

Neural Correlates of Written Emotion

Word Processing: an fMRI Study

Bachelor's Project in Cognitive Science

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Abstract

This event-related fMRI study investigated the neural correlates of emotion word processing during a demonstrative choice task. 29 healthy subjects were presented with one noun at a time and asked to match each noun with either the proximal demonstrative *this* or distal demonstrative *that*. The analysis was two-fold. In the first analysis, the difference in brain activation associated with viewing a word compared to viewing a fixation cross was estimated within the mass univariate general linear model framework implemented in Python. In line with what was hypothesised, the contrast revealed enhanced activation in various brain regions, including the parietal and occipital lobes in response to words. Subsequently, a second analysis was conducted to investigate whether reading emotional rather than neutral nouns elicited enhanced activation in the extrastriate cortex, an effect referred to as *emotional modulation*. Although findings of previous studies have indicated that the extrastriate cortex may be particularly sensitive to the emotional content of stimuli such as words, the second and main analysis provided no support for this hypothesis as no significant cluster of activation in the extrastriate cortex was found. The findings were discussed in the light of methodological limitations and potentially confounding variables not accounted for in the analysis. This was accompanied by a discussion of results suggesting enhanced activation in other brain regions including the supplementary motor area in response to emotional nouns. To assess whether enhanced activation in the motor area in response to emotional nouns was related to differences in behavioural measures, an exploratory analysis was conducted using a simple Bayesian general linear model. No credible difference in response time between trial types was observed. These results have implications for our understanding of emotional processing and are discussed in the context of the current literature.

Keywords: arousal, emotional modulation, extrastriate cortex, fMRI, valence, visual processing

GitHub Repository: code used in the analysis can be found on the following GitHub repository:

https://github.com/emmarisgaardolsen/BSc_project_fMRI

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1. Introduction (SW)

Emotions govern our senses and influence the way we perceive the world via mechanisms that are not yet fully understood. Whilst it might be intuitive to comprehend that what we perceive in the world influences our emotional reactions, it is a far less trivial task to comprehend how these emotional processes may in turn influence the way in which our perception is formed. A growing body of literature has found differences in behavioural as well as neuronal responses to emotional compared to neutral stimuli (Citron et al., 2014; Kissler et al., 2006, 2007; Kousta et al., 2009; Kuchinke et al., 2005). Such findings have entertained theories of emotional modulation, describing a modulatory process by which emotional states and affective properties of stimuli, rather than their strictly visual properties, elicit adaptive responses and influence the perceptual processing of that stimuli by enhancing neural responses to it (Vuilleumier & Driver, 2007). The present paper intends to explore and investigate how affective content of visually presented words might be processed differently than neutral words and potentially lead to altered behaviour and enhanced activation in sensory areas surrounding the visual cortex.

1.1. Defining Emotion (EO)

There is consensus among researchers that emotions influence perceptual and cognitive processes as well as elicit adaptive behaviour (Barrett et al., 2011; Vuilleumier, 2005). Emotion research has come far. However, as it covers a wide field of research on different domains of human functioning, various concepts are often used without clear definitions and models to conceptualise emotions. There is no scientific consensus on one single definition of the term *emotion* which remains difficult to define as a unitary concept. The term *emotion* can, depending on the context of usage, refer to both emotional states, traits, experience, connotations, or emotional expression. The current study will use the term *emotional* to refer to the emotional connotations of written words. Several theories and models have been proposed to describe emotions, yet the two-dimensional circumplex model (Larsen & Diener, 1992) of affect is the most widely applied in contemporary affective neuroscience, i.e., neuroscientific research of the neural basis of human emotional experience (Citron, 2012, Bear et al., 2016 p. 616 & 627). This dimensional theory posits that emotions can be understood within a two-dimensional circumplex space spanning the two orthogonal dimensions *valence* and *arousal*. Valence refers to the degree of positive or negative affectivity, often also described as the pleasantness or unpleasantness of a stimulus, emotion, or emotional state (Lang et al., 1997). Arousal refers to the degree of activation associated with an affect, often described in terms of a continuum from very calming to highly exciting or agitating, i.e., referring to perceived intensity of an emotion (Barrett & Russell, 1999; Lang et al., 1997; Reisenzein, 1994; Russell, 1980). High arousal words are generally believed to evoke a stronger emotional response than low arousal words due to their high intensity and tendency to be more vivid

