category modulation and whether the data was recorded with EEG or MEG because of fundamental differences in how these methods estimate cortical activity. Thus, it would be inappropriate to completely pool or average their source analysis results. Breaking down the interaction would also not be ideal, as it would limit results to a qualitative explanation and preclude the opportunity to integrate the complementary information. The Bayesian multi-level approach allows for an accounting of how EEG and MEG are distinct and thus enables a more meaningful overall estimate of activity, while retaining the option to break down the pattern of results between the two measures.

How Bayesian partial pooling accounts for random and fixed effects is useful, but another aspect of Bayesian models which is vital to the current study is their flexibility and ability to learn correlational structures. In review, our primary research question is whether the modulation of N170 versus EPN time windows are distinct in space (over sensors and sources). Traditionally, to increase the signal to noise ratio of an ERPF, channels close together are averaged together or a spatial PCA is used to create a linear combination of all the sensors. But because the current research question centers on spatial comparisons, neither of these options are ideal as the channels separate to understand where and for what scenes there are differences. Instead, the model was crafted such that it could use the correlation between channels to reduce uncertainty. Thus, correlational structure is also partially pooled and has posterior distribution. This comes with the usual benefits of partial pooling, but also allows the representation of all channels or sources as coming from a multi-variate normal distribution. This is what reduces uncertainty, each channel is one dimension of a distribution which is informed by all the other channels and dimensions. Learning this correlational structure allows for a more efficient fusion of different neuroimaging equipment. For example, although there are only 57 EEG channels from the Münster research site, the information from those 57 channels can be combined with the usual correlational structure of the Georgia 128 channel system to find posteriors for what the remaining channels most likely would have been.

To incorporate correlational structure, the model had to be upgraded into what is often called a Hierarchical Gaussian Process Model. Gaussian models are a diverse class of methods which are highly specialized for each phenomenon being analyzed. What is shared is an assumption that variables are grouped in some way by a multi-variate normal distribution with relationships that can be entirely defined by a covariance or kernel function. This is ideal for Bayesian modelling because priors for large matrices, such as covariances matrices, suffer from many constraints related to matrix algebra whereas a Gaussian

Process Model can be scaled to theoretically infinite dimensions. For the current model, the kernel function chosen for the MEG sensor and source analyses is a squared exponential function, which models that covariance decreases with distance exponentially. For the EEG data, a second mathematical statement was added such that covariation could switch to a negative covariation as distance approached Pi or 180 degrees away. What makes the currently implemented models “Hierarchical” Gaussian Process Models specifically is that partially pooling is applied via higher-level of shared information similar to simpler Bayesian multi-level models.

In the literature, similar models have been constructed primarily for classification and source analysis solutions. As described in a review by Wu and colleagues (2015), there are numerous published applications of Bayesian and Bayesian machine learning analyses for M/EEG data. The first arm of this work centers on better extracting the electromagnetic signal of interest for analysis or classification of brain states. Examples include modeling the inherent noise associated with M/EEG recording to extract activity related to stages of sleep (Schetinin et al., 2017; Babadi et al., 2011), epileptic seizures (Zandi et al., 2013; Quintero-Rincón et al., 2016), or to an event (Wu et al., 2014). Most of these applications are being developed for cases when there is a lot of noise and classification accuracy is necessary for single trials. There are examples of models proposed for quantifying ERPFs such as the BEEP algorithm that models experimental trials and conditions, noise, latency shifts, amplitude factors, and spatial covariance in a time series analysis (Wu et al., 2014). The second major area of work involves modeling to perform source analyses. Here, EEG and MEG data is used to best explain the underlying brain activity. These models are complex and specific. Not only is the inherent noise of the data modelled, but also the conductivity of the layers that surround the brain, as well as the neuronal structure informed by MRI images and the usual layout of pyramidal neurons and their connections (Wei et al., 2020).

These previous Bayesian model implementations are ultimately aimed at replacing the predominate blind source separation (e.g., ICA) and source analysis methods (e.g., L2-Minimum-Norm-Estimation) and are still being validated, whereas the current work is more concerned with efficient fusion of data recorded from different research sites. The present models employ a few of the elements of BEEP such as modeling the spatial relationships between sensors and the differences between experimental conditions. While BEEP could be a worthwhile future direction for disentangling the N170 and EPN, it is designed for fine-grained individual participant modelling and not combining different recording systems. The Bayesian source analysis methods mentioned also appear relevant at first, but they rely on MRI images which are not available in the present study. Furthermore, simulation studies suggest that without a priori source information and MRI images, L2-Minimum-Norm-Estimation is suited for characteristics of M/EEG data (Hauk, 2004). So, the current models can be thought of as simpler implementations of published work only modeling the most essential and feasible elements. However, this is still relatively novel as a means of combining data across research sites. This is important because it can be difficult to compare M/EEG data in which discrepancies can be caused by small variations in recording systems and procedures. To minimize these issues, large research projects often require funding for painstaking calibration across research sites. The current analyses, that models research site as a regularizing factor, can lessen the influence of differences between sites allowing for better data interpretation when multiple M/EEG systems are compared in a collaborative project. While this type of modeling is not a complete replacement for calibration and standardizing procedures, it may make it easier for teams to report a reliable and predictive result.

CHAPTER 3

METHODS

3.1 Participants

The first sample was college students from the University of Münster in the city of Münster, Germany. Thirty-seven participants (mean age = 22.7, SD = 3.1; females = 18) were recruited via ads and contact information provided from previous studies. The participants were compensated for their time with 35 Euros. Many may have participated in previous studies that used similar paradigms and imaging procedures, but the scene stimuli were novel compared to these past studies. These participants provided concurrent EEG, MEG, and pupil diameter recordings followed by self-reports on experienced valence and arousal in response to the scene stimuli.

The second and third samples were recruited from the University of Georgia (UGA) located in the city of Athens, Georgia in the United States of America. For MEG recordings, 42 college students (mean age = 18.8, SD = 1.7) were recruited from the UGA Psychology undergraduate population for course credit. These participants signed up for the study via an online portal. Two versions of the study were opened on the portal to recruit equivalently sized samples of White (mean age = 18.8, SD = 1.10) and Black women (mean age = 19, SD = 2.52). The last sample of 68 participants (mean age = 19, SD = 1.33), which provided EEG data, were recruited from UGA in a similar fashion. For this sample 22 Black women (mean age = 18.7, SD = 0.92), 22 White women (mean age = 19.3, SD = 1.68), and 24 participants (mean age = 18.9, SD = 1.31) that had a different identity (6 Asian women, 1 Asian man, 2 Hispanic women, 2 Hispanic men, 1 Multiracial woman, 3 Black men, and 9 White men). This final group was randomly collected from the research pool. The rationale for last group was to provide additional statistical power for source analyses as well as acting as a comparison group of similar size to the selected samples of White and Black identifying women.

Samples were chosen to best realize research goals within funding constraints, as well as to achieve subgroups large enough to be statistically meaningful. This is based on effect sizes from previous studies and the participants available in the resource pool. In previous EEG studies, moderate to large Cohen's D effect sizes for comparisons between the categories of interest suggesting sample sizes of 10 participants were sufficient to achieve statistically significant with only one scene presentation (Farkas et al, 2020, 2023). While we did not have a credible estimate for effect sizes for MEG data collection, targets of 40 participants for each sample seemed sufficient given the additional scene presentations (each scene present 4 times) and partial pooling between research sites. White and Black women were recruited for the tertiary aim of investigating own-race vs. other-race processing effects for the N170 and contribute to racial equity in ERPF research. The choice to recruit women and present male face scenes was based on feasibility and statistical control. There were relatively few Black men in the Psychology research pool and scenes of male faces are easier to match for perceptual features. By keeping the gender of the participants and faces the same, this allows for a more robust assessment at this single dimension which may have lacked statistical power if gender was not a constant.

3.2 Naturalistic scenes

In the Münster sample, the same set of scenes was used from a previous study (Farkas et al., 2023). This set of scenes was assembled in an attempt to balance valence, arousal, and body exposure. The set contains 9 content categories, including erotica, victorious sports moments, pleasant animals, neutral nude couples, neutral animals, neutral people, threatening people, threatening animals, and mutilation scenes. Each of these scene categories were made up of 15 scenes for a total of 135 scenes. Erotica scenes depict conventionally attractive couples engaging in consensual intercourse. Victorious sports displayed either men or women at the jubilant moment of victory or success during a sporting event. Nudists scenes depict unclothed couples walking in a variety of locations such as beaches and parks. The couples have neutral facial expressions and vary in age more than the erotic content. These nudist scenes elicited neutral ratings of valence and arousal in past studies (Farkas et al., 2020, 2023). The category of neutral people features clothed people in a variety of mundane situations, such as sitting in parks or conversing on buses. The category of threatening people features one or more people making aggressive postures and facial expressions, brandishing weapons, or engaged in violent acts. Threatening animal scenes depict predators aggressively posturing or attacking the viewer. Finally, mutilation scenes depict graphic injuries, open wounds, or mangled body parts.

For the UGA samples, the 3 animal scene contents were replaced by neutral face portraits and simple geometric ovals on contrasting backgrounds (Figure 3). The purpose of the face portraits was to elicit a face-evoked N170 ERPF to compare with our expected body-evoked N170. To contribute to a secondary aim of assessing if racial identity modulates the N170, face scenes were matched such that there were 21 matched pairs of White and Black male faces. Of these pairs, 7 were drawn from the MR2 face set (Strohminger et al., 2016) while the remaining 14 were assembled by the lab for this study from athletic roster photos from US college soccer teams. This was done to increase the amount of face scenes in the set, and to promote perceptual equivalence between the Black and White men face scenes. The rationale for selecting pairs from the same team roster is that the lighting, jersey colors, and composition are kept consistent. In addition to the face scenes, 7 pairs of gray ovals were included in the scene set as basic perceptual controls. The ovals were roughly the same dimensions as the face pictures, and they appeared as one of two versions: dark gray oval on a light gray background, or vice versa. The number of scenes were chosen based on experiment time constraints, such that we could maximize the number of usable trials for our face scenes of interest. Previous studies suggest that the different number of scenes across categories should have negligible effects on our ERPFs (Farkas et al., 2021; Schupp et al., 2021; de Cesarei et al., 2015).

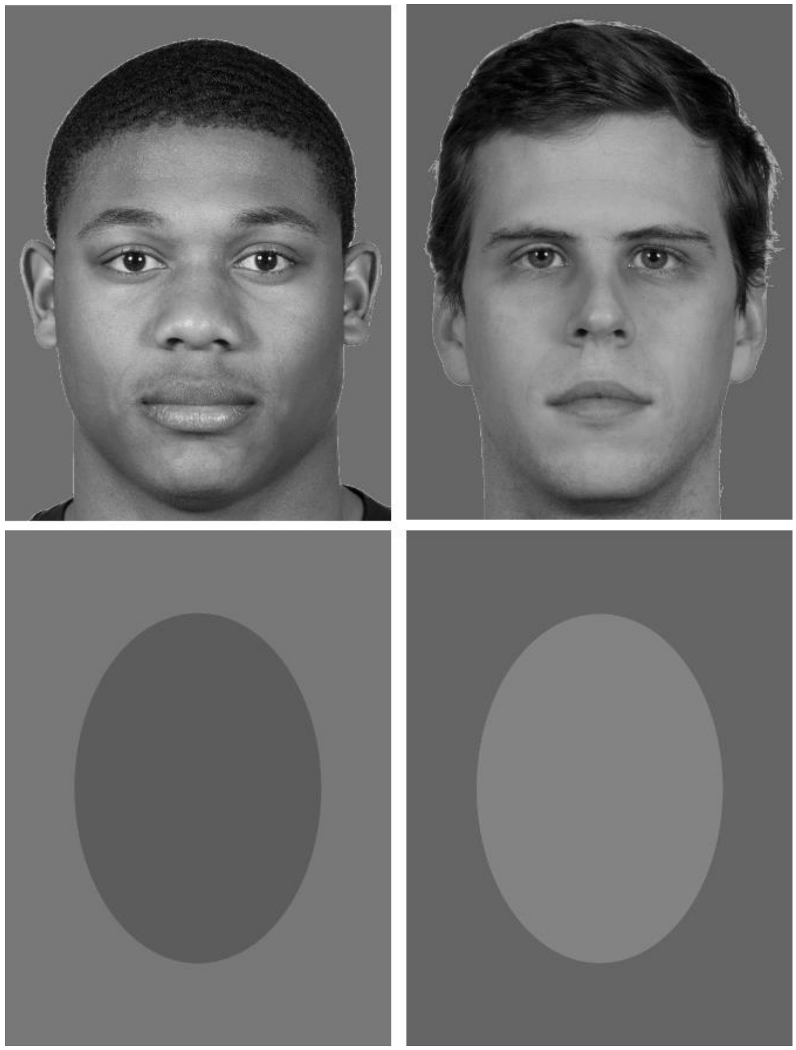

Figure 3. Examples of the face and oval pictures used for the University of Georgia (UGA) samples. These replaced the scene categories depicting animals used for the Münster participants and previous studies (Farkas et al., 2020, 2023).

We attempted to balance the low-level visual features of the scenes between categories. All scenes were 800 pixels wide by 600 pixels tall, except for the face and oval scenes which were 600 pixels wide by 800 pixels tall. Luminance and complexity were balanced using GNU Image Manipulation Program (GIMP; gimp.org). This was done by manipulating the scenes that had the most extreme values in each category until scene categories were found to be statistically equivalent (p-values > .2). For luminance, the brightness adjustment tool was used in GIMP. Complexity was indexed by JPEG file size, which serves as an adequate index of visual complexity (Donderi, 2006). To correct overly complex scenes, a 1x1 pixel Gaussian blur was used in GIMP, which slightly attenuates high spatial frequency information without noticeable impact on clarity.

3.3 Self-report questionnaires

Valence and arousal ratings for each scene were recorded after neuroimaging data collection in all samples. A computerized version of the Self-Assessment Manikin (SAM; Bradley et al., 1994) was used at both research sites. In the Münster sample, the rating procedure was implemented via computer using Psychtoolbox (Brainard, 1997; Kleiner et al., 2007). After instruction in the German language, ratings were collected via computer mouse. Participants moved a cursor along a scale to make their rating of how the scene made them feel. For UGA participants, the ratings were collected via a Qualtrics survey. Participants moved a slider underneath each scene by dragging and clicking directly on the scale. The Münster participant ratings were on a continuous scale from 0 to 100 while the UGA system was on a continuous scale from 1 to 9. Participants from both research sites self-reported their demographic information via a worksheet. This included racial or ethnic identity, age, gender, and handedness.

3.4 University of Münster procedures

Participants recruited through flyers and contact information from previous studies arrived at the Institute for Biomagnetism and Biosignalanalysis (IBB) for data collection. After arriving, they were given an informed consent document approved by the University human subjects review board. After agreeing to participate, a 57-channel EASYCAP EEG system (easycap.de) was fitted to the participant. The sensor positions and skull shape were then be mapped using a Polhemus system (Polhemus, Colchester, VT, USA; polhemus.com). This information was used for a more precise estimation of sensor locations in data analysis for both the EEG and MEG data. After the EEG cap fitting process was completed, the participant was guided into the MEG chamber. The MEG system is a 275 whole-head sensor system (CTF Systems). It has first-order axial gradiometers (Omega 275; CTF, VSM MedTech

Ltd., Coquitlam, Canada). The EEG and MEG data was recorded at a sample rate of 600 Hz. Fiducial coils placed at the nasion and ears were used as landmarks for the head position in the MEG scanner. An eye tracking system was then positioned to focus on the left eye to record pupil diameter of the participant at a sampling rate of 600 Hz. The scenes presented on this projector extended across 12.3 degrees of horizontal visual angle.

The 135 scenes were presented four times total, in two equal-sized blocks. Between each block, the participants were given a brief break before the data recording resumed. Each set of the 135 scenes was randomized such that no participant saw the same order. However, pre-experiment, the order of each set was specified such that the transition probability between the nine categories was nearly equivalent. Scenes were presented for 1 second each, with a random inter-trial interval varying between 1 - 2 seconds. Following the EEG and MEG data collection, participants were guided to a new room to then rate the scenes using the self-assessment manikin procedure (Bradley et al., 1994) via a computer mouse as described earlier. Following data collection, the participants were debriefed and paid for their participation.

3.5 University of Georgia procedures

The MEG participants were recruited from the UGA Psychology undergraduate research pool for course credit. Additionally, a checklist was used to make sure they did not have any unremovable metal on their body that would interfere with the MEG recordings (such as earrings, piercings, braces, or pacemakers). After giving informed consent, participants were positioned in the MEG system. The MEG scanner is a 143 whole-head sensor system (CTF Systems) featuring first-order axial gradiometers (Omega 143; CTF, VSM MedTech Ltd., Coquitlam, Canada). Landmark coils were placed at the nasion and just dorsal to the left and right temporomandibular joints which is anterior to the tragus of the ear lobe. While positioning the participant, towels were positioned between the skull of the participant and the MEG bore to make the participant more comfortable and to prevent movement during the study. The screen was located 27.5 inches from the participants eyes and took up 33 degrees of visual angle.

The 140 scenes were shown 4 times in total in two blocks, similar to the Münster sample. Each scene was presented for 1 second with an ITI ranging from 1 to 2 seconds. The 140 scenes were arranged into 4 pseudorandom set orders such that the content was evenly distributed (labeled A, B, C, and D). The first condition presented the first two sets (A and B) in a block. After a short break, sets C and D were then presented in the second block. For condition 2, the sets were ordered from B, C, D, and then A; condition 3 as C, D, B, then A; and finally condition 4 as D, A, B, and C. Data was recorded continuously at a sampling rate of 600 Hz. After MEG data collection was completed, participants rated their experienced valence and arousal using the Self-Assessment Manikin procedure as described earlier. They then filled out the post experiment questionnaire that provides demographic information. The participant was then debriefed and walked out of the MEG facility.

For EEG data collection, participants were recruited in the same way as the MEG portion of the project. Participants arrived at the UGA Psychology building based on the information from an online portal. Participants were then given an informed consent document. After, the participants were guided into a Faraday chamber for EEG preparation. Continuous EEG data was recorded using a 128-channel BioSemi ActiveTwo system (BioSemi), which uses pre-amplified electrodes positioned according to the 10/20 system. The electrode voltage was referenced to two additional common mode electrodes (CMS and DRL). The sampling rate was 512 Hz. ActiView acquisition software (actiview.org) was used to ensure offsets are between –50 to 50 millivolts during set up. The same software was used for data recording and monitoring data acquisition.

The same 140 scenes from the UGA MEG data collection were presented to participants 3 times in total over two blocks. We reused the same first three set scene orders (A, B, and C). There were six conditions counterbalanced between participants. In each condition, two sets of scenes were presented for a duration of 1 second with an ITI between 1 and 2 seconds (“fast”), while the third set was presented for 2 seconds with an ITI duration between 3.5 to 5.5 seconds (“slow”). Thus, we had a presentation speed which was the same as the MEG data collection from both sites and a slower presentation speed which matched the previous two studies (Farkas et al. 2020, 2023). Six conditions allowed for sets A, B, and C to alternate orders as in the MEG data collection, while also alternating the order of fast and slow blocks.

Following EEG data collection, the participants rated the scenes using the same Qualtrics survey used for the participants recruited for the MEG data collection. Participants then completed the brief post experiment questionnaire and were debriefed.

3.6 MEG and EEG data reduction

MEG and EEG data were processed using the MATLAB based Electro Magnetic Encephalography Software analysis package (EMEGS; emegs.org; Peyk et al., 2011). EMEGS preprocessing filters for the MEG data were applied using functions from the Fieldtrip MATLAB software package (fieldtriptoolbox.org; Oostenveld et al., 2011). EEG and MEG data from Münster were down sampled from 600 to 300 Hz. Epochs for data recorded from Münster were from 200 ms before scene onset to 1000 ms after. Epochs for UGA data included from 125 ms before scene onset to 1000 ms after. The filters used were a low-pass Butterworth filter with a stopband of 40 Hz and a passband of 30 Hz, as well as a high-pass Butterworth filter with a stopband of 0.05 Hz and passband of 0.1 Hz. To account for the interference from the power grid, all MEG epochs received an additional notch filter around 60 Hz for the UGA sample and around 50 Hz for the Münster data with a width of 3 Hz around the target frequency.

We applied the guidelines suggested by Junghöfer and colleagues (2000) for finding and correcting artifacts in dense array studies via EMEGS. This involved finding unreliable sensors and trials for each participant by creating a composite measure for each sensor by trial. The maximum voltage, standard deviation, and first derivative are combined to create a composite measure of the quality of the given sensor by trial. Confidence intervals centered around the median value of these composite measures are used to identify unreliable channels and trials. Unreliable trials were removed from the study and unreliable sensors were replaced by spherical spline interpolation of the surrounding sensors. Following this, the remaining trials were averaged together per category. Participants that are missing more than

60% of trials from a category were removed from the final analyses. The shorter ERPF epochs were baselined with the average voltage from 100 ms before scene onset.

An L2-Minimum-Norm-Estimation method (L2-MNE) was used to approximate the underlying cortical activity responsible for EEG and MEG recordings (Hämäläinen et al., 1994). The source analysis estimates were generated separately for each EEG and MEG sample because simultaneous joint estimation is not currently a reliable option (Tadel et al., 2019; Baillet et al., 1999). The L2-MNE procedure, which was implemented in the EMEGS software, uses a sphere model with scalp, skull, cerebrospinal fluid layers followed by a dipole shell. A sphere model appears to be optimally suited for source analysis without a priori information of the generating sources, because it accurately captures the information that is present in the data (Hauk, 2004). The result of the L2-MNE procedure is the estimated activity over time for 350 evenly distributed dipoles measured in nanoamperes (nA). The dipoles represent activity amplitude, and not dipole orientation. A source estimate was found for each category per participant.

3.7 Pupil-diameter data reduction

Pupil diameter was measured using an EyeLink 1000 Plus eye tracker (SR Research Ltd., Canada) at a sampling rate of 600 Hz as a separate channel with the MEG data. The data was preprocessed with the EMEGs software similar to the EEG and MEG data. The epochs for each trial are similar to the ERPF data, 133 ms before scene onset and 1250 ms after. Unlike the ERPF data, no band pass filters were used during preprocessing. Artifact contaminated trials were identified and removed using the EMEGS goal function like the EEG and MEG data. This works by creating a composite measure for each trial based on each trial's absolute maximum diameter, maximum standard deviation, and maximum first derivative which is the rate of change. The composite measure for each trial was compared to a confidence interval centered around the median of all trials per participant. If a trial was outside the confidence interval, it was removed from the final analysis. Pupil diameter was baselined from the average diameter recorded 100 ms before scene onset. The average pupil diameter between 625 to 1125 ms following scene onset was used for the final analyses.

3.8 General statistical procedures

Descriptive statistics were found with the R programming language (r-project.org). Inferential statistics for the main research questions were found via a series of Hierarchical Gaussian Process Models for the ERPF data. There are many benefits to Bayesian multi-level models which were described in more detail in section 2.5. In short, these models allow for an efficient fusion of data from different research sites and modalities (i.e., EEG and MEG). This is because of the feature of partial pooling and modeling flexibility. In these kinds of models, each factor can be specified as coming from a higher-level distribution. For example, participants can be specified as coming from a distribution of participants. This allows information to be shared such that the estimates for one level are informed by all other observations. It can be thought of as a compromise between averaging (complete pooling) and treating conditions as completely independent (no pooling). This allows for more precise posterior estimates as well as regularizing and correcting for multiple comparisons similar to models corrected by cross validation (McElreath, 2020). By applying a Hierarchical structure here, we can account for how research sites and imaging modalities are different while combining their results in a principled procedure.

A more specific beneficial feature for the present research goals, is how Gaussian Process Models can be used to account for the correlation structure of the EEG and MEG data to decrease uncertainty and while maintaining the ability to assess topological ERPF spatial differences. A Gaussian Process Model uses the assumption that the relationship between a group of observations can be defined by a “kernel” function. Here, this assumption was used to account for how channels and estimated sources close to each other are likely to be correlated. This is a common assumption most EEG researchers use to justify averaging channels together or creating a linear combination of channels via PCA. By combining channels in some way, statistical power can be increased by averaging out noise. With the implementation of this in a Gaussian Process Model, we can claim much of the same benefits while maintaining separate inferential statistics for each channel. This is ideal for the present research questions which center on spatial differences. Because the model has hierarchical elements, the results will also have regularization and multiple comparison corrections. A final benefit is that the correlation structure is learned by the model and is used to compute posteriors for channels that do not exist on some of the systems. For example, the Münster EEG system only has 57 channels, but posterior distributions were found at the same 128 channel locations of the Athens EEG system because of the shared information in the model.

There were two kernel functions used for the Gaussian Process Models; one for EEG data and one for the source analysis data. The covariance between estimated dipoles was modeled by the commonly used squared exponential equation:

$$cov = \eta^2 \cdot exp(-\rho \cdot d^2)$$

Here the eta-squared represents the maximum amount of covariance between two sensors. The second part of the equation models how correlation drops off exponentially with distance in radians. If "*d*" for distance is 0, the exponential function evaluates to 1, while the function decreases as d increases. The rho parameter signifies how quickly correlation decreases with distance. Additional domain knowledge was applied for the EEG kernel function. Because the data is presented in terms of an average reference and it is common to see a negative deflection 180 degrees away from a positive voltage, an additional element was used for the EEG kernel function:

$$cov = (\eta^2 \cdot exp(-\rho^2 \cdot d^2)) - ((\eta^2 \cdot \gamma) \cdot exp(-\rho_2^2 \cdot (d - \pi)^2))$$

The additional section applies a negative correlation, which increases as the distance away from a channel approaches Pi which is 180 degrees. The gamma parameter scales the maximum negative covariance. These parameters are estimated in the model in Bayesian model, so they receive priors and result in posterior distributions.

Each model can be represented in mathematical notation. Below are the full models for each research question. Adding more complexity to the model can be prohibitively expensive. For that reason, the data was z-scored within each participant so that the random effect between participants did not have to be estimated. Additionally, possible effects of ITI length and demographic identity were not evaluated in all models. Lastly, also to limit complexity, only data from the 6 shared human scene categories of erotica, victory, nudists, neutral people, and mutilation were used for the main research questions. For the first three research questions, EEG data was analyzed with the following model.

EEG Model for Research Questions 1 and 3

$(\textbf{Likelihood})$

$$erp_i \sim Normal(\mu_i,\ \sigma_{erp})$$

$$\mu_i = \alpha_{chan[i]} + \beta_{1\ category[i],chan[i]} + \beta_{2\ site[i],chan[i]} + \beta_{3\ category[i],site[i],chan[i]}$$

$(\textbf{Adaptive Priors})$

$$\alpha \sim MVNormal(0,\ \mathbf{S}_{erp})$$

$$\beta_{1\ category[j]} \sim MVNormal(0,\ \mathbf{S}_{erp}\ \cdot \sigma^2_{category})$$

$$\beta_{2\ site[k]} \sim MVNormal(0,\ \mathbf{S}_{erp}\ \cdot \sigma^2_{site})$$

$$\beta_{3\ category[j],site[k]} \sim MVNormal(0,\ \mathbf{S}_{erp}\ \cdot \sigma^2_{category,site})$$

$(\textbf{Kernel Function})$

$$S_{erp[i,j]} = (\eta^2 exp(-\rho^2 d^2_{i,j})) - ((\eta^2\gamma) exp(-\rho^2_2 (d_{i,j} - \pi)^2))$$

$(\textbf{Fixed Uninformative Priors})$

$$\sigma_{erp}, \sigma_{category}, \sigma_{site}, \sigma_{category,site} \sim HalfNormal(0,1)$$

$$\eta^2 \sim HalfNormal(0,2)$$

$$\rho^2, \rho^2_2 \sim HalfNormal(0.5,4)$$

$$\gamma \sim Beta(1.25,1.25)$$

In the linear equation, the alpha term accounts for the average amplitude at each channel. Beta-one and two are the main effects of scene category and research site respectively. Beta-three is the interaction term for category and site at each channel. The adaptive or hyper priors which cause partial pooling and regularize the model are multi-variate normal distributions which are normal distributions that span more than one dimension. They specify that pulling one observation comes with 128 interrelated values, one for each EEG channel. The covariance is defined by the already described kernel function. The same covariance matrix is used for each linear model term, but the betas are scaled by an additional parameter. The covariance matrix is found via the kernel function explained earlier. Finally, the last lines specify the uninformative priors necessary for the additional parameters that must be estimated.

For the source analysis model for the primary research questions, more regression parameters were added to account for whether the source estimation results were found via the *method* of MEG or EEG. The only other difference is the simpler kernel function as described earlier. Here, 350 interrelated observations are drawn for each observation from the multi-variate normal distribution.

Source Model for Research Questions 1 and 3

(**Likelihood**)

$erp_i \sim Normal(\mu_i,\ \sigma_{erp})$

$\mu_i = \alpha_{chan[i]} +$

$\beta_{1\ category[i],chan[i]} + \beta_{2\ site[i],chan[i]} + \beta_{3\ method[i],chan[i]} +$

$\beta_{4\ category[i],site[i],chan[i]} + \beta_{5\ category[i],method[i],chan[i]} + \beta_{6\ method[i],site[i],chan[i]} +$

$\beta_{7\ category[i],site[i],method[i],chan[i]}$

(**Adaptive Priors**)

$\alpha \sim MVNormal(0,\ \mathbf{S}_{erp})$

$\beta_{1\ category[j]} \sim MVNormal(0,\ \mathbf{S}_{erp}\ \cdot \sigma^2_{category})$

$\beta_{2\ site[k]} \sim MVNormal(0,\ \mathbf{S}_{erp}\ \cdot \sigma^2_{site})$

$\beta_{3\ method[l]} \sim MVNormal(0,\ \mathbf{S}_{erp}\ \cdot \sigma^2_{method})$

$\beta_{4\ category[j],site[k]} \sim MVNormal(0,\ \mathbf{S}_{erp}\ \cdot \sigma^2_{category,site})$

$\beta_{5\ category[j],method[l]} \sim MVNormal(0,\ \mathbf{S}_{erp}\ \cdot \sigma^2_{category,method})$

$\beta_{6\ method[l],site[k]} \sim MVNormal(0,\ \mathbf{S}_{erp}\ \cdot \sigma^2_{method,site})$

$\beta_{7\ category[j],method[l],site[k]} \sim MVNormal(0,\ \mathbf{S}_{erp}\ \cdot \sigma^2_{category,method,site})$

(**Kernel Function**)

$S_{erp[i,j]} = \eta^2 exp(-\rho^2 d^2_{i,j})$

(**Fixed Uniformative Priors**)

$\sigma_{erp}, \sigma_{category}, \sigma_{site}, \sigma_{method} \sim HalfNormal(0,1)$

$\sigma_{category,site}, \sigma_{category,method}, \sigma_{method,site} \sim HalfNormal(0,1)$

$\sigma_{category,method,site} \sim HalfNormal(0,1)$

$\eta^2 \sim HalfNormal(0,2)$

$\rho^2 \sim HalfNormal(0.5,4)$

All of the ERPF models were fit in the same analysis for each ERPF (i.e., N170, EPN, LPP) such that their posteriors could be compared. These models were fit using the cmdstanr R package (Stan Development Team, 2023), which is an interface for the Stan Bayesian modeling software (Stan Development Team, 2023). The Stan software is built in the C++ language to perform high-performance statistical modeling and computation. The software is mainly known for its high-quality implementation of Hamiltonian Monte Carlo sampling method (Duane et al., 1987). This method is similar to other Markov Chain Monte Carlo algorithms in that it uses chained mass sampling to estimate posterior distributions. But instead of sampling via random steps, it gives that last sample momentum and simulates where the next sample would be as it moves along the posterior via Hamiltonian equations as if it were a moving object governed my classical mechanics. This appears to be superior because it gives more accurate posterior estimates when there are many dimensions and is more computationally efficient because nearly all proposed samples are accepted (McElreath, 2020).

Following the best practices suggested by McElreath (2020), the models were built iteratively, from simple versions with only a few parameters of interest, to the more complex variants that include more variables and interacting effects. To determine if enough samples are drawn from the posterior, we will use the suggested metrics of number of effective samples and R-hat (a measure for assessing convergence in Markov Chain Monte Carlo sampling; Vehtari et al., 2021), as well as visualizations of the trace plots to further assess convergence of sampling.

The first research question is to determine if scene-evoked activity is spatially distinct between 130 to 200 ms after scene onset when compared to 200 to 300 ms. To understand the spatial pattern of effects, each scene category was contrasted with the neutral people category per channel for each relevant ERPF. Channels that had greater than 95% of posterior samples below zero for the N170 and EPN were reported as being meaningfully different. For the LPP, it was the percentage of posterior samples above zero. This percentage reflects the posterior probability that there is an effect. Additionally, contrasts were made between nudists and erotica. This was done for the EEG and source analysis models, but for the source analysis this was limited to only the N170 and EPN time windows for computation feasibility. The pattern of results were compared to pupil-diameter and arousal ratings to answer the second research question.

For the third research question the consistency of the findings between research sites was assessed. More specifically, posteriors for each of the six categories were compared between research sites for the relevant time periods. The channels selected for reporting the raw EEG ERP amplitudes per research site were chosen based off the statistically significant channels that were found for the first research question. These channels for the N170 and EPN were TP9, P9, PO7, PO9, O9/I1, Iz, O10/I2, PO10, PO8, P10, and TP10. For the LPP, the channels chosen were C1, CP1, Cz, CPz, C2, and CP2 (Figure 4).

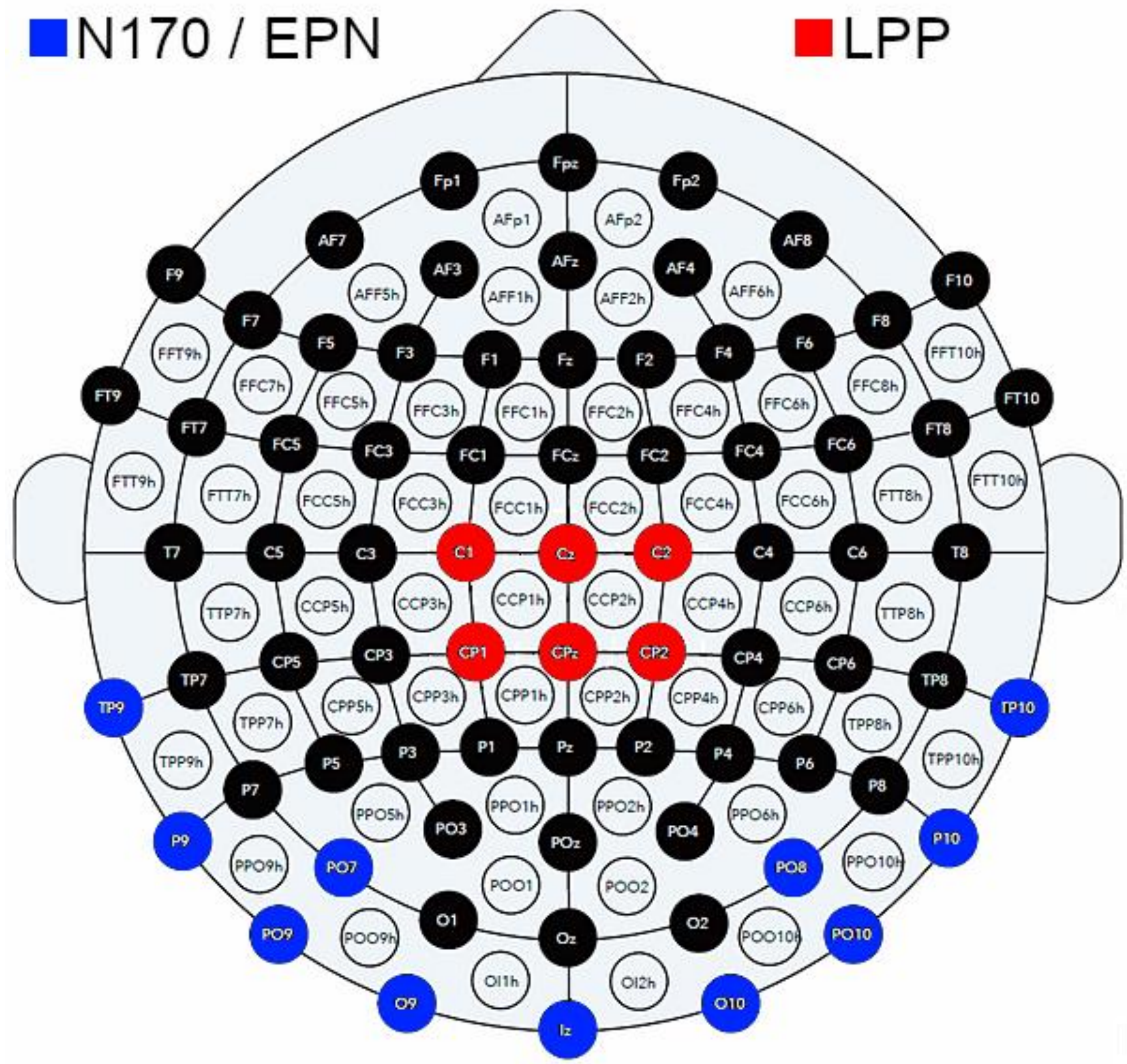

Figure 4. The EEG sensors used for analyses comparing University of Georgia and Münster results. Channels were chosen based on spatial information statistics from research question one and sensors available from both EEG systems.

Pupil diameter, and ERPs relevant to the auxiliary research questions of face and ITI effects were understood via traditional repeated measures ANOVAs instead of the Bayesian approach. This is because these research questions did not rely on estimating a spatial distribution. Additionally, it allows for the results to be more interpretable for research teams that commonly use these methods. The channels chosen for the auxiliary questions for the N170 and EPN ERPs were TP9, TPP9h P9, P7, PPO9h, PO7, PO9, POO9h, O9/I1, O1h, Iz, OI2h, O10/I2, POO10h, PO10, PO8, PPO10h, P8, P10, and TP10. For the LPP, the channels used were FCC1h, C1, CPP1h, CP1, Cz, CPz, FCC2h, C2, CCP2h, and CP2 (Figure 5).

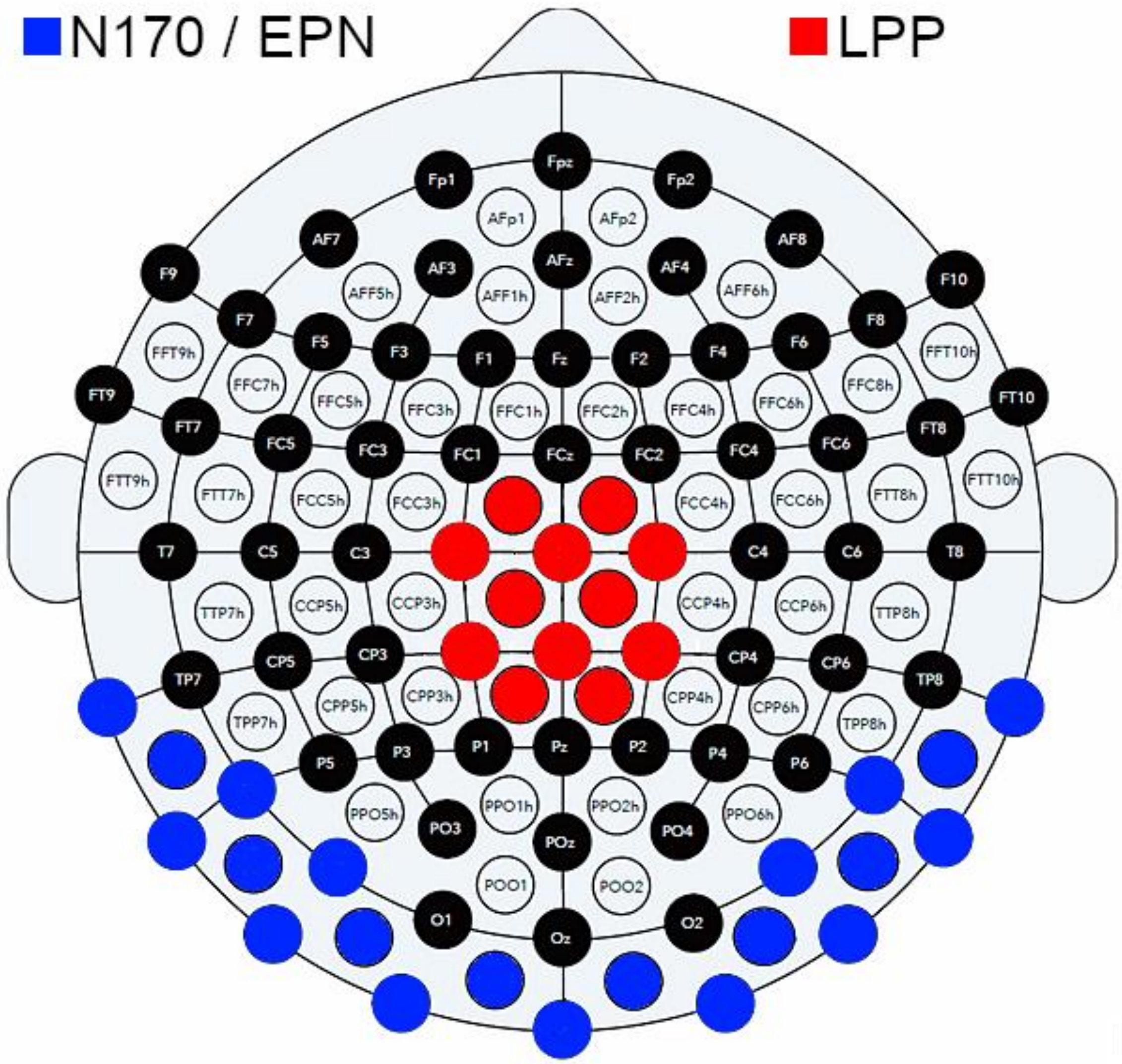

Figure 5. The EEG sensors used for analyses of auxiliary research questions.