and evocative (Hinojosa et al., 2012; Sereno et al., 2015) and some adherents of the two-dimensional circumplex model of affect have argued that arousal and intensity are the main primary features of stimuli driving amygdala activation (Fossati, 2012; Russell, 2003).

Whether the dimensions *valence* and *arousal* provide a sufficient means of characterising emotions is a subject of debate. It has been suggested that measures of familiarity, self-reference, and dominance are also relevant in the characterisation of emotion (Citron, 2012). Making a formal model that sufficiently defines emotion is difficult due to its inherent subjectivity. Emotions are complex and possibly influenced by a wide range of contextual factors, resulting in them ultimately being experienced differently by different individuals. However, the two-dimensional model provides a simplified framework for understanding complex emotions and provides a standardised way to organise research on how various aspects of emotions are expressed in the brain.

Evidence supporting such dimensional models comes amongst others from cross-cultural studies that have shown that all known languages have words for a pleasant-unpleasant dimension and that this dimension exists in all cultures (Russell, 1991; Wierzbicka, 1999). Alternative models of emotions have been proposed, describing emotions in terms of a set of basic discrete emotions (anger, fear, disgust, happiness, etc.) that all engage specific circuitries in the nervous system (Levenson, 2011). Although the dimensional model may not capture all aspects of emotions, it provides a suitable framework for the current study as it intends to focus on processing of general emotional connotations of words (Citron, 2012). That is, while there are alternative models of emotions, Citron (2012) argues, that when investigating general effects of emotional content, rather than differences between discrete emotions, dimensional models provide a better-suited framework

Neuroimaging research has also provided evidence for the validity of this two-dimensional model. Studies have found a dissociation in patterns of brain activation between emotional valence and arousal. Saliency of the valence dimension is suggested to be associated with the appraisal of an emotional situation, recruiting brain regions that are activated in response to more cognitively demanding tasks such as the orbitofrontal cortex and the dorsolateral prefrontal cortex, suggesting that valence represents a relatively controlled higher-order cognitive dimension of emotion (Citron, 2012). On the contrary, arousal is associated with more immediate, uncontrolled physiological reactions and has been shown to recruit brain regions associated with more automatic and perceptual-based processes, such as the amygdala (Citron, 2012). However, as suggested by studies manipulating the dimensions separately, they do seem to interact in complex ways (Citron, 2011; Citron et al., 2014; Compton et al., 2003; Larsen et al., 2008; Lewis et al., 2007; Posner et al., 2009). In 2007, Lewis and colleagues found large brain regions where activity was modulated by an interaction of valence and arousal in negative words, indicating a

varying valence-specific interdependence of these two dimensions. The effect was not found for positive words. However, they found that the subgenual cingulate and head of caudate responded to increasing arousal in *positive* but not *negative* words, whereas other regions such the insula and amygdala responded to increasing arousal in *negative* but not *positive* words (Lewis et al., 2007). Additionally, Citron and colleagues (2014) found an interaction effect between valence and arousal, expressed via increased neural responses within the right insular cortex to positive high-arousal and negative low-arousal stimuli compared to positive low-arousal and negative high-arousal stimuli. Although the exact mechanisms by which these dimensions interact is not fully known, there's general agreement that they can be used in a combination to distinguish emotional content from neutral content (Citron, 2012).