CHAPTER 4

RESULTS

4.1 Research Question 1: EEG sensor level results

The model for EEG sensor-level results found that most categories differed from neutral people for each of the ERPs of interest. Figure 6 depicts the Z-score posterior median and certainty of the effect above zero for each category contrasted with neutral people scenes. For the N170, all categories except for mutilation scenes had a significant negativity over posterior electrodes. For these categories, all or greater than 95% of posterior samples were below zero for many inferior-occipital and lateral occipital sensors. Moving from the left to the right side of the head, these significant channels during the N170 over the back of the head were TP9, TP7, P9, P7, PPO9h, PO9, PO7, POO9h, O9/I1, O1, OI1h, Iz, Oz, OI2h, O10/I2, O2, POO10h, PO8, PO10, PPO10h, P8, TPP8h, P10, TP8, and TP10. Threatening people scenes were also significant at the channel T8 for threatening people. Victorious athlete scenes were also significant at T8, as well as further right temporal sensors of T7, P6, FTT10h, and FT10. Threatening people, nudist, and erotic content significance extended to additional superior-occipital sensors that were different from the other categories: POz, PO3, PPO5h, CP6, CPP6h, P4, PPO6h, and PO4. In summary, all categories during the N170 had a significant response over occipital sensors compared to neutral people. Victorious athletes featured additional significance over anterior temporal sensors, while nudist and erotic content had additional differences at more parietal sensors.

For the EPN ERP, all categories reached occipital significance when contrasted with neutral people scenes. These channels included TP9, TP7, P9, P7, TPP7h, PO9, PO7, POO9h, O9/I1, O1, OI1h, Iz, Oz, OI2h, O10/I2, O2, POO10h, PO10, PO8, PPO10h, P10, P8, TPP8h, TP10, and TP8. The EPN during erotic scenes also had significance at superior-occipital channels of PO3, P5, PP05h, P3, POO2, PPO6h, PO4, POz, PPO2h, P4, P6, CPP6h, CP6, TTP8h, and POO1. Victory featured changes more on the temporal regions; FT9, FTT9h, T7, PPO6h, P6, and TTP8h. Nudist content featured additional superior-occipital differences at PO3, P5, PP05h, POO2, PPO6h, PO4, POz, P4, P6, CPP6h, CP6, TTP8h, and POO1. Threatening people was significantly more negative at PO3, P5, PP05h, POO2, PPO6h, PO4, P6, and POO1. Finally, mutilation was additionally significant at PO3, P5, POO2, PO4, and POO1.

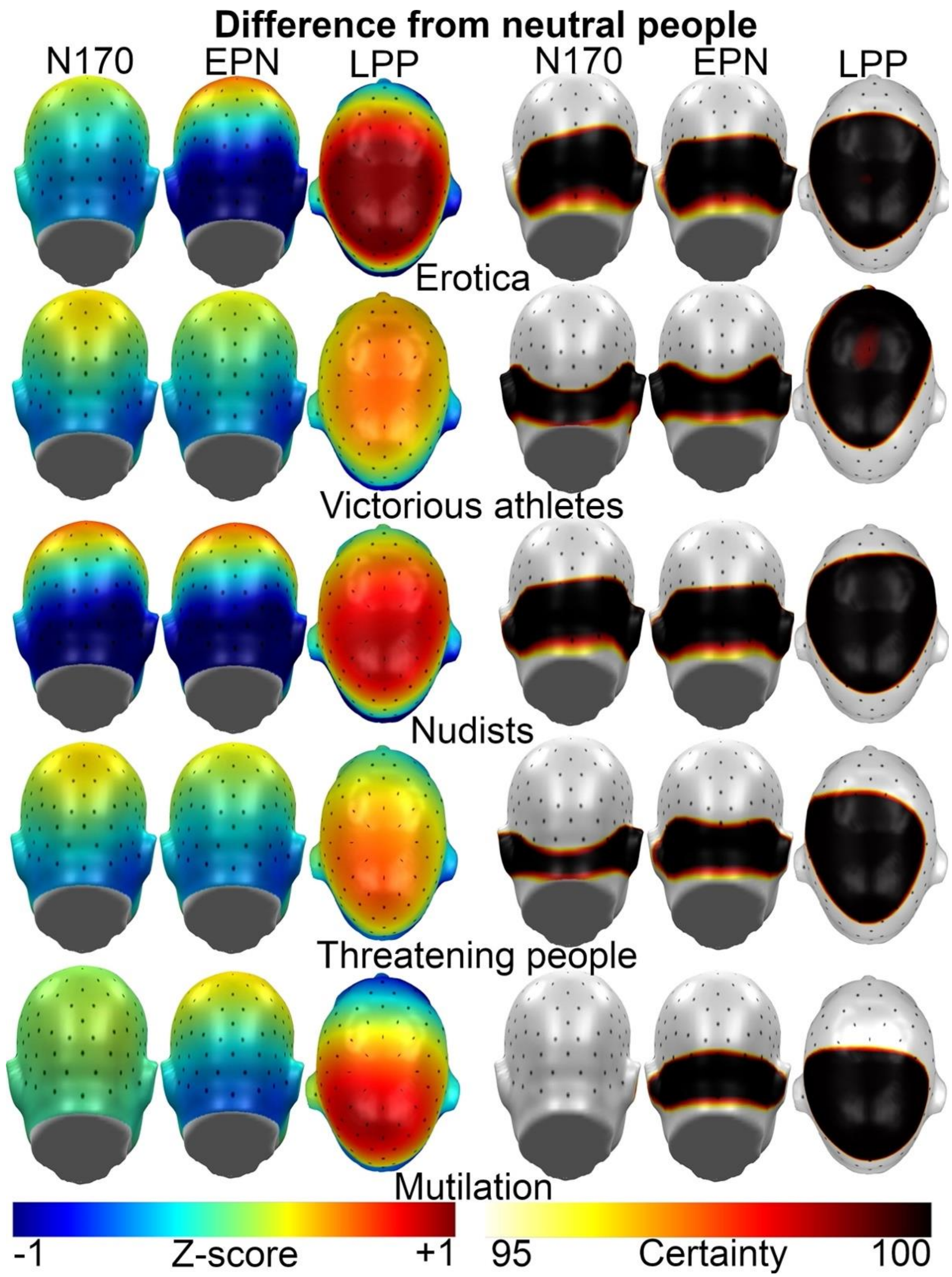

Figure 6. The EEG topological contrasts with neutral people scenes. The left three columns depict the median posterior over the scalp. The right three columns show where and what percentage of the posterior samples were below zero (certainty).

For the LPP, all categories featured a positive voltage over dorsal sensors. Moving from the top left to bottom right in rows, all categories were significant at FC3, FC1, FCz, FC2, FCC5h, FCC3h, FCC1h, FCC2h, FCC4h, C3, C1, Cz, C2, C4, CCP5h, CCP3h, CCP1h, CCP2h, CCP4h, CP3, CP1, CPz, CP2, CPP3h, CPP1h, CPP2h, CPP4h, P1, Pz, and P2. Erotica was additionally meaningful at central frontal sensors of F3, FFC5h, FFC3h, Fz, F2, FC5, FC4, C5, CP4, CPP5h, CPP6h, P3, P2, P4, PPO1h, PPO2h, and POz. Victory scenes extended the most anteriorly with significance all the way to the anterior-most channels; FPz, FP2, AF8, AF3, AFP1, AFP2, AF4, AFF5h, AFz, AFF6h, F3, AFF1h, AFF2h, F4, F6, F8, FFC5h, FFC3h, Fz, F2, FFT8h, FC5, FC4, and FC6. Nudists also featured more anterior positive voltages; F3, AFF1h, AFF2h, F4, F6, FFC5h, FFC3h, Fz, F2, FC5, FC4, FC6, C5, CP4, CPP5h, P3, P2, PPO1h, and PPO2h. Threatening scenes were additionally significant at FFT7h, FFC5h, FFC3h, C5, CP4, CPP5h, P3, P2, PPO1h, PPO2h, and POz. Lastly, mutilation content featured an LPP significant on additional posterior sensors; C5, CP4, CP6, TPP7h, CPP5h, CPP6h, P5, P3, P2, P4, PPO5h, PPO1h, PPO2h, PPO6h, PO3, POz, PO4, and POO1.

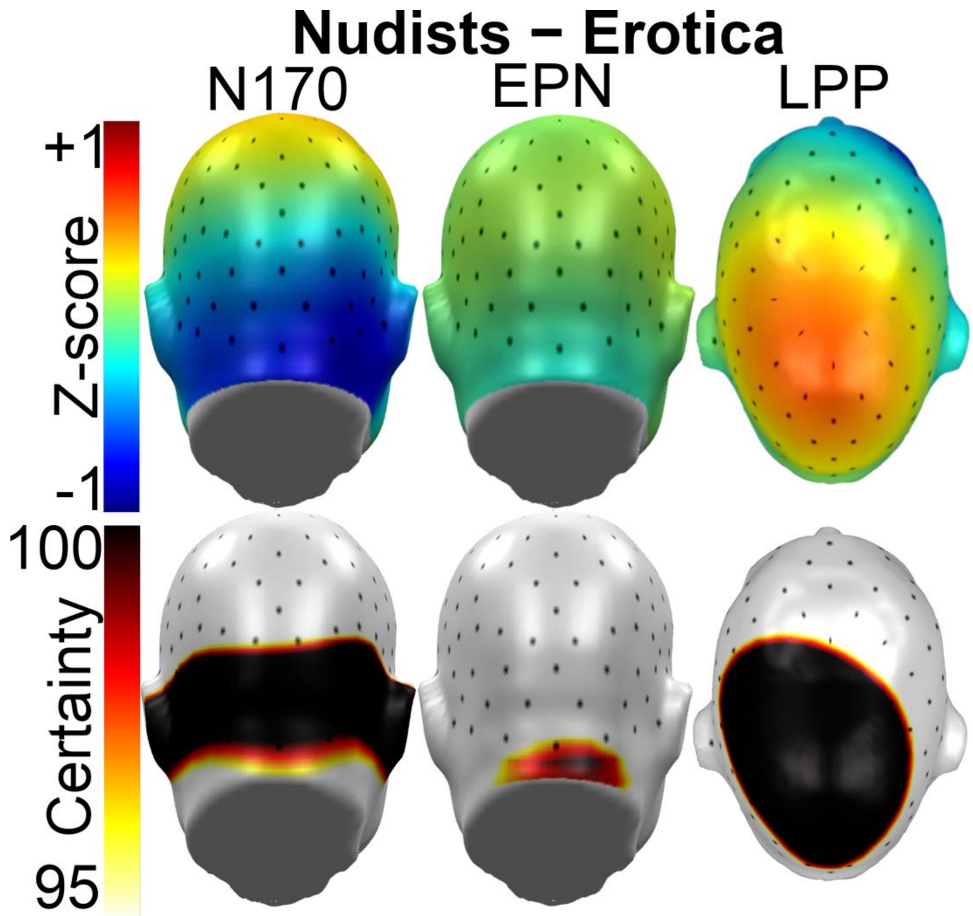

Figure 7. The results of the contrast between nudist and erotic content. The top row depicts the median Z-score difference, with blue indicating where nudist content had a more negative voltage than erotica. Red indicates where erotic content was more positive. The second row shows the statistical certainty of the model of which sensors showed a greater than 95% probability of the categories being different.

An additional contrast was made for each ERP between nudist and erotic content because this was a contrast of interest between the body exposure of nudist content versus the more emotional erotic scenes. In the N170 time window, nudist content was more negativity than erotica at TP9, TP7, P9, P7, TPP7h, PPO9h, P5, PO9, PO7, PPO5h, POO9h, PO3, O9/I1, O1, OI1h, POO1, Iz, Oz, POz, OI2h, POO2, O10/I2, O2, PO4, POO10h, PPO6h, PO10, PO8, PPO10h, P6, P10, P8, TPP8h, TP10, and TP8. In the EPN time window only the sensors of O9/I1, Iz, O10/I2, and PO10 had a significantly larger voltage for nudists compared to erotica. For the LPP, erotica featured a more positive amplitude than nudists at FFC1h, FFC2h, FC3, FC1, FCz, FC2, FCC5h, FCC3h, FCC1h, FCC2h, C3, C1, Cz, C2, CCP5h, CCP3h, CCP1h, CCP2h, CCP4h, CP3, CP1, CPz, CP2, CP4, CPP5h, CPP3h, CCP1h, CPP2h, CPP5h, P3, P1, Pz, P2, P4, PP05h, PPO1h, PPO2h, PO3, POz, POO1, and POO2.

4.2 Research Question 1: EEG and MEG source analysis results

For the source analysis model, the main effect found between each emotional category from neutral people identified three categories that differed during the N170 and EPN time windows. These effects can be seen in Figure 8. For the N170, nudist content was the only category that was significantly different than neutral people. This difference was estimated to be in the right posterior temporal lobe. Larger and more likely differences were found in the EPN time window for erotic and nudist content in bilateral posterior temporal lobes.

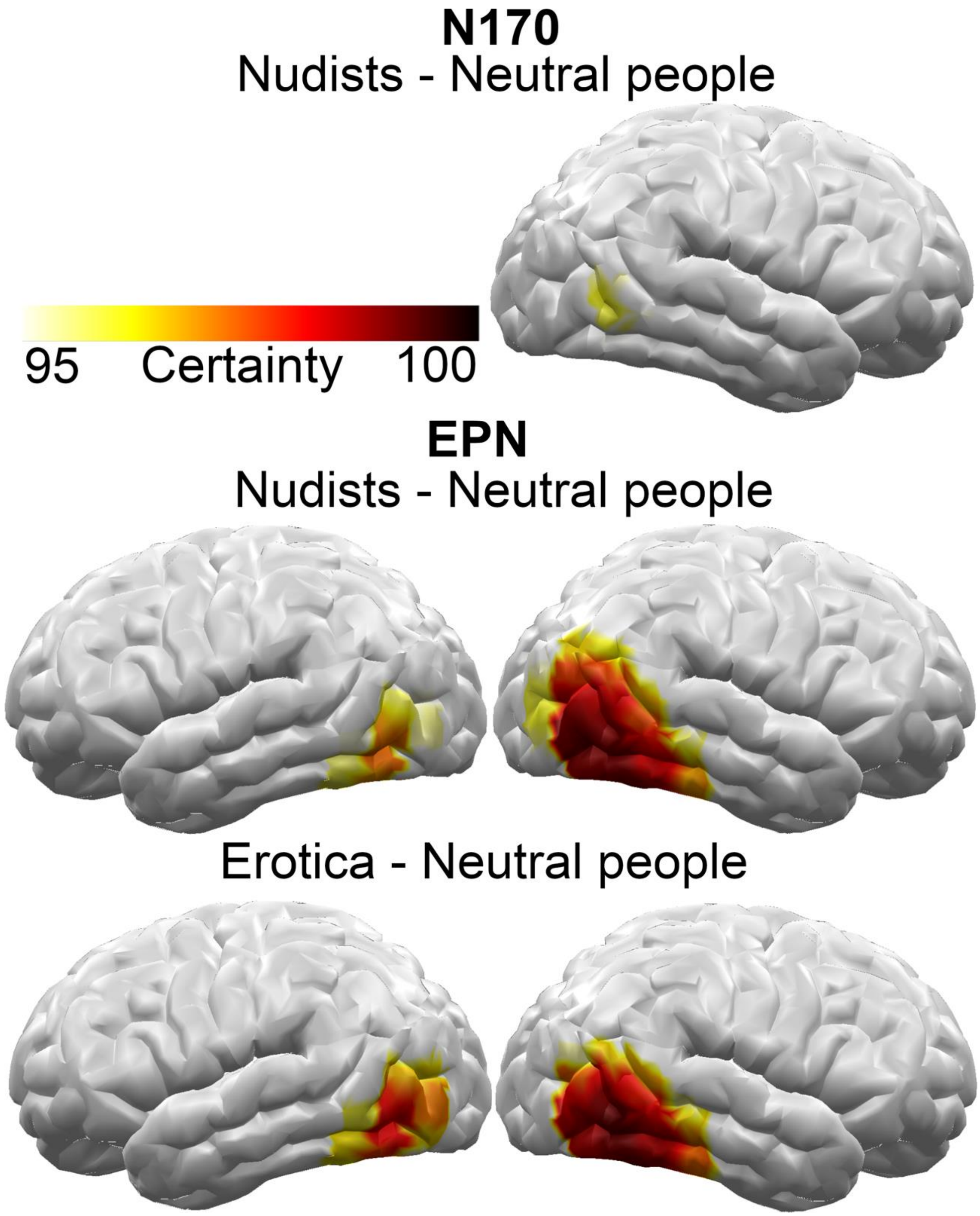

Figure 8. The significant source analysis contrasts with neutral people scenes. This is the main effect of both research sites and the imaging modalities of EEG and MEG.

Each category was then broken down by the imaging modalities of EEG and MEG in which statistically significant median posteriors are plotted (Figure 9 & 10). Both time windows found significant temporal activity in the EEG source analysis, but not for the MEG collected data. The categories of erotica and nudists featured larger posterior differences in the same posterior temporal regions for the N170 and EPN periods. Nudist content had a larger recorded activity than erotica in the N170 window, while they were more similar in the EPN period. In the EPN period more widespread activity across all EEG source analyses was found, with significant differences over the entire cortical surface for erotic and nudist content. The EPN time window was also distinct in that right inferior temporal activity was detected for the other emotional categories in the EEG source analysis. For the MEG source analyses in the EPN window, there was significant bilateral frontal activity.

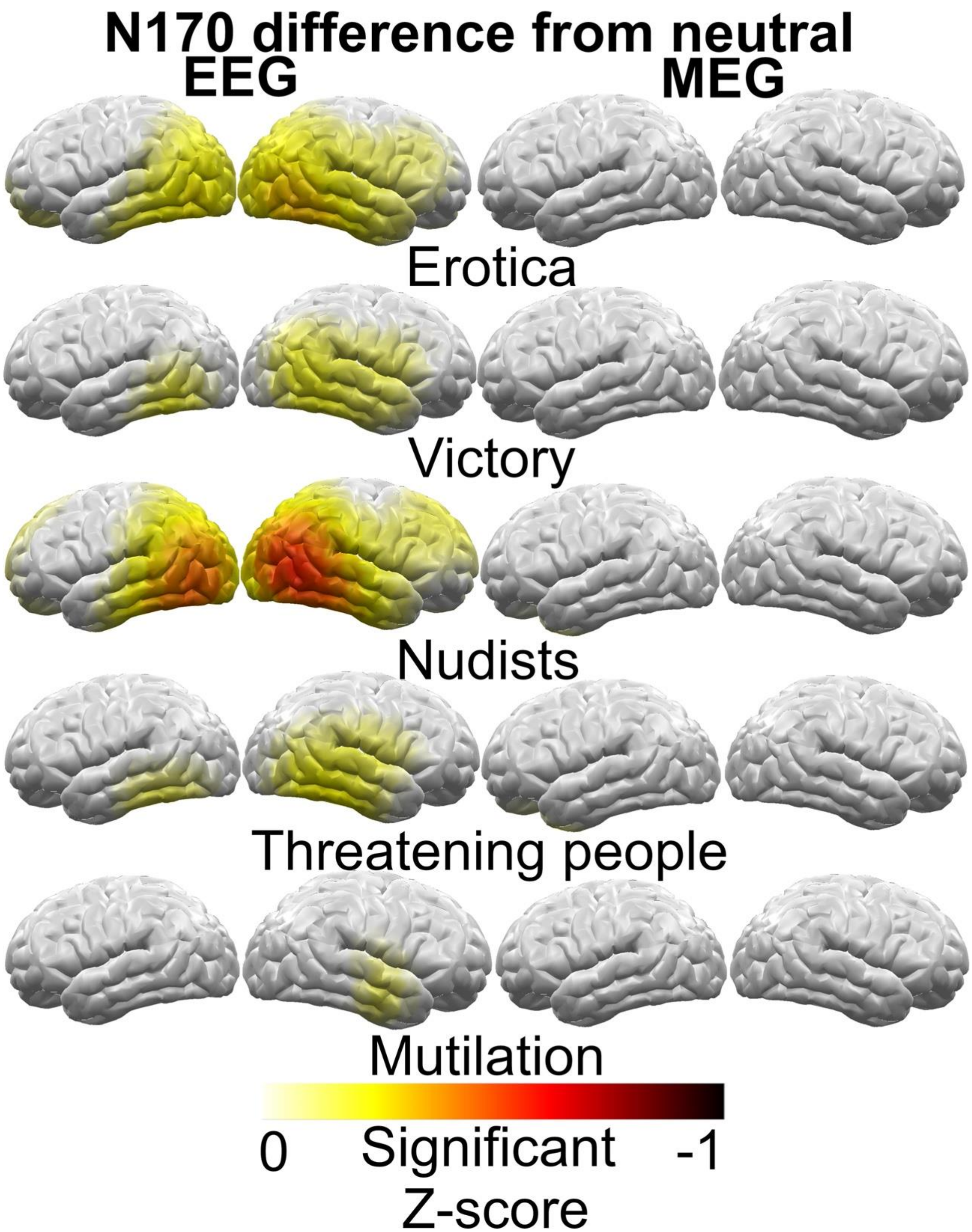

Figure 9. Source analysis contrasts broken down by EEG and MEG for the N170. Plotted is the median of the contrast posterior. Anywhere that has color is where the difference is more than 95% likely.

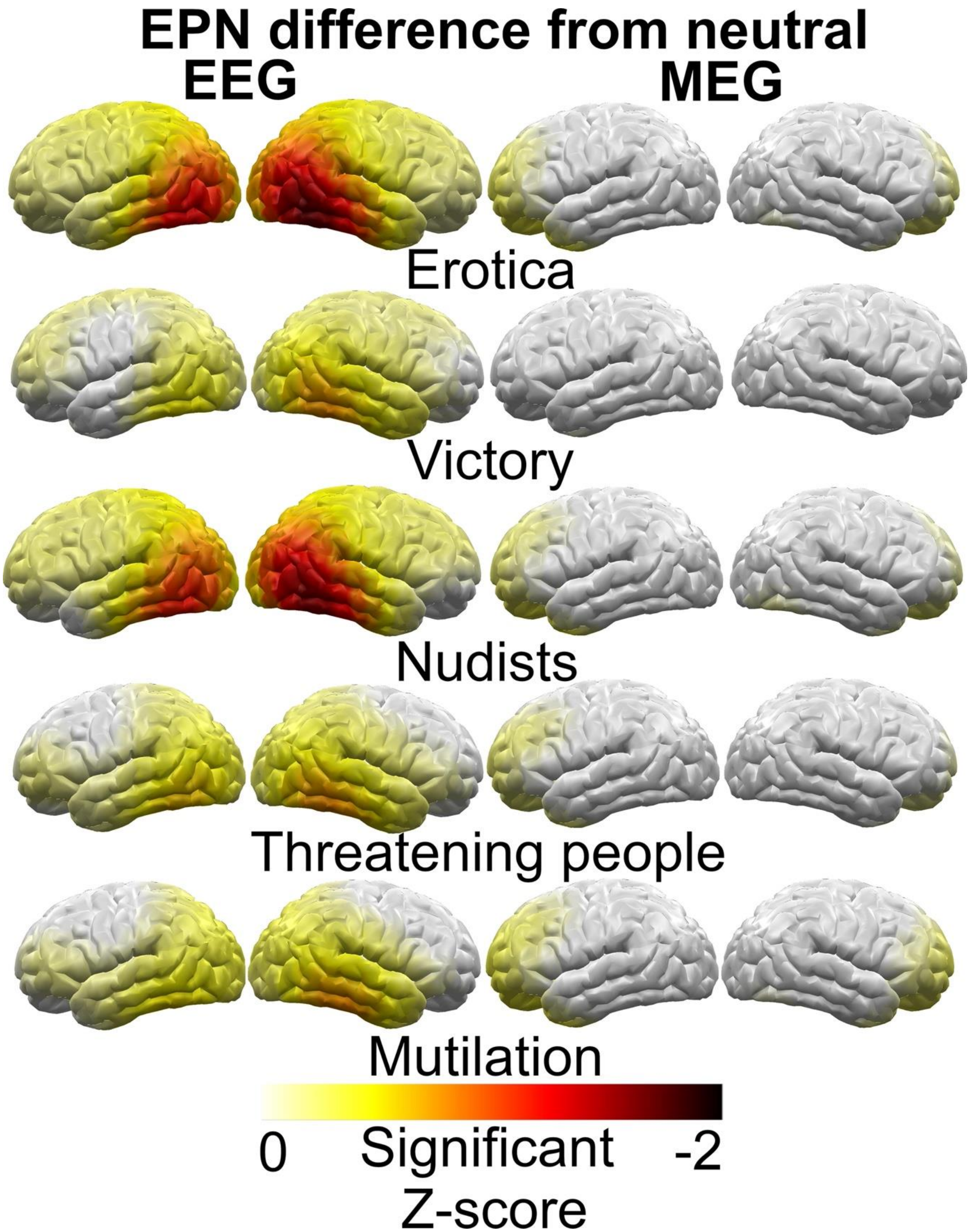

Figure 10. Source analysis contrasts broken down by EEG and MEG for the EPN. Plotted is the median of the contrast posterior. Note that the scale is twice as large as Figure 9.

4.3 Research Question 2: Measures of arousal for scene categories

To further assess how physiologically arousing each scene category was, ratings were compared to pupil diameter measured during scene viewing from the Münster participants. The pupil diameter change from baseline is presented in Figure 11 and the average values are presented with the ratings from both sites in Figure 12. A repeated measure ANOVA found a significant effect of scene category; F (5, 210) = 32.9, $p < .001$; $\eta^2_g = .224$. Erotica elicited the largest pupil diameter increase (M = 0.046, SE = 0.013), followed by nudists (M = 0.014, SE = 0.011), threatening people (M = -0.003, SE = 0.012), mutilation (M = -0.021, SE = 0.012), neutral people (M = -0.040, SE = 0.011), and finally victorious athletes (M = -0.086, SE = 0.013).

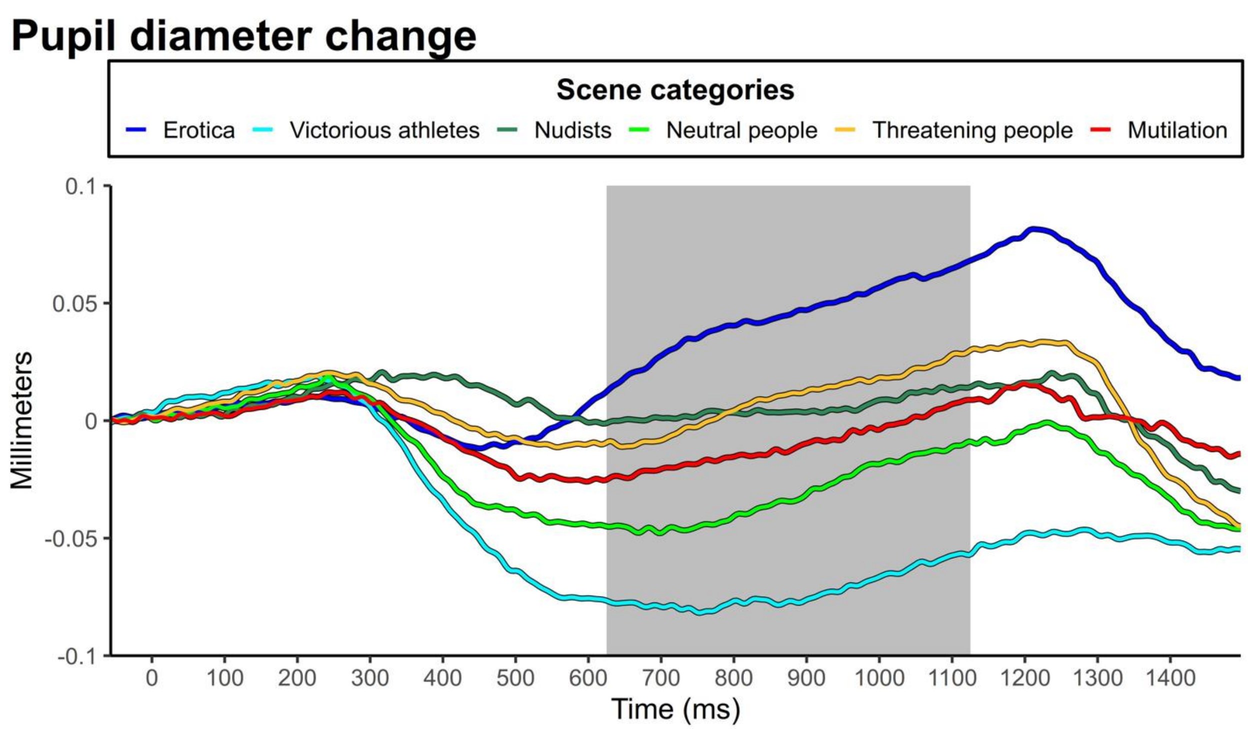

Figure 11. Change in normalized pupil diameter over time. Positive values indicate more pupil dilation from baseline whereas negative values indicate pupil constriction.

Valence and arousal ratings were made on a 1 to 9 scale for UGA participants. Münster ratings were made on a 0 to 100 scale but have been converted to 1 to 9 scale here. The UGA participants that participated in the EEG portion of the study rated victorious athletes as the most pleasant category (M = 6.95, SE = 0.123), followed by erotica (M = 5.53, SE = 0.161), neutral people (M = 5.24, SE = 0.064), nudist couples (M = 4.62, SE = 0.130), threatening people (M = 3.39, SE = 0.120), and mutilation content (M = 2.51, SE = 0.153). For the UGA MEG sample, victorious athletes were again rated as the most pleasant (M = 6.95, SE = 0.160), but the second most pleasant category changed to neutral people (M = 5.10, SE = 0.070). This was followed by erotica (M = 5.01, SE = 0.234), nudists (M = 4.07, SE = 0.203), threatening people (M = 3.55, SE = 0.167), and mutilation scenes (M = 2.59, SE = 0.238). Münster participants also rated victorious athlete scenes as the most pleasant category (M = 7.62, SE = 0.173), followed by erotica (M = 6.98, SE = 0.215), nudists (M = 6.16, SE = 0.168), neutral people (M = 5.94, SE = 0.137), threatening people (M = 2.71, SE = 0.162), and lastly mutilation content (M = 2.52, SE = 0.191).

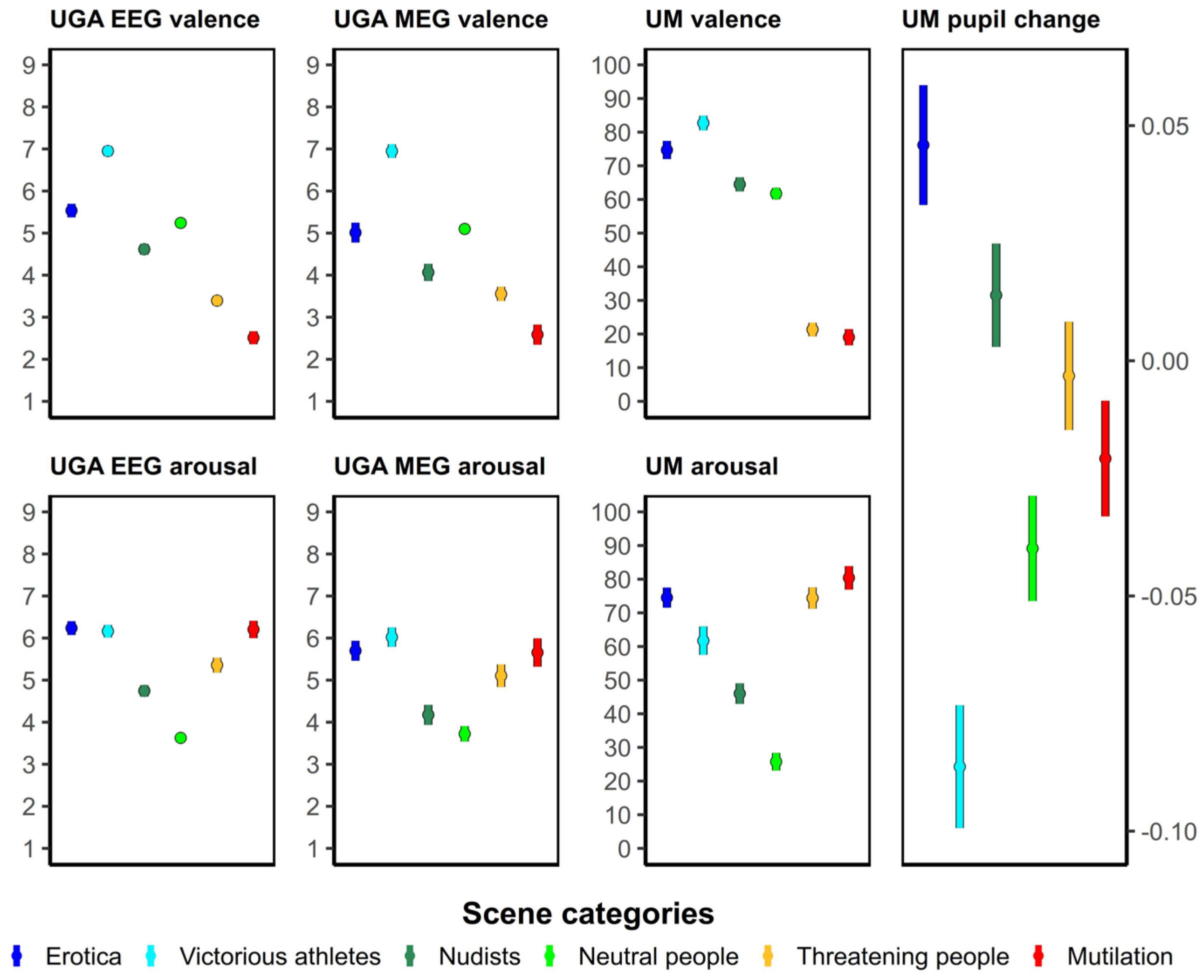

Figure 12. Average ratings from each research site and pupil diameter. Bars represent the standard error.

UGA EEG participants rated erotica as the most arousing scenes (M = 6.24, SE = 0.162), followed by mutilation content (M = 6.21, SE = 0.205), victorious athletes (M = 6.16, SE = 0.149), threatening people (M = 5.36, SE = 0.175), nudists (M = 4.74, SE = 0.136), and lastly neutral people (M = 3.63, SE = 0.113). The UGA MEG sample instead rated victorious athletes as the most arousing content (M = 6.02, SE = 0.229), followed by erotica (M = 5.70, SE = 0.238), mutilations (M = 5.66, SE = 0.337), threatening people (M = 5.11, SE = 0.267), nudists (M = 4.17, SE = 0.237), and finally neutral people (M = 3.72, SE = 0.182). Münster participants rated mutilation content as the most arousing (M = 7.43, SE = 0.280), followed by erotica (M = 6.96, SE = 0.238), threatening people (M = 6.95, SE = 0.253), victorious athletes (M = 5.94, SE = 0.337), nudists (M = 4.68, SE = 0.244), and finally neutral people (M = 3.06, SE = 0.208).

4.4 Research Question 3: EEG sensor level results

To assess the consistency of the results across research sites, the raw data was broken down by research sites with inferential statistics from the relevant Gaussian Process Models. The raw ERP data can be seen in Figure 13. The ERP posteriors for the N170, EPN, and LPP are depicted in Figures 14, 15, and 16 respectively. These plots also showed the predictions made from a frequentist equivalent linear regression with 95% confidence intervals. This allowed for a visualization of the extent of partial pooling and increased statistical power for the Bayesian approach.

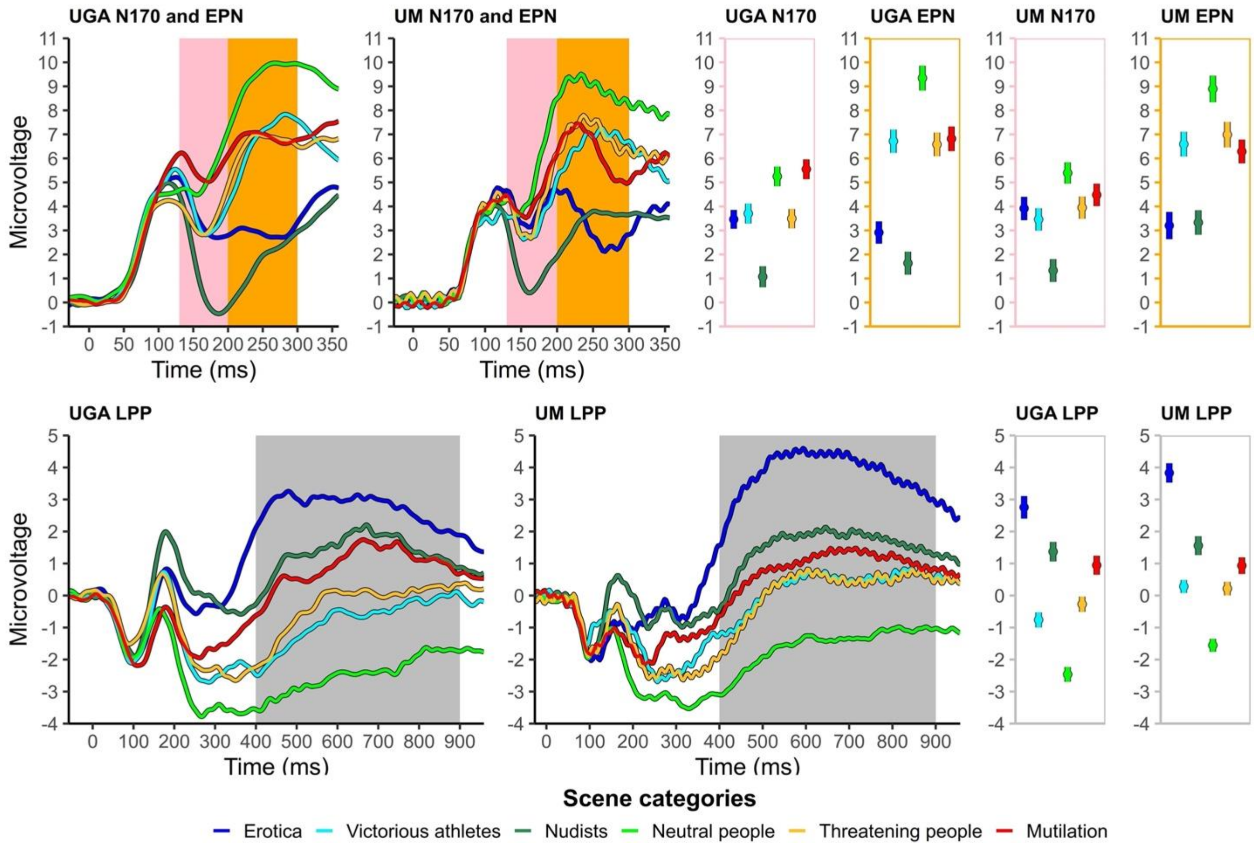

Figure 13. Average ERP waveform and mean results from both research sites. The shaded areas indicate the time periods used for each ERP. Pink relates to the N170, orange to the EPN, and gray to the LPP.

The N170 for the UGA sample was largest for nudist content (M = 1.07, SE = 0.438) followed by erotica (M = 3.46, SE = 0.391), threatening people (M = 3.49, SE = 0.401), victorious athletes (M = 3.70, SE = 0.414), neutral people (M = 5.25, SE = 0.406), and lastly mutilations (M = 5.55, SE = 0.411). The Münster sample also had the largest evoked N170 for nudist content (M = 1.33, SE = 0.475) followed by victorious athletes (M = 3.46, SE = 0.465), erotica (M = 3.91, SE = 0.486), threatening people (M = 3.95, SE = 0.463), mutilations (M = 4.48, SE = 0.465), and neutral people (M = 5.39, SE = 0.443). The largest EPN for the UGA participants was for the nudist content (M = 1.64, SE = 0.478) then erotica (M = 2.91, SE = 0.463), threatening people (M = 6.58, SE = 0.493), victorious athletes (M = 6.72, SE = 0.485), mutilations (M = 6.82, SE = 0.508), and neutral people (M = 9.35, SE = 0.515). The Münster participants had the largest EPN for erotica (M = 3.20, SE = 0.567), then nudists (M = 3.33, SE = 0.508), mutilations (M = 6.29, SE = 0.), victorious athletes (M = 6.59, SE = 0.516), threatening people (M = 6.99, SE = 0.533), and lastly neutral people (M = 8.89, SE = 0.552). For the LPP, UGA participants had the largest amplitude for erotica (M = 2.75, SE = 0.350), then nudists (M = 1.37, SE = 0.305), mutilations (M = 0.95, SE = 0.296), threatening people (M = -0.271, SE = 0.239), victorious athletes (M = -0.761, SE = 0.234), and lastly neutral people scenes (M = -2.46, SE = 0.230). Similarly, Münster participants had the largest LPP amplitude for erotica (M = 3.83, SE = 0.302), followed by nudist couples (M = 1.56, SE = 0.294), and mutilations (M = 0.93, SE = 0.259). However, their fourth largest amplitude was recorded for victorious athletes (M = 0.28, SE = 0.202), then threatening people (M = 0.216, SE = 0.212), and lastly neutral people (M = -1.56, SE = 0.202).

The Bayesian model for the N170 (Figure 14), suggests nudist content was the largest for both research sites and was equivalent between research sites. The next largest was threatening content for the UGA participants which was equivalent to the amplitude evoked by victorious athletes for Münster participants. This category was in turn statistically equivalent to the UGA N170 to erotica. Next, UGA victorious athletes were equivalent to the Münster N170 to erotica. There was not enough evidence that the Münster erotica amplitude was different from the amplitude to threatening people. The next largest N170 amplitude was to the mutilation content for Münster participants. The final two categories were the neutral people evoked amplitude for UGA participants followed by the same content for the Münster sample.

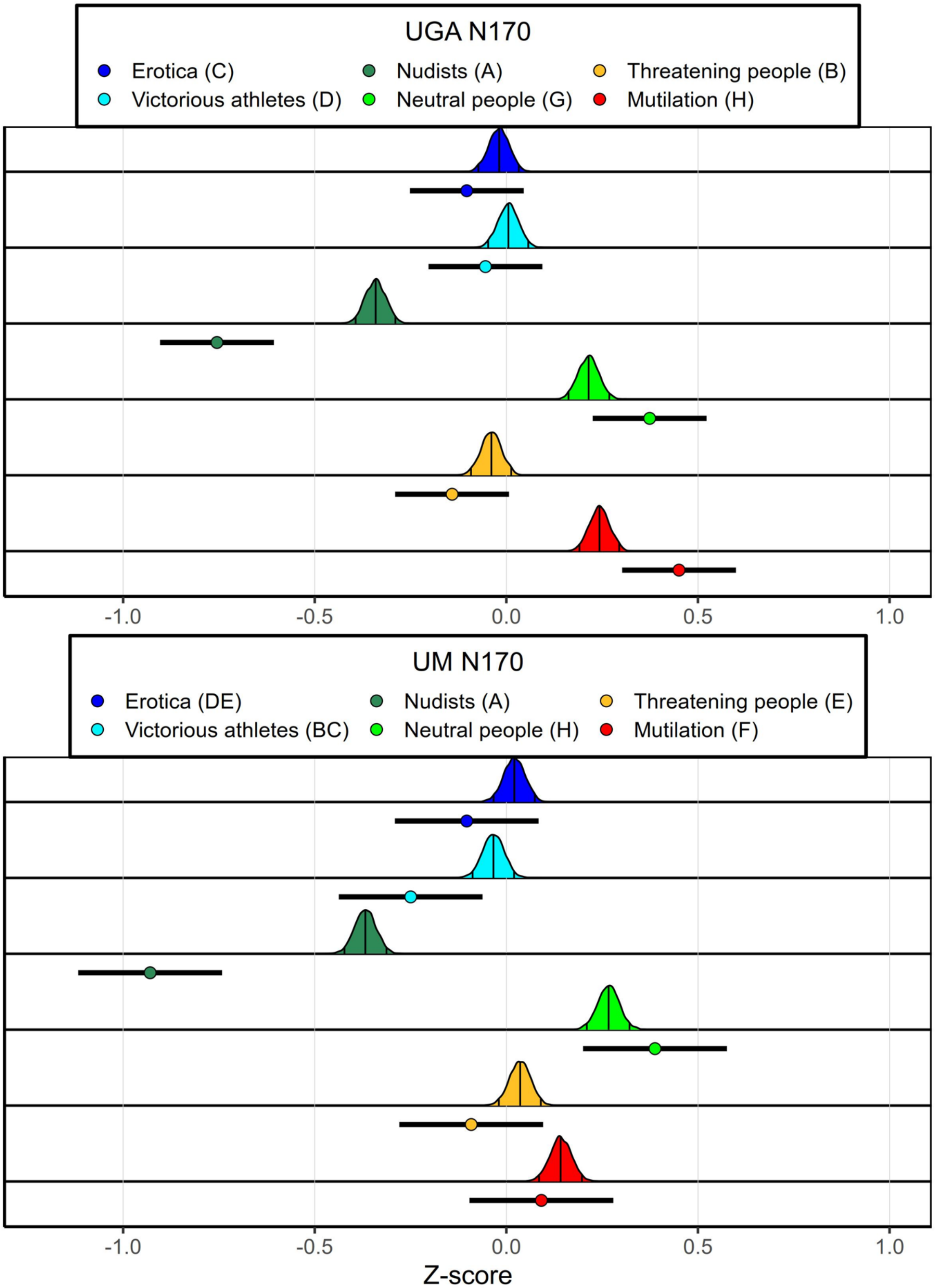
UGA N170
Erotica (C)
Nudists (A)
Threatening people (B)
Victorious athletes (D)
Neutral people (G)
Mutilation (H)
-1.0
-0.5
0.0
0.5
1.0
UM N170
Erotica (DE)
Nudists (A)
Threatening people (E)
Victorious athletes (BC)
Neutral people (H)
Mutilation (F)
-1.0
-0.5
0.0
0.5
1.0
Z-score

Figure 14. The posterior estimates for each category by research site for the N170. Underneath each posterior is the prediction made by multiple regression with the same linear model as the Bayesian model. The error bar is the 95% confidence interval of the prediction uncorrected for multiple comparisons. Letters next to each category relay statistical information about which scene categories were more than 95% likely to be different based on the Bayesian analysis. Posteriors that share the same letter are statistically equivalent. Comparisons are made within and between research sites, so letters also indicate which categories are equivalent between research sites.

For the EPN (Figure 15), UGA participants had the largest amplitude for nudist content. This was followed by the nudist and erotic content for the Münster participants; there was no evidence that these categories were different. The next largest amplitude was erotic content for the UGA sample. This was followed by the Münster response to mutilation content which was not different from victorious athletes from the same participants or the threatening people from the UGA participants. This last category from the UGA sample was not different from their response to victorious athletes which in turn was equivalent to their response to mutilation content. This last category was not different from the Münster amplitude to threatening people. Lastly, the z-scored EPN was smaller for the Münster participants than the UGA participants.

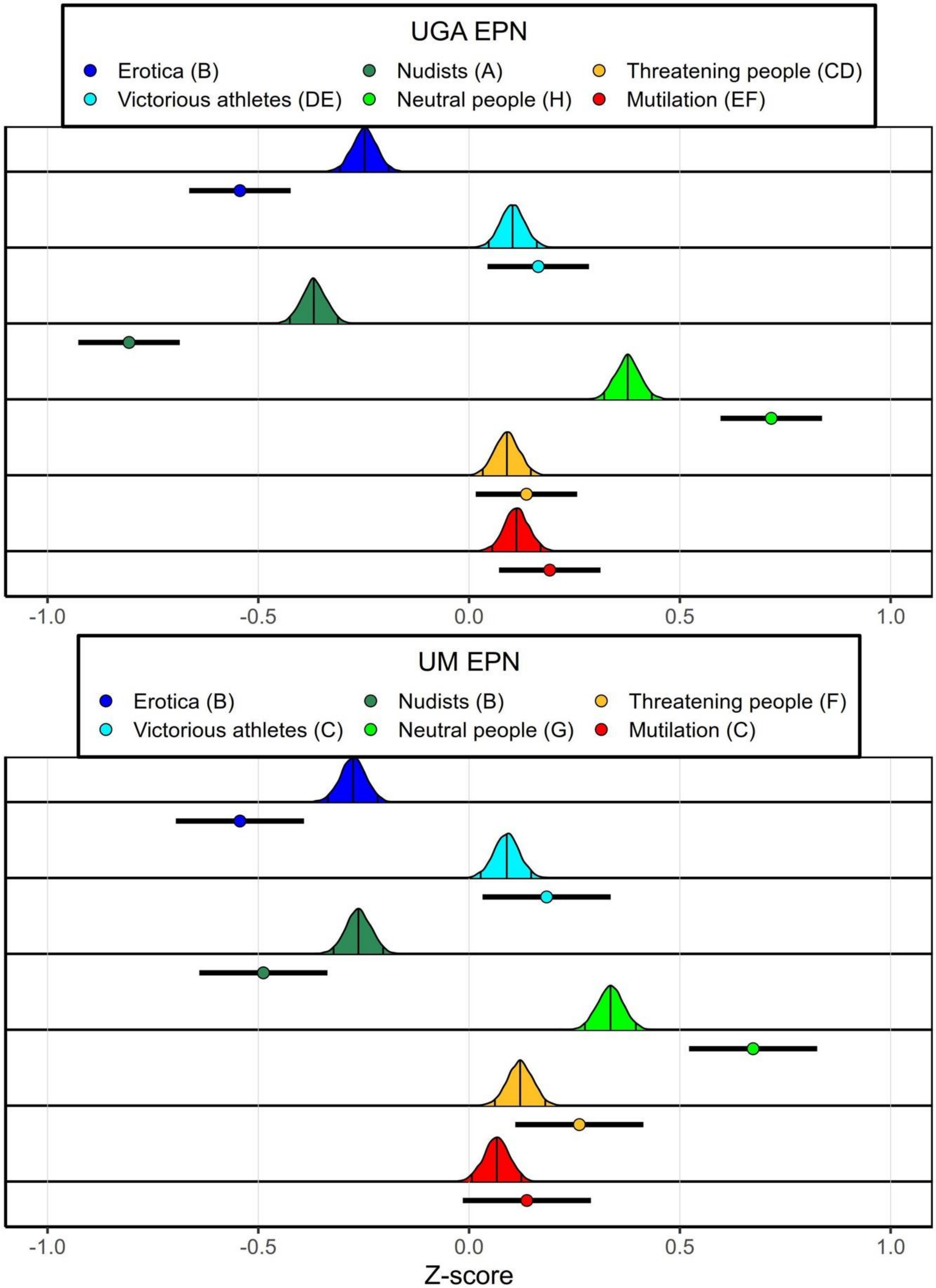

Figure 15. The posterior estimates for each category by research site for the EPN.

The last relevant ERP, known as the LPP (Figure 16), found the largest response was the Münster response to erotica, followed by the UGA amplitude to the same content. Nudist content evoked the second largest response for both participant groups equally. The next largest response was to mutilation content equally between participant groups. The amplitude to threatening people for the UGA participants was the next largest and was equivalent to the amplitude of threatening people and victorious people for the Münster participants. These last two categories were equivalent to the UGA amplitude to victorious athletes. Finally, the smallest LPP amplitude was for neutral people which was equivalent between participant groups.

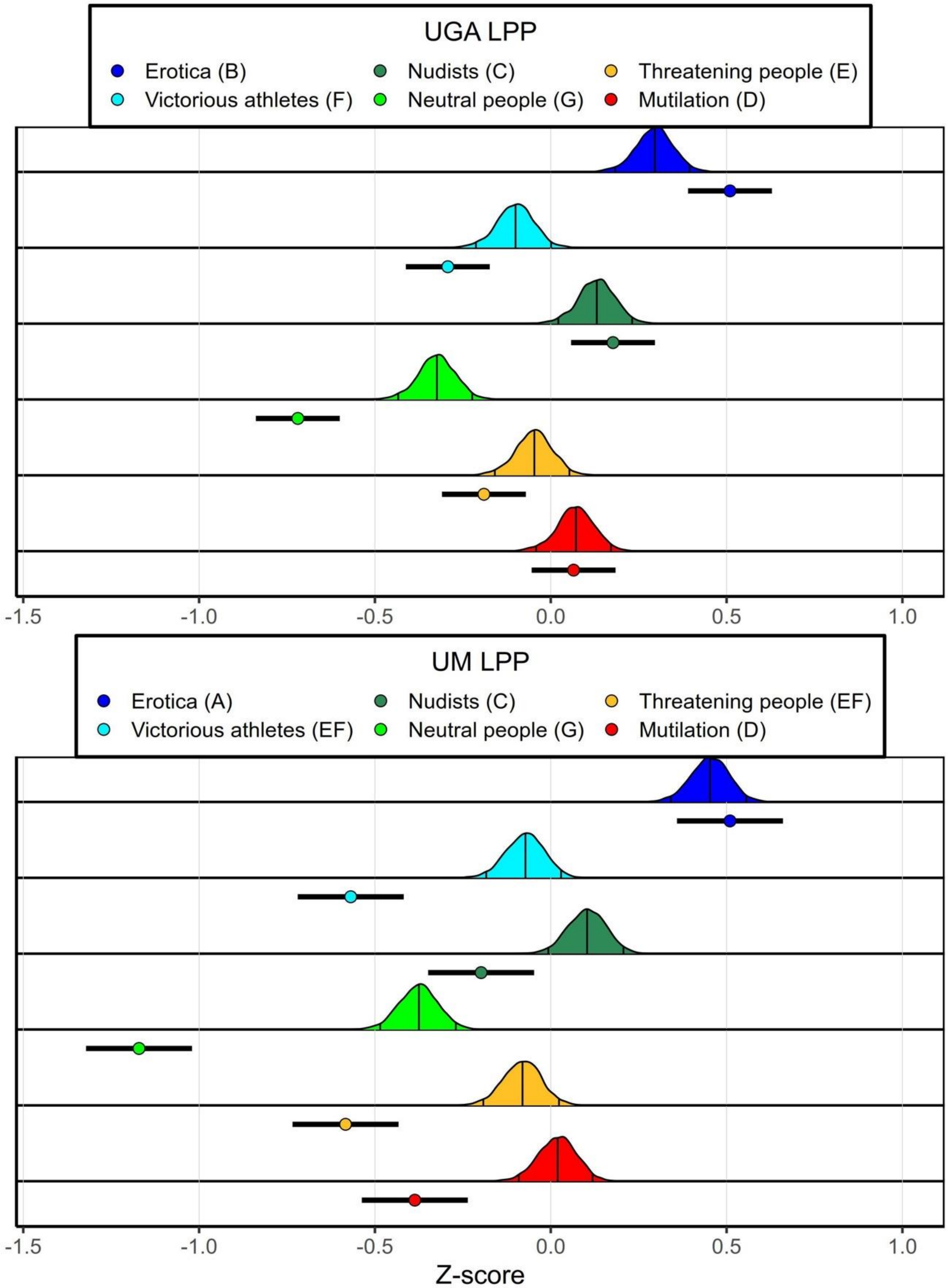

Figure 16. The posterior estimates for each category by research site for the LPP.

4.5 Research Question 3: EEG and MEG source analysis results

To visualize possible differences from the source analyses performed by EEG and MEG by research site, the z-scored results are plotted here for the N170 and EPN time windows (Figure 17). Overall, more posterior temporal activity is seen for the EEG source analyses compared to MEG. Another noticeable difference was that the UGA MEG source analyses projected more dorsally onto parietal regions compared to all other source analyses. The EEG source analyses differed in that the UGA analysis projected toward more anterior and inferior locations along the temporal lobe compared to the Münster EEG results. Noticeable reductions in source activity were visible during erotica and nudists content in EEG source analyses for both ERPs at both research sites in the lateral occipital and posterior temporal regions. These regions, which are estimated to be less active overall in the MEG source analyses, did not have visible reductions in activity for any of the categories.

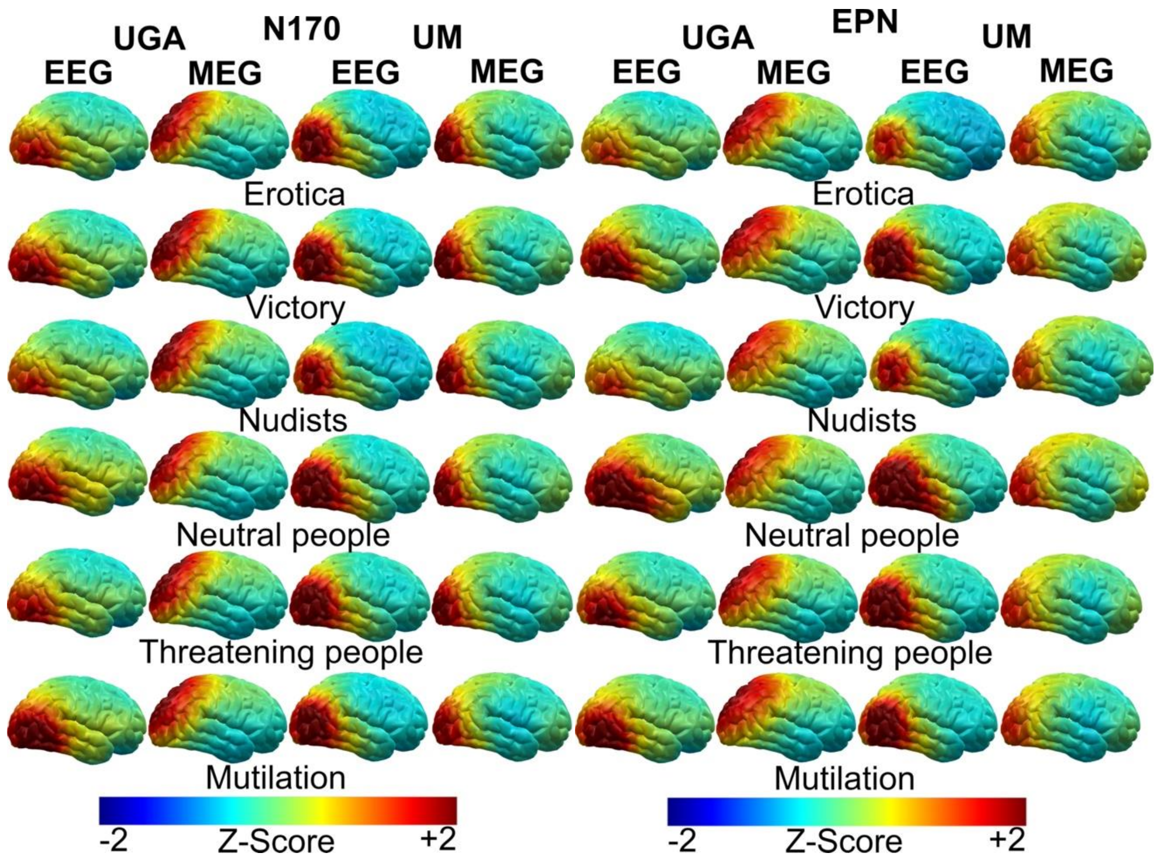

Figure 17. Topological posterior median source analysis results.

4.6 Auxiliary Aim 1: Group comparisons of face evoked N170

The racial identity of the participants did not influence the N170 during the processing of faces of White and Black people (Figure 18). A repeated measures ANOVA found that the interaction between face type and participant race was not significant, excluding ovals; F (2, 64) = 0.37, p = .696; η^2_g < .001. The main effect of race was also not significant; F (2, 64) = 0.27, p = .761; η^2_g = .008. The main effect of face type was significant; F (1, 64) = 36.55, p < .001; η^2_g = .038. For Black female participants, faces of Black people elicited a larger N170 (M = 2.08, SE = 0.61) than faces of White people (M = 3.33, SE = 0.55); t (21) = 4.56, p < .001. This was also true for White female participants' N170 amplitude to faces of Black people (M = 1.87, SE = 0.80) and White people (M = 3.28, SE = 0.59); t (21) = 3.51, p = .002. This was also true for participants that did not identify as a Black or White woman, who showed a larger N170 to faces of Black people (M = 1.58, SE = 0.72) than to faces of White people (M = 2.58, SE = 0.68); t (23) = 2.78, p = .01. The dark versus light gray ovals did not differ. This was true for the interaction between ovals and racial identity (F (2, 64) = 1.01, p = .369; η^2_g = .005), as well as for the main effect of oval shade (F (1, 64) = 0.32, p = .573; η^2_g < .001). The main effect of ovals by demographic group also did not differ (F (2, 64) = 2.67, p = .077; η^2_g = .066).

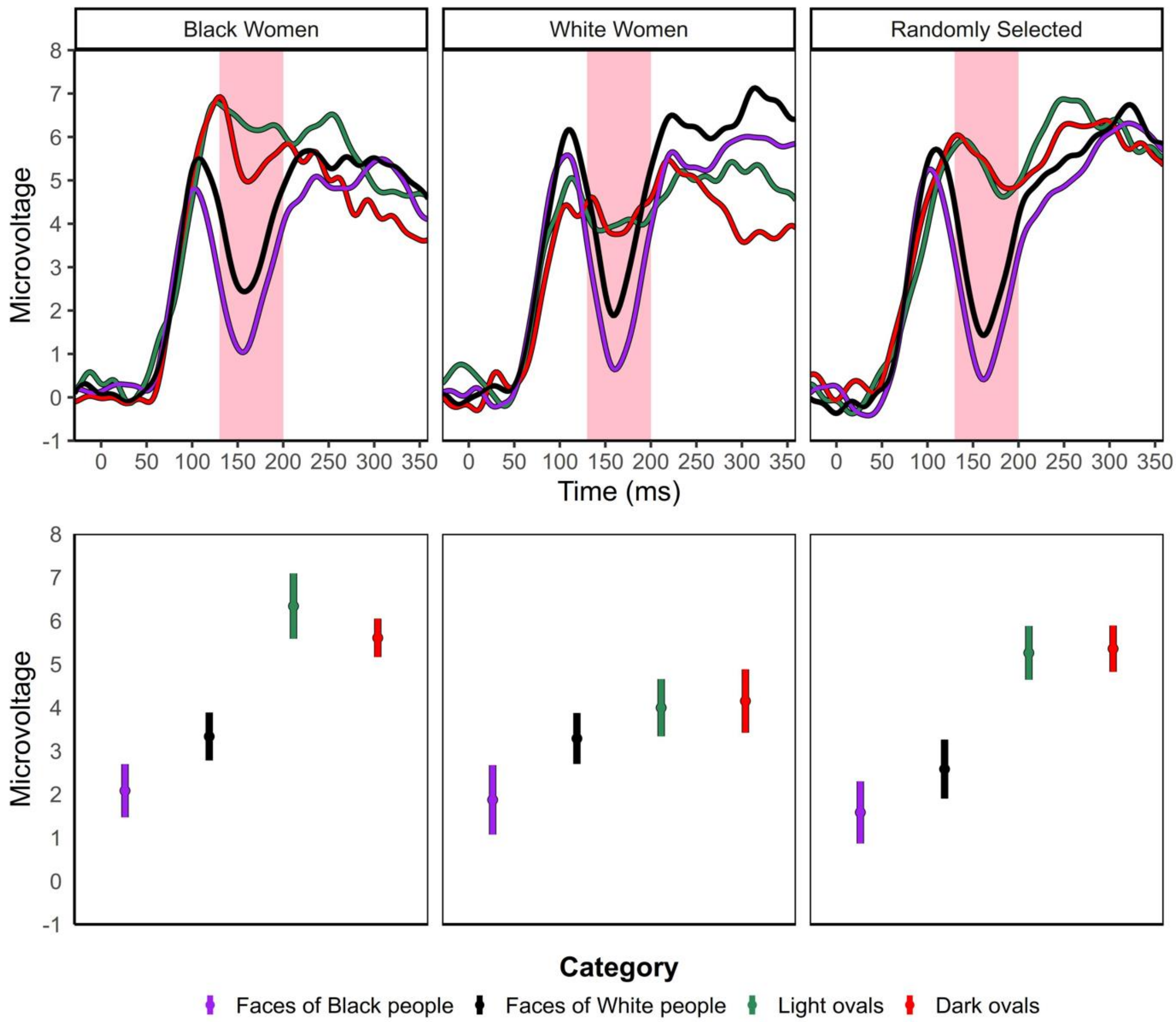

Figure 18. The N170 from each participant group for faces and ovals.

4.7 Auxiliary Aim 2: Effect of intertrial interval length on emotion related ERPs

In the UGA sample, ERPs showed significant main effects of scene category (F (5, 330) = 74.97, $p < .001$; $\eta^2_g = .137$), presentation speed (F (1, 66) = 19.82, $p < .001$; $\eta^2_g = .014$), and the interaction between category and presentation speed (F (5, 330) = 2.80, $p = .017$; $\eta^2_g = .004$). This was also true for the EPN where main effects were of category (F (5, 330) = 141.97, $p < .001$; $\eta^2_g = .254$), presentation speed (F (1, 66) = 26.51, $p < .001$; $\eta^2_g = .022$), and the interaction (F (5, 330) = 2.76, $p = .024$; $\eta^2_g = .003$). For the LPP, there were significant main effects of category (F (5, 330) = 99.12, $p < .001$; $\eta^2_g = .283$) and presentation speed (F (1, 66) = 20.95, p < .001; η^2_g = .026), but not the interaction (F (5, 330) = 1.97, p = .090; η^2_g = .004). Mean amplitudes and standard errors can be seen in Figure 19 and Table 1.

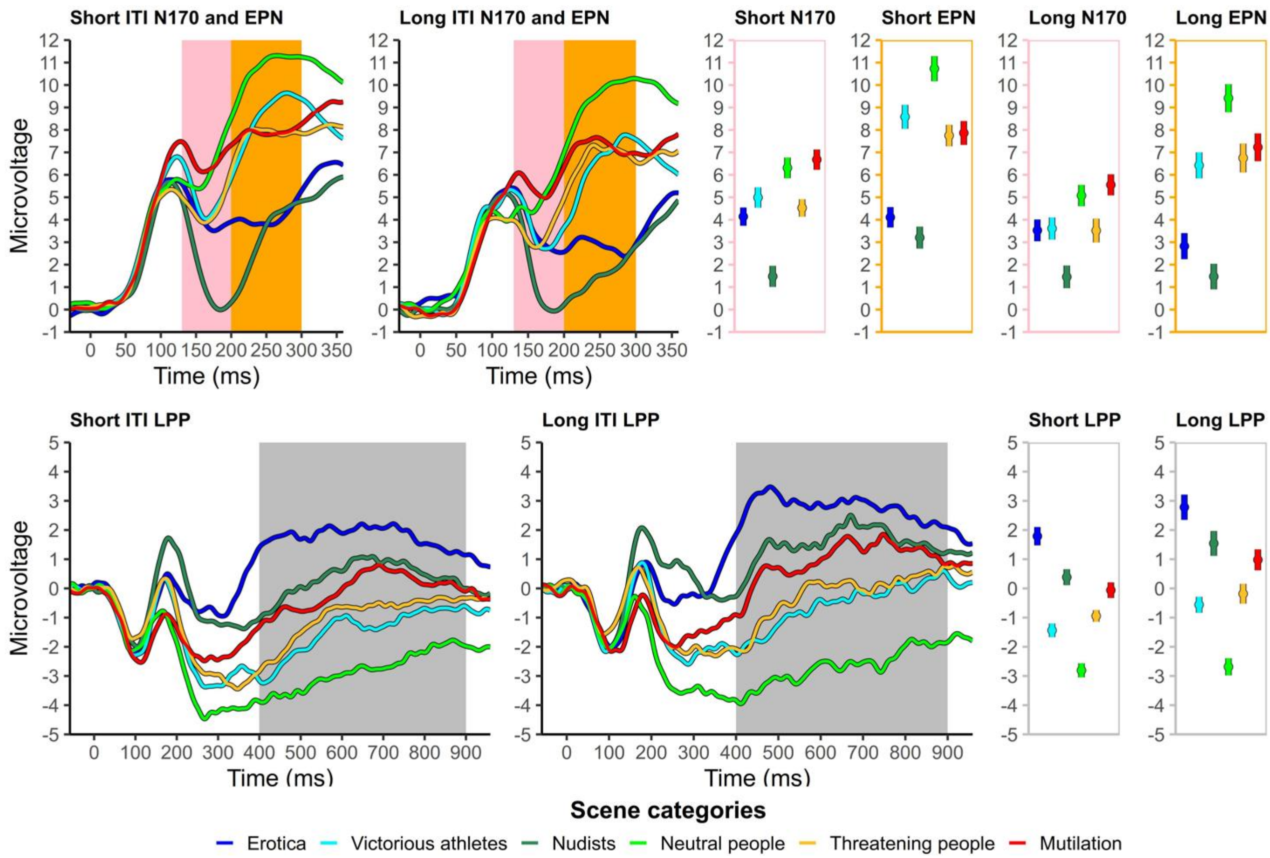

Figure 19. Within-participant comparison of ERPs evoked with short or long ITIs.

	N170		EPN		LPP	
Category	Short ITI	Long ITI	Short ITI	Long ITI	Short ITI	Long ITI
Erotica	4.14(0.405)	3.53(0.481)	4.11(0.453)	2.82(0.580)	1.79(0.312)	2.78(0.431)
Victorious athletes	4.99(0.451)	3.61(0.493)	8.58(0.534)	6.42(0.578)	-1.44(0.232)	-0.560(0.274)
Nudists	1.48(0.466)	1.46(0.504)	3.21(0.488)	1.47(0.569)	0.384(0.272)	1.54(0.426)
Neutral People	6.31(0.460)	5.08(0.475)	10.7(0.558)	9.41(0.624)	-2.81(0.240)	-2.69(0.292)
Threatening People	4.53(0.387)	3.52(0.527)	7.75(0.476)	6.75(0.639)	-0.944(0.199)	-0.184(0.339)
Mutilations	6.68(0.450)	5.55(0.466)	7.87(0.528)	7.23(0.618)	-0.061(0.265)	0.980(0.356)

Table 1. The mean and standard errors by category per short or long ITI paradigms.

CHAPTER 5

DISCUSSION

5.1 Results summary

The main objective of this study was to understand how distinct the scene-evoked N170 is from the EPN in terms of its spatial topography and pattern of reactivity to different scene content. To do this, a relatively novel implementation of Bayesian Hierarchical Gaussian Process Modeling was used to efficiently combine a large data set of EEG and MEG recorded data from two research sites. The models found that spatial topography was similar between the two ERPFs, but the pattern of reactivity across scene content was markedly different. Consistent with previous EEG studies that used the same set of scenes, nudist content evoked a large negative deflection between 130 – 300 ms after scene onset (Farkas et al., 2020, 2023). In the early N170 time window (130 – 200 ms), nudist content also evoked the largest response compared to all other contents. Unlike the N170 evoked by faces, the negative deflection for nudists extends across the back of the head instead of mostly behind the ears. Except for the mutilation content, all other emotional scene categories elicited more negativity during the N170 compared to scenes of neutral people. Moving into the EPN time window of 200 to 300 ms, the emotional categories evoked larger EPN amplitudes relative to neutral content. Relatedly, the mutilation scenes reached statistical significance for the EPN. For the LPP, we again found a similar pattern of results as our previous recent studies in which erotica evoked the largest response followed by nudists and the rest of the categories considered emotional, all of which were greater than the LPP evoked by neutral people.

The source analysis results did not support our hypotheses of a spatial difference between scenes depicting body exposure versus emotional qualities. MEG recorded source analyses appeared to be insensitive to much of the N170 and EPN activity related to the perception of bodies or emotional features. For the analysis that combined both imaging modalities, only the largest effects of the two scene categories that depicted bodies, erotica and nudists couples evoked significant temporal activity. When breaking down the effect by imaging modality, the N170 period featured no significant MEG source analysis effects between each category contrasted with neutral people. For the EEG source analyses, there was the greatest posterior temporal activity for the erotic and nudist content, while the other emotional categories also affected this region. For the EPN time window, there was more widespread activity in the EEG source analyses, but the main effect of emotional categories still appeared in the posterior temporal area. In this later time window, the MEG data again yielded no significant differences in the occipital and temporal regions with only small differences in frontal regions.

The second research question addressed a limitation from the previous studies that nudist content may be more physiologically arousing than participants are willing or capable of reporting. To extend this assessment of arousal, pupil diameter and arousal ratings were collected from a sample of students at the University of Münster, and compared to ratings data from UGA participants. Overall, ratings were more similar than different between samples, although there was a greater spread to the ratings for the Münster participants. Nudist content was reported as being unarousing, however, pupil diameter did suggest that nudist scenes evoked physiological arousal like other emotional categories, with a similar pattern of effects seen in the LPP. This was in line with our prediction that pupil diameter would show nudist content was more evocative than neutral people, while erotic content is still more arousing, thus not explaining the reliable N170 and EPN body part effects. A surprising finding was that victorious athletes evoked the least amount of pupil dilation. It is unclear why this occurred because the scenes were balanced for brightness and contrast that are known to affect pupil diameter (Bradley et al., 2017), and victorious athletes were rated as emotionally arousing in all samples.

The final main research question concerned the consistency of the effects at different research sites. Raw data and the statistical information from the Bayesian model suggested the pattern of effects was very similar between sites despite differences in culture and data collection instruments. There were slight differences that suggested Münster participants had a larger N170 to mutilation versus other categories, as well as a larger EPN and LPP amplitude to erotica. This may be because of the greater proportion of men in the Münster sample. Previous research suggests that there is a slight tendency for men to have larger physiological responses to erotica versus mutilation, as compared to women (Cuthbert et al., 2000; Bradley et al., 2001a; Bradley et al., 2001b; Sabatinelli et al., 2004; Versace et al., 2023). However, despite this and men reliably rating erotica as more pleasant and arousing than women do, the LPP is typically not larger for this content for men (Weinberg et al., 2010). So, sex differences are likely small if they exist. Sex effects should be further explored in future analyses with more complex models and larger samples that can take this factor into consideration.

This study also had two auxiliary aims to 1) examine if the N170 differs depending on the race of the participant or the face scenes shown and 2) assess the impact of inter-trial interval length on ERP emotional modulation. The first of two auxiliary research questions sought to contribute to work on the social perception of faces. Our work did not corroborate the findings that the N170 is larger for faces of races different than the participant's own race. We found that the amplitude was larger for faces of Black people for all participant groups. The current study is important because it is one of the first to recruit a sample of Black participants to examine this research question. While this appears to be evidence against the theory that the N170 amplitude is larger for faces of a different race than the participant's race, more work is needed before drawing conclusions. It is possible that balancing luminance between the face scenes inadvertently affected some other low-level visual aspect such as contrast. In the last aim, we found that ITI duration between scene presentations had small effects on the N170, EPN, and LPP. The overall pattern of emotion effects remained essentially unchanged. An interaction between the pattern of the effects was found with the change in presentation speed for the N170 and EPN, but not for the LPP.

5.2 Distinctiveness of N170 and EPN

The present work suggests that the N170 and EPN originate from the same region of cortex. However, a caveat is that the MEG data recording did not work as expected to add spatial resolution to the present results. The reasons for this are unclear but may involve the orientation of cortex in this lateral occipitotemporal area. While the EPN has been shown to be quite robust in MEG sensor space, the current implementation of L2-MNE source localization did not find significant source activity during the selected time periods. This does provide some useful information about the N170 and EPN. MEG is known to be much less sensitive to radial sources. So, given that the EEG source analysis seemed to indicate the N170 and EPN originate from the posterior temporal lobe, it may be likely that at this position there is a radial source contributing to these ERPFs. Another possibility is that the MEG data has a quicker onset and offset for the two ERPFs because the signal is more temporally stable than the EEG amplitudes which are distorted by the conduction through the tissues that surround the brain. MEG studies that have looked at the EPN have typically used permutation-based statistics to find the regions and time periods of interest. Published work has found emotional effects in the temporal regions from 130-180 ms (Junghofer et al., 2010) while other work found significant emotional activity in the lateral occipital regions from 112 – 176 ms and temporal activity from 260 – 308 ms, but no significant activity between those two periods (Peyk et al., 2008). From our present EEG results and other published work, there does appear to be two temporally distinct peaks. Taken together, when recording with MEG the N170 may be more temporal distinct from the EPN dissipating around 180 ms. Future work may attempt to correct for expected timing differences due to the differences of recording electrical voltages versus magnetic fields to properly combine their results.

While the cortical origins of the N170 and EPN do not appear to be very different, the pattern of activity to different scene content at the same EEG sensors certainly were. The study closely replicated EEG findings from previous studies that found nudist content greatly affects the N170 and EPN relative to the traditional emotional scene categories. This was also true for the data recorded from a different site with different equipment. The ERPFs appear to be influenced by content like a gradient, in which the early N170 is more sensitive to body exposure while the EPN is more sensitive to emotional content. Notably, both are influenced by the emotional qualities and body exposure depicted. Taken in the context of other studies that examine early and late ERPFs, more personally relevant or task-relevant information seems to grow in importance for later ERPFs. In a recent study by Schindler & Straube (2020), participants were shown emotional scenes and were asked to respond to either pleasant, neutral, or unpleasant content. They found that the earlier ERPs of the P100 and N170 (termed N1 in this study) were best explained by emotion alone, while the later EPN and LPP were best fit by the overlapping influences of emotion and task relevance. The present work extends this finding by suggesting that early sources react more to clearly distinguished features associated with motivationally relevant content (i.e., upright exposed bodies), while later activity becomes increasingly sensitive to a participant's interpretation of a scene's emotional qualities. This would explain why the N170 is larger for upright nudists, while entangled erotic couples and the unusual gashes or disfigured limbs of mutilation scenes evokes comparatively larger amplitudes for the EPN and LPP.

5.3 Bodies and visual perception

Due to a lack of noticeable spatial differences between scenes featuring exposed bodies versus primarily emotional content, a tentative conclusion is that nude bodies cause stronger early “motivated attention” than other emotional content. The source analyses suggest widespread early activity across much of the brain including frontal regions. Specific areas of the brain are known to be specialized for the perception and recognition of bodies (Peelen and Downing, 2008), but the present work extends this suggesting that bodies act as a more salient stimulus than previously thought, possibly orienting attention and activating the same regions as other emotional content.

However, a potential confound is the possibility that genitalia exposure could be the primary modulator of the results. Object perception studies of the ‘body N170’ that have present bodies on blank backgrounds, have found that the same bodies with a swimsuit covering sexual areas reduce the N170 amplitude (Hietanen et al., 2011; 2014). Future studies will have to explore this possibility, perhaps by editing the nudist scenes to mask genitalia. This could refine the interpretation of the present findings that the sexual areas of a body act on the brain in this early stage.

Future studies are necessary to link these large early ERPFs amplitudes to attention orienting to make sure it is consistent with other work on the EPN. This could be accomplished by utilizing attentional blink paradigms in which the perceptional awareness of stimuli after nudist content is measured (Shapiro et al., 1997). Another option would be to measure eye-movement saccades when presenting scenes side by side during an attention task. Saccades have been shown to be an objective measure of cognitive control (Peirce et al., 2019) and perhaps could indicate behavior differences caused by the increased attention capture of bodies. Another option would be to use scenes as a competing stimulus in inattentional blindness task (Mack et al., 1998) that has been used to find silhouettes and stick figures of bodies draw more attention than other neutral objects (Downing et al., 2004).

5.4 Implications and recommendations for scene ERPF research

This work suggests that research teams should keep in mind the different sensitivities of these emotion-related ERPFs to fully leverage their results to understand naturalistic scene perception. The most obvious aspect is how scenes that feature body exposure influence early and late amplitudes which may not represent experienced emotional arousal. Thus, the amount of body exposure in experimental scene sets should be considered before a study is conducted. The second implication is that early versus late activity likely provides unique information. Although emotion effects are smaller for the N170 and heavily influenced by bodies, depending on the research question it may be important to assess emotion or what features are salient at this earlier time period. Work on saccade eye-movements suggests that humans on average segment time in 200 ms, or otherwise stated take this minimum amount of time before another behavioral action can begin (Ballard, 2015). Thus, the N170 may offer the ability to measure a portion of an emotional experience less affected by top-down influences. Of course, there will be other research questions that need to measure the experienced emotional arousal or both, utilizing the early and the late ERPFs related to emotional perception.

Two hypothetical implementations of the differences in early and late ERPFs could be in the study of people with addiction or anhedonia related to schizophrenia. There is developing research that addiction may be better assessed by physiological reactions to cues or signs related to the addiction. This may relay to clinicians that the addiction is driven by the salience of an addiction relevant cues or related to some other psychological factor (Versace et al., 2014). A combination of early and late ERPFs may further improve these assessments and broaden our understanding of addiction.

Separately, anhedonia is a deleterious symptom suffered by people with schizophrenia in which there is a diminished ability to experience pleasure. Recent research suggests that the capacity for pleasure may still be preserved, but deficits in approach behaviors (Bartolomeo et al., 2023) or emotion regulation (Bartolomeo et al., 2020) cause difficulties in maintaining pleasurable states (Strauss et al., 2020). Particularly relevant to the present work is a subset of anhedonia known as sexual anhedonia or separately sexual dysfunction related to schizophrenia which is common and may even be underreported (Tharoor et al., 2015). Although ERP research is already being conducted to understand emotional processing in schizophrenia (Bartolomeo et al., 2020; Abdelmageed et al., 2020; Trotti et al., 2020, 2021, 2023), the present work on exposed bodies may provide an opportunity to more specifically assess how early and late processing differs. Analyzing the N170 for this population may help to understand if the visual system is similarly active to cues related to sexual opportunity. This could in turn be important for contextualizing the present results by better understanding if exposed bodies are so important to the visual system because it is related to sexual opportunity.

5.5 Hierarchical Gaussian Process Models as a cross-site research tool

The current implementations of Bayesian Gaussian Process Models worked as expected improving spatial accuracy, increasing statistical power, and providing principled regularized estimates for thousands of parameters all while providing a correction for multiple comparisons. Figures 14 to 16 provide the clearest demonstration of the value of this approach compared to a standard multiple regression. Estimates for each of the categories are significantly shrunk towards each other, while the inner 95% of the posteriors are tighter than the 95% confidence intervals of the multiple regression predictions, despite there being no explicit correction for multiple comparisons for the traditional regression. However, in many ways the two models perhaps should not be compared, as they have fundamentally different statistical assumptions. In the frequentist model, there is an assumption that there is a true value, and the goal of statistical implementation is to estimate how often that true value would be found if the study was repeated many times. The Bayesian model expresses the degree to which our evidence suggests the categories are different without the assumption that there is a true value. If our two previous studies that examined this effect were added to the model, we would likely see less shrinkage for the nudist and erotic categories for all three ERPFs, because they closely matched the present results (Farkas et al., 2020, 2023). This mirrors our interpretations as researchers as we gradually became more confident of the categorical differences with each experimental replication. The Bayesian multi-level approach for the present study provided benefits over traditional statistics, and supports recommendations from researchers that these methods should be the default for statistical inference (McElreath, 2020). Specific to EEG data, using the Gaussian Process Model to understand the correlational structure of ERPFs was particularly helpful in integrating recording systems with different numbers of channels. Lastly, it gave a unique solution for interpreting topological differences, allowing for exploratory analyses that were again still corrected for multiple comparisons.

Despite all the benefits, the complexity and computation expense of the Bayesian models led to many tradeoffs and will likely limit its mass adoption if not alleviated. To fit the present model, the random effect of participant could not be estimated, and each participant had to be z-scored so that the within-participant effects could be captured. This makes it more difficult to communicate and compare the results since they are no longer in the relevant units. Additionally, the Gaussian Process Model approach had to be used, as estimating each individual correlation between sensors was computationally unfeasible. This involved writing the models in Stan code which adds a technical hurdle that some labs may have difficulty achieving. Despite these compromises, to adequately sample the relevant posteriors for each model required up to 10 days to complete, while running on a powerful computer using a dedicated graphics card to handle matrix and vector computations. Switching to a supercomputer may only provide some benefits as samples are dependent on previous samples and thus must be computed sequentially.

The computational inefficiency may be due to the specification of the model that creates posteriors that are difficult to explore. For example, highly correlated posteriors can create sharp and steep gradients leading to divergent transitions between samples that would have to be repeated

(McElreath, 2020). Based on diagnostics from the present models, the problem is more likely an issue coined degeneracy. Degenerate models can occur for numerous reasons, but results in a posterior that is difficult to explore or extend to infinity in some way because of superfluous parameters or logical inconsistencies in which two parameters can both account for the same effect. This does not lead to divergent transitions, but can hamper the model from learning the appropriate "leapfrog" step-size to use, thus forcing the algorithm to evaluate the gradient more times between each prosed sample. Solutions can include reparametrizing the model, which means specifying an identical model with an extra step that transforms the posteriors so they can be easier to sample from. That was implemented here by coding the model with a "non-centered" parameterization in which the data is transformed using Cholesky factors such that the correlations are still captured while the posteriors are centered and decorrelated. Further solutions involve visualizing each pair of parameters to look for degenerate issues, which was not feasible due to the number of parameters.

To allow the approach to be more widely used, the model will need to be scrutinized, improved, and made more accessible for EEG/MEG researchers. Future work may be able to find the issues that led to inefficient sampling. Another solution would be the use of variational Bayesian techniques for estimating posteriors. This technique involves proposing posteriors instead of mass sampling. A criteria such as the Kullback–Leibler divergence is used to judge how close the proposal is to the true posterior. This can be more efficient than mass sampling and is common in Bayesian approaches for EEG component extraction and fMRI dynamic causal modeling (Wu et al., 2015). However, it can be less accurate, and it is very sensitive to initial conditions. For example, in a study that was trying to estimate individual ERP components via the variation approach, the starting condition was found via independent component analysis which was very close to final model results (Wu et al., 2014). In the present study, the variational Bayes approach was attempted to find the posteriors. However, the initial starting conditions were never suitable even when the result of a successful mass sampling models were used as the initial parameter values. If these difficulties leading to computation inefficiency are overcome, then the model could be packaged such that it was ready to be used for EEG and MEG researchers without the need for as much technical expertise. This could lead to more principled and accurate results while enabling better cross-site collaborations between teams that have different EEG and MEG systems.

CHAPTER 6

CONCLUSION

The measurement of scene-evoked potentials and fields are a well-established and widely used method, but recent work suggested clearly exposed bodies influence early ERPF activity as well (Farkas et al., 2020, 2023). In the present research, we used complementary EEG and MEG with source-analysis methods to scrutinize early ERPF spatial and content-modulation differences. We found a similar spatial effect for the N170 and EPN time-windows over occipital EEG sensors as well as the posterior temporal cortex. However, nudist content was more effective during the N170, and erotica featured a comparably large response for the EPN time period. We also replicated our previous studies that found these specific erotica scenes evoked the largest response in the LPP followed by nudists and the other arousing categories.

This study also had four additional research aims (RA) addressing limitations from previous studies and contributing to other areas of research, listed here as RA2 through RA5. In RA2, we addressed the possibility that early ERPF amplitudes reflect physiological arousal that is not well measured from participant's self-reports. To do this, pupil diameter was recorded during the scene presentation paradigm from the University of Münster participants. This validated measure of sympathetic activity found that nudist scenes do evoke more arousal than self-reports suggest, but not to a degree that would explain N170 and EPN amplitudes. However, the pupil diameter pattern of effects was similar to the LPP results. For RA3, we compared the results between the participants recruited at Universities of Georgia and Münster. Despite likely cultural differences and different research equipment, the results were strikingly similar. The main pattern of effect of the scene categories were the same between research sites, thus point to a reliable and robust effect. In RA4, we explored an entirely separate research question based on face pictures and race. Dozens of studies have looked at if the race of a participant and the race of a face in a picture somehow predict the amplitude of the N170. Our study was one of the first to look at this effect with a meaningfully large sample of Black participants—a group that has been systematically excluded from ERPF studies—and found no differences between the groups sampled. For the last aim (RA5), we manipulated the presentation speed of the scenes within-participants for the University of Georgia EEG sample. This was done as an experimental control because MEG data collection requires a faster presentation speed to acquire more trials, but this manipulation has important implications for the scene paradigm more generally if it does change ERPFs associated with emotion. Only very small interacting effects were found for the effect of category and speed on N170 and EPN, and there was not an effect for the LPP. The collection of these secondary aims suggests that the relevant physiological activity is mostly stable between participants and research sites.

For our primary research aim, results suggest that the emotionality and body-exposure in a scene modulate similar areas of the brain. However, the N170 was greater for the exposed bodies of the nudist content while the EPN was larger for emotion scenes. This pattern continued for the last occurring relevant potential known as the LPP which was most influenced by the arousing content. A limitation of the current results was a lack of significant effects from the MEG recorded data suggesting this method did not significantly improve spatial resolution as predicted. Based on our results and the literature, we speculate this MEG result occurred because the N170 and EPN are a result of a posterior temporal radial source that is not well captured by MEG because of the physical properties of magnetic fields. An alternative explanation is that combining data from the chosen time windows limits the influence of the MEG results because a permeating magnetic field likely has a quicker onset and offset than a conducting electrical amplitude. If our interpretations are not altered by refined future analyses that can account for differences in the EEG and MEG methods, the present study implies that clearly exposed features commonly associated with salient content (i.e., body parts) are more influential in early ERPFs. Continuing, later ERPFs may be a better measure of experienced emotional arousal. This research further clarifies the nuances of cortical activity associated with emotion and may allow teams to better measure emotion in the future.

REFERENCES

Abdelmageed, S., Trotti, R., Parker, D., Sabatinelli, D., Tamminga, C., Gershon, E., ... & Clementz, B. A. (2020). Effects of stimulus repetition on emotional processing in psychosis biotypes: findings from bipolar-schizophrenia network on intermediate phenotypes (B-SNIP) consortium. Biological Psychiatry, 87(9), S389. DOI:https://doi.org/10.1016/j.biopsych.2020.02.996

Adrian, E. D., & Matthews, B. H. C. (1934a). The Berger rhythm: Potential changes from the occipital lobes of man. *Brain. 57*,355385

Alho, J., Salminen, N., Sams, M., Hietanen, J. K., & Nummenmaa, L. (2015). Facilitated early cortical processing of nude human bodies. *Biological Psychology*, *109*, 103-110. https://doi.org/10.1016/j.biopsycho.2015.04.010

Amunts, K., Malikovic, A., Mohlberg, H., Schormann, T., & Zilles, K. (2000). Brodmann's areas 17 and 18 brought into stereotaxic space—where and how variable?. *Neuroimage*, *11*(1), 66-84. https://doi.org/10.1006/nimg.1999.0516

Anthony, T., C. Copper, and Mullen, B. (1992). Cross-Racial Facial Identification: A Social Cognitive Integration. *Personality and Social Psychology Bulletin 18*: 296- 301. https://doi.org/10.1177/0146167292183005

Babadi, B., McKinney, S. M., Tarokh, V., & Ellenbogen, J. M. (2011). DiBa: a data-driven Bayesian algorithm for sleep spindle detection. IEEE Transactions on Biomedical Engineering, 59(2), 483-493. DOI: 10.1109/TBME.2011.2175225

Baillet, S. (2017). Magnetoencephalography for brain electrophysiology and imaging. *Nature neuroscience*, *20*(3), 327-339. 10.1038/nn.4504.

Bentin, S., Allison, T., Puce, A., Perez, E., & McCarthy, G. (1996). Electrophysiological studies of face perception in humans. *Journal of cognitive neuroscience*, *8*(6), 551-565. https://doi.org/10.1162/jocn.1996.8.6.551

Berger, H. (1934). Über das elektrenkephalogramm des menschen. *DMW-Deutsche Medizinische Wochenschrift*, *60*(51), 1947-1949.

Bothwell, R. K., Brigham, J. C., & Malpass, R. S. (1989). Cross-racial identification. *Personality and Social Psychology Bulletin*, *15*(1), 19-25. https://doi.org/10.1177/0146167289151002

Bitsios, P., Szabadi, E., & Bradshaw, C. M. (1996). The inhibition of the pupillary light reflex by the threat of an electric shock: a potential laboratory model of human anxiety. *Journal of psychopharmacology*, *10*(4), 279-287. https://doi.org/10.1177/026988119601000404

Bitsios, P., Szabadi, E., & Bradshaw, C. M. (2004). The fear-inhibited light reflex: importance of the anticipation of an aversive event. *International Journal of Psychophysiology*, *52*(1), 87-95. https://doi.org/10.1016/j.ijpsycho.2003.12.006

Bradford, D. E., DeFalco, A., Perkins, E. R., Carbajal, I., Kwasa, J., Goodman, F. R., ... & Joyner, K. J. (2022). Whose Signals Are Being Amplified? Toward a More Equitable Clinical Psychophysiology. Clinical Psychological Science, 21677026221112117. https://doi.org/10.1177/21677026221112117

Bradley, M. M., & Lang, P. J. (1994). Measuring emotion: the self-assessment manikin and the semantic differential. *Journal of behavior therapy and experimental psychiatry*, *25*(1), 49-59. https://doi.org/10.1016/0005-7916(94)90063-9

Bradley, M. M., Codispoti, M., Cuthbert, B. N., & Lang, P. J. (2001a). Emotion and motivation I: defensive and appetitive reactions in picture processing. Emotion, 1(3), 276. https://doi.org/10.1037/1528-3542.1.3.276

Bradley, M. M., Codispoti, M., Sabatinelli, D., & Lang, P. J. (2001b). Emotion and motivation II: sex differences in picture processing. Emotion, 1(3), 300. https://doi.org/10.1037/1528-3542.1.3.300

Bradley, M. M., Hamby, S., Löw, A., & Lang, P. J. (2007). Brain potentials in perception: picture complexity and emotional arousal. *Psychophysiology*, *44*(3), 364-373.https://doi.org/10.1111/j.1469-8986.2007.00520.x

Bradley, M. M., & Lang, P. J. (2007). Emotion and motivation. In J. T. Cacioppo, L. G. Tassinary, & G. G. Berntson (Eds.), *Handbook of psychophysiology* (pp. 581–607). Cambridge University Press. https://doi.org/10.1017/CBO9780511546396.025

Bradley, M. M. (2009). Natural selective attention: Orienting and emotion. *Psychophysiology*, *46*(1), 1-11. https://doi.org/10.1111/j.1469-8986.2008.00702.x

Bradley, M. M., Sapigao, R. G., & Lang, P. J. (2017). Sympathetic ANS modulation of pupil diameter in emotional scene perception: Effects of hedonic content, brightness, and contrast. *Psychophysiology*, *54*(10), 1419-1435. https://doi.org/10.1111/psyp.12890

Bradley, M. M., Sambuco, N., & Lang, P. J. (2022). Affective perception: The power is in the picture. Human Perception of Visual Information: Psychological and Computational Perspectives, 59-83. https://doi.org/10.1007/978-3-030-81465-6_3

Baillet, S., Garnero, L., Marin, G., & Hugonin, J. P. (1999). Combined MEG and EEG source imaging by minimization of mutual information. *IEEE transactions on biomedical engineering*, *46*(5), 522-534. DOI: 10.1109/10.759053

Ballard, D. H. (2015). Brain computation as hierarchical abstraction. MIT press.

Bartolomeo, L. A., Culbreth, A. J., Ossenfort, K. L., & Strauss, G. P. (2020). Neurophysiological evidence for emotion regulation impairment in schizophrenia: The role of visual attention and cognitive effort. Journal of abnormal psychology, 129(6), 670. https://doi.org/10.1037/abn0000580

Bartolomeo, L. A., Raugh, I. M., & Strauss, G. P. (2023). The positivity offset theory of anhedonia in schizophrenia: evidence for a deficit in daily life using digital phenotyping. Psychological Medicine, 1-9. DOI: https://doi.org/10.1017/S0033291722003774

Brainard, D. H., & Vision, S. (1997). The psychophysics toolbox. *Spatial vision*, *10*(4), 433-436.

Cacioppo, J. T., Crites, S. L., Gardner, W. L., & Berntson, G. G. (1994). Bioelectrical echoes from evaluative categorizations: I. A late positive brain potential that varies as a function of trait negativity and extremity. Journal of personality and social psychology, 67(1), 115. https://doi.org/10.1037/0022-3514.67.1.115

Caharel, S., Montalan, B., Fromager, E., Bernard, C., Lalonde, R., & Mohamed, R. (2011). Other-race and inversion effects during the structural encoding stage of face processing in a race categorization task: An event-related brain potential study. *International Journal of Psychophysiology*, *79*, 266e271.

Caldara, R., Thut, G., Servoir, P., Michel, C. M., Bovet, P., & Renault, B. (2003). Face versus non-face object perception and the 'other-race'effect: a spatio-temporal event-related potential study. *Clinical Neurophysiology*, *114*(3), 515-528. https://doi.org/10.1016/S1388-2457(02)00407-8

Caldara, R., Rossion, B., Bovet, P., & Hauert, C. A. (2004). Event-related potentials and time course of the 'other-race'face classification advantage. *Neuroreport*, *15*(5), 905-910.

Chiao, J. Y., & Cheon, B. K. (2010). The weirdest brains in the world. Behavioral and Brain Sciences, 33(2-3), 88-90. DOI: 10.1017/S0140525X10000282

Choy, T., Baker, E., & Stavropoulos, K. (2022). Systemic racism in EEG research: considerations and potential solutions. Affective Science, 3(1), 14-20. https://doi.org/10.1007/s42761-021-00050-0

Cichy, R. M., & Oliva, A. (2020). AM/EEG-fMRI fusion primer: resolving human brain responses in space and time. Neuron, 107(5), 772-781. https://doi.org/10.1016/j.neuron.2020.07.001

Collura, T. F. (1993). History and evolution of electroencephalographic instruments and techniques. *Journal of clinical neurophysiology*, *10*(4), 476-504.

Cuthbert, B. N., Schupp, H. T., Bradley, M. M., Birbaumer, N., & Lang, P. J. (2000). Brain potentials in affective picture processing: covariation with autonomic arousal and affective report. Biological psychology, 52(2), 95-111. https://doi.org/10.1016/S0301-0511(99)00044-7

David, O., Kiebel, S. J., Harrison, L. M., Mattout, J., Kilner, J. M., & Friston, K. J. (2006). Dynamic causal modeling of evoked responses in EEG and MEG. *NeuroImage, 30*(4), 1255-1272. https://doi.org/10.1016/j.neuroimage.2005.10.045

De Cesarei, A., & Codispoti, M. (2011). Affective modulation of the LPP and α-ERD during picture viewing. *Psychophysiology*, *48*(10), 1397-1404. https://doi.org/10.1111/j.1469-8986.2011.01204.x

Donderi, D. C. (2006). An information theory analysis of visual complexity and dissimilarity. *Perception*, *35*, 823–835. https://doi.org/10.1068/p5249

Dougherty, R. F., Koch, V. M., Brewer, A. A., Fischer, B., Modersitzki, J., & Wandell, B. A. (2003). Visual field representations and locations of visual areas V1/2/3 in human visual cortex. *Journal of vision*, *3*(10), 1-1.https://doi.org/10.1167/3.10.1

Downing, P. E., Bray, D., Rogers, J., & Childs, C. (2004). Bodies capture attention when nothing is expected. Cognition, 93(1), B27-B38. https://doi.org/10.1016/j.cognition.2003.10.010

Duane, S., Kennedy, A. D., Pendleton, B. J., & Roweth, D. (1987). Hybrid monte carlo. *Physics letters B*, *195*(2), 216-222. https://doi.org/10.1016/0370-2693(87)91197-X

Eimer, M. (2000). The face-specific N170 component reflects late stages in the structural encoding of faces. *Neuroreport*, *11*(10), 2319-2324.

Farkas, A. H., Oliver, K. I., & Sabatinelli, D. (2020). Emotional and feature-based modulation of the early posterior negativity. *Psychophysiology*, *57*(2), e13484. https://doi.org/10.1111/psyp.13484

Farkas, A. H., Wanger, T. J., & Sabatinelli, D. (2021). Do rare emotional scenes enhance LPP modulation?. *Biological Psychology*, *166*, 108204. https://doi.org/10.1016/j.biopsycho.2021.108204

Farkas, A. H., & Sabatinelli, D. (2023). Emotional Perception: Divergence of Early and Late Event-related Potential Modulation. *Journal of Cognitive Neuroscience*, 1-16. https://doi.org/10.1162/jocn_a_01984

Feingold CA (1914). The Influence of Environment on Identification of Persons and Things./. of Crim. *Law and Criminal*, *5*, 39-51.

Ferrari, V., De Cesarei, A., Mastria, S., Lugli, L., Baroni, G., Nicoletti, R., & Codispoti, M. (2016). Novelty and emotion: Pupillary and cortical responses during viewing of natural scenes. *Biological Psychology*, *113*, 75-82. https://doi.org/10.1016/j.biopsycho.2015.11.008

Ferrari, V., Mastria, S., & Codispoti, M. (2020). The interplay between attention and long-term memory in affective habituation. *Psychophysiology*, *57*(6), e13572. https://doi.org/10.1111/psyp.13572

Filkowski, M. M., & Haas, B. W. (2017). Rethinking the use of neutral faces as a baseline in fMRI neuroimaging studies of axis-I psychiatric disorders. *Journal of Neuroimaging*, *27*(3), 281-291. https://doi.org/10.1111/jon.12403

Gloor, P. (1969). Hans Berger on the electroencephalogram of man (Gloor, P., Trans.) Amsterdam: Elsevier.

Grand View Research. (Accessed 2023, March 18th). Magnetoencephalography Market Size, Share & Trends Analysis Report By Application (Clinical Diagnostics, Research), By Region (North America, Europe, APAC, Latin America, MEA), And Segment Forecasts, 2023 - 2030. Grand View Research. https://www.grandviewresearch.com/industry-analysis/magnetoencephalography-market-report

Hadjikhani, N., Kveraga, K., Naik, P., & Ahlfors, S. P. (2009). Early (N170) activation of face-specific cortex by face-like objects. *Neuroreport*, *20*(4), 403.10.1097/WNR.0b013e328325a8e1

Hajcak, G., MacNamara, A., & Olvet, D. M. (2010). Event-related potentials, emotion, and emotion regulation: an integrative review. *Developmental neuropsychology*, *35*(2), 129-155. https://doi.org/10.1080/87565640903526504

Hämäläinen, M. S., & Ilmoniemi, R. J. (1994). Interpreting magnetic fields of the brain: minimum norm estimates. *Medical & biological engineering & computing*, *32*, 35-42. https://doi.org/10.1007/BF02512476

Hansen, P., Kringelbach, M., & Salmelin, R. (Eds.). (2010). *MEG: An introduction to methods*. Oxford university press.

Harel, A., Ullman, S., Epshtein, B., & Bentin, S. (2007). Mutual information of image fragments predicts categorization in humans: Electrophysiological and behavioral evidence. *Vision Research*, *47*(15), 2010–2020. https://doi.org/10.1016/j.visres.2007.04.004

Hauk, O. (2004). Keep it simple: a case for using classical minimum norm estimation in the analysis of EEG and MEG data. *Neuroimage*, *21*(4), 1612-1621. https://doi.org/10.1016/j.neuroimage.2003.12.018

Henderson, R. R., Bradley, M. M., & Lang, P. J. (2014). Modulation of the initial light reflex during affective picture viewing. *Psychophysiology*, *51*(9), 815-818. https://doi.org/10.1111/psyp.12236

Henderson, R. R., Bradley, M. M., & Lang, P. J. (2018). Emotional imagery and pupil diameter. *Psychophysiology*, *55*(6), e13050. https://doi.org/10.1111/psyp.13050

Herrmann, M. J., Schreppel, T., Jäger, D., Koehler, S., Ehlis, A. C., & Fallgatter, A. J. (2007). The other-race effect for face perception: an event-related potential study. *Journal of neural transmission*, *114*(7). DOI: 10.1007/s00702-007-0624-9

Hietanen, J. K., & Nummenmaa, L. (2011). The naked truth: the face and body sensitive N170 response is enhanced for nude bodies. *PLoS One*, *6*(11), e24408. https://doi.org/10.1371/journal.pone.0024408

Hietanen, J. K., Kirjavainen, I., & Nummenmaa, L. (2014). Additive effects of affective arousal and top-down attention on the event-related brain responses to human bodies. *Biological psychology*, *103*, 167-175. https://doi.org/10.1016/j.biopsycho.2014.09.003

Hinds, O. P., Rajendran, N., Polimeni, J. R., Augustinack, J. C., Wiggins, G., Wald, L. L., ... & Fischl, B. (2008). Accurate prediction of V1 location from cortical folds in a surface coordinate system. *Neuroimage*, *39*(4), 1585-1599. https://doi.org/10.1016/j.neuroimage.2007.10.033

Hinojosa, J. A., Mercado, F., & Carretié, L. (2015). N170 sensitivity to facial expression: A meta-analysis. *Neuroscience & Biobehavioral Reviews*, *55*, 498-509. https://doi.org/10.1016/j.neubiorev.2015.06.002

Ito, T. A., & Urland, G. R. (2003). Race and gender on the brain: electrocortical measures of attention to the race and gender of multiply categorizable individuals. *Journal of personality and social psychology*, *85*(4), 616. https://doi.org/10.1037/0022-3514.85.4.616

Ito, T. A., Thompson, E., & Cacioppo, J. T. (2004). Tracking the timecourse of social perception: The effects of racial cues on event-related brain potentials. *Personality and Social Psychology Bulletin*, *30*(10), 1267-1280. DOI: 10.1177/0146167204264335

Ito, T. A., & Urland, G. R. (2005). The influence of processing objectives on the perception of faces: An ERP study of race and gender perception. *Cognitive, Affective, & Behavioral Neuroscience*, *5*(1), 21-36. https://doi.org/10.3758/CABN.5.1.21

Junghöfer, M., Bradley, M. M., Elbert, T. R., & Lang, P. J. (2001). Fleeting images: a new look at early emotion discrimination. *Psychophysiology*, *38*(2), 175-178. DOI: https://doi.org/10.1111/1469-8986.3820175

Junghöfer, M., Kissler, J., Schupp, H. T., Putsche, C., Elling, L., & Dobel, C. (2010). A fast neural signature of motivated attention to consumer goods separates the sexes. *Frontiers in Human Neuroscience*, *4*, 179. https://doi.org/10.3389/fnhum.2010.00179

Kharkar, S., & Knowlton, R. (2015). Magnetoencephalography in the presurgical evaluation of epilepsy. *Epilepsy & behavior*, *46*, 19-26. https://doi.org/10.1016/j.yebeh.2014.11.029

Kiebel, S. J., Garrido, M. I., Moran, R. J., & Friston, K. J. (2008). Dynamic causal modelling for EEG and MEG. *Cognitive neurodynamics*, *2*(2), 121-136. https://doi.org/10.1007/s11571-008-9038-0

Kiloh, L. G., McComas, A. J., & Osselton, J. W. (2013). *Clinical electroencephalography*. Butterworth-Heinemann.

Kleiner, M., Brainard, D., & Pelli, D. (2007). What's new in Psychtoolbox-3?.

Leahy, R. M., Mosher, J. C., Spencer, M. E., Huang, M. X., & Lewine, J. D. (1998). A study of dipole localization accuracy for MEG and EEG using a human skull phantom. *Electroencephalography and clinical neurophysiology*, *107*(2), 159-173. https://doi.org/10.1016/S0013-4694(98)00057-1

La Vaque, T. J. (1999). The history of EEG hans berger: psychophysiologist. A historical vignette. *Journal of Neurotherapy*, *3*(2), 1-9. https://doi.org/10.1300/J184v03n02_01

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (1997). Motivated attention: Affect, activation, and action. *Attention and orienting: Sensory and motivational processes*, *97*, 135.

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (1997). International affective picture system (IAPS): Technical manual and affective ratings. *NIMH Center for the Study of Emotion and Attention*, *1*(39-58), 3.

Lang, P., & Bradley, M. M. (2007). The International Affective Picture System (IAPS) in the study of emotion and attention. *Handbook of emotion elicitation and assessment*, *29*, 70-73.

Langeslag, S. J., & van Strien, J. W. (2019). Romantic love and attention: Early and late event-related potentials. *Biological Psychology*, *146*, 107737. https://doi.org/10.1016/j.biopsycho.2019.107737

Levin, D. T. (2000). Race as a visual feature: using visual search and perceptual discrimination tasks to understand face categories and the cross-race recognition deficit. *Journal of Experimental Psychology: General*, *129*(4), 559. https://doi.org/10.1037/0096-3445.129.4.559

Louis, C. C., Webster, C. T., Gloe, L. M., & Moser, J. S. (2022). Hair me out: Highlighting systematic exclusion in psychophysiological methods and recommendations to increase inclusion. Frontiers in Human Neuroscience, 16, 1058953. https://doi.org/10.3389/fnhum.2022.1058953

Löw, A., Bradley, M. M., & Lang, P. J. (2013). Perceptual processing of natural scenes at rapid rates: Effects of complexity, content, and emotional arousal. *Cognitive, Affective, & Behavioral Neuroscience*, *13*, 860-868. https://doi.org/10.3758/s13415-013-0179-1

Mack, A., & Rock, I. (1998). Inattentional blindness: Perception without attention. Visual attention, 8(01).

Maxwell, J. C. (1890). *The Scientific Papers of James Clerk Maxwell..* (Vol. 2). University Press.

McElreath, R. (2020). *Statistical rethinking: A Bayesian course with examples in R and Stan*. CRC press.

Meissner, C. A., & Brigham, J. C. (2001). Thirty years of investigating the own-race bias in memory for faces: A meta-analytic review. *Psychology, Public Policy, and Law*, *7*(1), 3. https://doi.org/10.1037/1076-8971.7.1.3

Murakami, H., Wang, Z. I., Marashly, A., Krishnan, B., Prayson, R. A., Kakisaka, Y., ... & Alexopoulos, A. V. (2016). Correlating magnetoencephalography to stereo-electroencephalography in patients undergoing epilepsy surgery. *Brain*, *139*(11), 2935-2947. https://doi.org/10.1093/brain/aww336

Neymotin, S. A., Daniels, D. S., Caldwell, B., McDougal, R. A., Carnevale, N. T., Jas, M., ... & Jones, S. R. (2020). Human Neocortical Neurosolver (HNN), a new software tool for interpreting the cellular and network origin of human MEG/EEG data. *Elife*, *9*, e51214. https://doi.org/10.7554/eLife.51214

Niedermeyer, E., & da Silva, F. L. (Eds.). (2005). *Electroencephalography: basic principles, clinical applications, and related fields*. Lippincott Williams & Wilkins.

Nissen, I. A., Stam, C. J., Citroen, J., Reijneveld, J. C., & Hillebrand, A. (2016). Preoperative evaluation using magnetoencephalography: experience in 382 epilepsy patients. *Epilepsy research*, *124*, 23-33. https://doi.org/10.1016/j.eplepsyres.2016.05.002

Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J. M. (2011). FieldTrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Computational intelligence and neuroscience*, *2011*, 1-9. doi: 2011:156869.

O'Tootle, A. J., Deffeenbacher, K. A., Valentin, D., and Abdi, H. (1994). Structural aspects of face recognition and the other-race effect. *Memory & Cognition*, *22*(2), 208. https://doi.org/10.3758/BF03208892

Partala, T., & Surakka, V. (2003). Pupil size variation as an indication of affective processing. *International journal of human-computer studies*, *59*(1-2), 185-198. https://doi.org/10.1016/S1071-5819(03)00017-X

Peelen, M. V., & Downing, P. E. (2007). The neural basis of visual body perception. *Nature reviews neuroscience*, *8*(8), 636-648. https://doi.org/10.1038/nrn2195

Penner, F., Wall, K. M., Guan, K. W., Huang, H. J., Richardson, L., Dunbar, A. S., ... & Rutherford, H. J. (2023). Racial disparities in EEG research and their implications for our understanding of the maternal brain. Cognitive, Affective, & Behavioral Neuroscience, 23(1), 1-16. https://doi.org/10.3758/s13415-022-01040-w

Pierce, J. E., Clementz, B. A., & McDowell, J. E. (2019). Saccades: fundamentals and neural mechanisms. Eye movement research: An introduction to its scientific foundations and applications, 11-71.

Philiastides, M. G., Ratcliff, R., & Sajda, P. (2006). Neural representation of task difficulty and decision making during perceptual categorization: a timing diagram. *Journal of Neuroscience*, *26*(35), 8965-8975. https://doi.org/10.1523/JNEUROSCI.1655-06.2006

Platz, S. J., & Hosch, H. M. (1988). Cross-Racial/Ethnic Eyewitness Identification: A Field Study 1. *Journal of Applied Social Psychology*, *18*(11), 972-984. https://doi.org/10.1111/j.1559-1816.1988.tb01187.x

Peyk, P., Schupp, H. T., Elbert, T., & Junghöfer, M. (2008). Emotion processing in the visual brain: a MEG analysis. Brain topography, 20, 205-215. DOI 10.1007/s10548-008-0052-7

Quintero-Rincón, A., Prendes, J., Pereyra, M., Batatia, H., & Risk, M. (2016, July). Multivariate Bayesian classification of epilepsy EEG signals. In 2016 IEEE 12th Image, Video, and Multidimensional Signal Processing Workshop (IVMSP) (pp. 1-5). IEEE. DOI: 10.1109/IVMSPW.2016.7528180

Rossion, B., & Jacques, C. (2008). Does physical interstimulus variance account for early electrophysiological face sensitive responses in the human brain? Ten lessons on the N170. *Neuroimage*, *39*(4), 1959-1979. https://doi.org/10.1016/j.neuroimage.2007.10.011

Sabatinelli, D., Flaisch, T., Bradley, M. M., Fitzsimmons, J. R., & Lang, P. J. (2004). Affective picture perception: gender differences in visual cortex?. Neuroreport, 15(7), 1109-1112.

Sabatinelli, D., Keil, A., Frank, D. W., & Lang, P. J. (2013). Emotional perception: correspondence of early and late event-related potentials with cortical and subcortical functional MRI. Biological psychology, 92(3), 513-519. http://dx.doi.org/10.1016/j.biopsycho.2012.04.005

Sabatinelli, D., Frank, D. W., Wanger, T. J., Dhamala, M., Adhikari, B. M., & Li, X. (2014). The timing and directional connectivity of human frontoparietal and ventral visual attention networks in emotional scene perception. Neuroscience, 277, 229-238. https://doi.org/10.1016/j.neuroscience.2014.07.005

Sambuco, N., Bradley, M., Herring, D., Hillbrandt, K., & Lang, P. J. (2020). Transdiagnostic trauma severity in anxiety and mood disorders: Functional brain activity during emotional scene processing. Psychophysiology, 57(1), e13349. https://doi.org/10.1111/psyp.13349

Sambuco, N., Bradley, M. M., & Lang, P. J. (2021). Trauma-related dysfunction in the fronto-striatal reward circuit. Journal of Affective Disorders, 287, 359-366. https://doi.org/10.1016/j.jad.2021.03.043

Schetinin, V., & Jakaite, L. (2017). Extraction of features from sleep EEG for Bayesian assessment of brain development. PloS one, 12(3), e0174027. https://doi.org/10.1371/journal.pone.0174027

Schindler, S., & Straube, T. (2020). Selective visual attention to emotional pictures: Interactions of task-relevance and emotion are restricted to the late positive potential. Psychophysiology, 57(9), e13585. https://doi.org/10.1111/psyp.13585

Schupp, H. T., Flaisch, T., Stockburger, J., & Junghöfer, M. (2006). Emotion and attention: event-related brain potential studies. *Progress in brain research*, *156*, 31-51. https://doi.org/10.1016/S0079-6123(06)56002-9

Schupp, H. T., & Kirmse, U. M. (2021). Case-by-case: Emotional stimulus significance and the modulation of the EPN and LPP. *Psychophysiology*, *58*(4), e13766. https://doi.org/10.1111/psyp.13766

Senholzi, K. B., & Ito, T. A. (2013). Structural face encoding: How task affects the N170's sensitivity to race. *Social Cognitive and Affective Neuroscience*, *8*(8), 937-942. https://doi.org/10.1093/scan/nss091

Shapiro, K. L., Raymond, J. E., & Arnell, K. M. (1997). The attentional blink. Trends in cognitive sciences, 1(8), 291-296. DOI:https://doi.org/10.1016/S1364-6613(97)01094-2

Snowden, R. J., O'Farrell, K. R., Burley, D., Erichsen, J. T., Newton, N. V., & Gray, N. S. (2016). The pupil's response to affective pictures: Role of image duration, habituation, and viewing mode. *Psychophysiology*, *53*(8), 1217-1223. https://doi.org/10.1111/psyp.12668

Stahl, J., Wiese, H., & Schweinberger, S. R. (2008). Expertise and own-race bias in face processing: an event-related potential study. *Neuroreport*, *19*(5), 583-587. DOI: 10.1097/WNR.0b013e3282f97b4d

Stekelenburg, J. J., & de Gelder, B. (2004). The neural correlates of perceiving human bodies: an ERP study on the body-inversion effect. *Neuroreport*, *15*(5), 777-780. DOI: 10.1097/01.wnr.0000119730.93564.e8

Strauss GP, Esfahlani FZ, Granholm E, Holden J, Visser KF, Bartolomeo LA, Sayama H. Mathematically Modeling Anhedonia in Schizophrenia: A Stochastic Dynamical Systems Approach. Schizophr Bull. 2020 Feb 26;46(5):1191–201. doi: 10.1093/schbul/sbaa014. Epub ahead of print. PMID: 32103266; PMCID: PMC7505187.

Strohminger, N., Gray, K., Chituc, V., Heffner, J., Schein, C., & Heagins, T. B. (2016). The MR2: A multi-racial, mega-resolution database of facial stimuli. *Behavior research methods*, *48*, 1197-1204. https://doi.org/10.3758/s13428-015-0641-9

Suess, F., Rabovsky, M., & Abdel Rahman, R. (2015). Perceiving emotions in neutral faces: expression processing is biased by affective person knowledge. *Social Cognitive and Affective Neuroscience*, *10*(4), 531-536. https://doi.org/10.1093/scan/nsu088

Tadel, F., Bock, E., Niso, G., Mosher, J. C., Cousineau, M., Pantazis, D., ... & Baillet, S. (2019). MEG/EEG group analysis with brainstorm. *Frontiers in neuroscience*, 76. https://doi.org/10.3389/fnins.2019.00076

Tanaka, J. W., & Pierce, L. J. (2009). The neural plasticity of other-race face recognition. *Cognitive, Affective, & Behavioral Neuroscience*, *9*(1), 122-131. https://doi.org/10.3758/CABN.9.1.122

Tatum, W. O., Rubboli, G., Kaplan, P. W., Mirsatari, S. M., Radhakrishnan, K., Gloss, D., ... & Beniczky, S. (2018). Clinical utility of EEG in diagnosing and monitoring epilepsy in adults. *Clinical Neurophysiology*, *129*(5), 1056-1082. https://doi.org/10.1016/j.clinph.2018.01.019

Tharoor, H., Kaliappan, A., & Gopal, S. (2015). Sexual dysfunctions in schizophrenia: professionals and patients perspectives. Indian Journal of Psychiatry, 57(1), 85. doi: 10.4103/0019-5545.148532

Thierry, G., Pegna, A. J., Dodds, C., Roberts, M., Basan, S., & Downing, P. (2006). An event-related potential component sensitive to images of the human body. *Neuroimage*, *32*(2), 871-879. https://doi.org/10.1016/j.neuroimage.2006.03.060

Trotti, R., Parker, D., Sabatinelli, D., Tamminga, C., Gershon, E., Keedy, S., ... & Clementz, B. A. (2018). S188. Emotional processing in Bipolar Disorder With and Without Psychosis: Findings From the Psychosis and Affective Research Domains and Intermediate Phenotypes Consortium. Biological Psychiatry, 83(9), S420. DOI:https://doi.org/10.1016/j.biopsych.2018.02.1080

Trotti, R. L., Abdelmageed, S., Parker, D. A., Sabatinelli, D., Tamminga, C. A., Gershon, E. S., ... & Clementz, B. A. (2021). Neural processing of repeated emotional scenes in schizophrenia, schizoaffective disorder, and bipolar disorder. Schizophrenia bulletin, 47(5), 1473-1481. https://doi.org/10.1093/schbul/sbab018

Trotti, R. L., Parker, D. A., Sabatinelli, D., Tamminga, C. A., Gershon, E. S., Keedy, S. K., ... & Clementz, B. A. (2020). Electrophysiological correlates of emotional scene processing in bipolar disorder. Journal of psychiatric research, 120, 83-90. https://doi.org/10.1016/j.jpsychires.2019.10.005

Trotti, R. L., Parker, D. A., Sabatinelli, D., Keshavan, M. S., Keedy, S. K., Gershon, E. S., ... & Clementz, B. A. (2023). Emotional scene processing in biotypes of psychosis. Psychiatry Research, 324, 115227. https://doi.org/10.1016/j.psychres.2023.115227

Van Strien, J. W., Franken, I. H., & Huijding, J. (2014). Testing the snake-detection hypothesis: larger early posterior negativity in humans to pictures of snakes than to pictures of other reptiles, spiders and slugs. *Frontiers in Human Neuroscience*, *8*, 691. https://doi.org/10.3389/fnhum.2014.00691

Versace, F., Lam, C. Y., Engelmann, J. M., Robinson, J. D., Minnix, J. A., Brown, V. L., & Cinciripini, P. M. (2012). Beyond cue reactivity: Blunted brain responses to pleasant stimuli predict long-term smoking abstinence. Addiction biology, 17(6), 991-1000.

Versace, F., Sambuco, N., Deweese, M. M., & Cinciripini, P. M. (2023). Electrophysiological normative responses to emotional, neutral, and cigarette-related images. Psychophysiology, 60(3), e14196. https://doi.org/10.1111/psyp.14196

Vehtari, A., Gelman, A., Simpson, D., Carpenter, B., & Bürkner, P. C. (2021). Rank-normalization, folding, and localization: An improved R ˆfor assessing convergence of MCMC (with discussion). *Bayesian analysis*, *16*(2), 667-718. DOI: 10.1214/20-BA1221

Walker, P. M., Silvert, L., Hewstone, M., & Nobre, A. C. (2008). Social contact and other-race face processing in the human brain. *Social Cognitive and Affective Neuroscience*, *3*(1), 16-25. https://doi.org/10.1093/scan/nsm035

Watanabe, S., & Opper, M. (2010). Asymptotic equivalence of Bayes cross validation and widely applicable information criterion in singular learning theory. *Journal of machine learning research*, *11*(12).

Wei, H., Jafarian, A., Zeidman, P., Litvak, V., Razi, A., Hu, D., & Friston, K. J. (2020). Bayesian fusion and multimodal DCM for EEG and fMRI. Neuroimage, 211, 116595. https://doi.org/10.1016/j.neuroimage.2020.116595

Weinberg, A., & Hajcak, G. (2010). Beyond good and evil: the time-course of neural activity elicited by specific picture content. Emotion, 10(6), 767. https://doi.org/10.1037/a0020242

Weinberg, A., Perlman, G., Kotov, R., & Hajcak, G. (2016). Depression and reduced neural response to emotional images: Distinction from anxiety, and importance of symptom dimensions and age of onset. *Journal of abnormal psychology*, *125*(1), 26. https://doi.org/10.1037/abn0000118

Wiese, H. (2013). Do neural correlates of face expertise vary with task demands? Event-related potential correlates of own- and other-race face inversion. Frontiers in *Human Neuroscience, 7*. https://doi.org/10.3389/Fnhum.2013.00898.

Wiese, H., & Schweinberger, S. R. (2018). Inequality between biases in face memory: Event-related potentials reveal dissociable neural correlates of own-race and own-gender biases. *Cortex*, *101*, 119–135. https://doi.org/10.1016/j.cortex.2018.01.016

Wu, W., Wu, C., Gao, S., Liu, B., Li, Y., & Gao, X. (2014). Bayesian estimation of ERP components from multicondition and multichannel EEG. NeuroImage, 88, 319-339. https://doi.org/10.1016/j.neuroimage.2013.11.028

Wu, W., Nagarajan, S., & Chen, Z. (2015). Bayesian Machine Learning: EEG\/MEG signal processing measurements. IEEE Signal Processing Magazine, 33(1), 14-36. DOI: 10.1109/MSP.2015.2481559

Zandi, A. S., Tafreshi, R., Javidan, M., & Dumont, G. A. (2013). Predicting epileptic seizures in scalp EEG based on a variational Bayesian Gaussian mixture model of zero-crossing intervals. IEEE Transactions on Biomedical Engineering, 60(5), 1401-1413. DOI: 10.1109/TBME.2012.2237399