1.2. Emotional Modulation and the Extrastriate Cortex (SW)

In the literature within the field of affective neuroscience, emotional processing is often associated with activation of brain structures within the so-called *limbic system* (Bear et al., 2016, ch. 18). Historically, affective neuroscience has particularly emphasised the contribution of the amygdala, an almond-shaped nucleus in the anterior medial temporal lobe with widespread connections to many other brain regions (Davis & Whalen, 2001; LeDoux, 2000), to processing of negative emotional stimuli. However, more recent evidence suggests that positive emotional stimuli activate the amygdala as well, emphasising the need for a more precise definition of the computational role served by the amygdala (Fossati, 2012). Nonetheless, it has become increasingly clear that emotions cannot be adequately understood through the lens of a single brain structure or a discrete emotional system (Bear et al, 2016, ch. 18).

Widespread projections are sent from the amygdala to a range of subcortical as well as cortical structures including the basal forebrain, nucleus accumbens and sensory cortices (Fossati, 2012). While the exact functional consequences of these projections remain to be fully understood, research is moving towards uncovering the underlying details. For instance, research using functional magnetic resonance imaging (fMRI) has found enhanced processing of emotional words in the visual cortex to be paralleled by enhanced amygdala activation for emotional words in comparison to neutral words (Herbert et al., 2009). This is consistent with findings of bidirectional modulatory connections between the amygdala and the extrastriate cortex, so-called re-entrant processing loops, in non-human primates (Amaral & Price, 1984), and is supported by human lesion data on the processing of emotional faces and words (Anderson & Phelps, 2001; Herbert et al., 2009; Vuilleumier et al., 2004). The extrastriate cortex is a region of the brain located in the occipital lobe just beyond the primary visual cortex that is involved in the processing of visual information. It is often divided into several sub-regions, each of which serves specialised functions (Bear et al., 2016, ch. 10). The extrastriate cortex is especially relevant for the current paper as it has been found to respond to word stimuli and be particularly sensitive to a word's lexical and semantic aspects (Cohen et al., 2002; Gaillard et al., 2006; Jobard et al., 2003; Nobre et al.,

1994; Petersen et al., 1990; Vigneau et al., 2005). More specifically, previous research has found a significant cluster of enhanced activation in the extrastriate cortex in response to emotional rather than neutral words (Citron et al., 2014; Compton et al., 2003; Herbert et al., 2009). Many authors have favoured re-entrant processing as a way to explain facilitated sensory processing in the visual cortex. In some imaging studies, activity in the amygdala and the extrastriate cortex has been shown to be correlated or, at least, to exhibit parallel responses. Given this assumed functional interplay between the amygdala and the extrastriate cortex during reading of words, the extrastriate cortex is a relevant brain region to investigate in fMRI studies on emotional modulation.

1.3. Neural Underpinnings of Emotional Modulation (EO)

Even though research suggests that emotional visual stimuli have the capability of enhancing response in brain regions involved in visual processing (Vuilleumier et al., 2004), the exact mechanisms behind this modulation are still not fully understood. Some argue that emotional modulation operates via the attention system, meaning that the enhanced sensory activation is “caused” by emotional stimuli attracting more attention, a position conceiving emotional modulation as a “top-down” influence of emotion (Hopfinger et al., 2000). Others argue that the effect is independent from the attention system and instead operates via limbic structures as the amygdala (Vuilleumier, 2005; Vuilleumier & Huang, 2009). These two positions will be elaborated upon in the following sections.

1.3.1 Emotional Modulation and the Attention System (SW)

1.3.1.1 Bottom-Up and Top-Down Influence on Perception

The human brain’s ability to extract and interpret visual information from the world around us depends on ongoing dynamic interactions between bottom-up (B.U.) and top-down (T.D.) processes operating within a hierarchically organised complex visual system. B.U. processing refers to low-level processing of incoming sensory information starting with light passing through the cornea of the human eye (Bear et al., 2016, ch. 9-10). This creates projections on the retina, stimulating photoreceptor cells situated within the retina. Stimulation of the photoreceptors creates an electrical signal eventually reaching the visual receiving area of the brain. As a part of B.U. processing, incoming visual information thus flows unidirectionally from the retina to eventually reach higher cortical areas such as the visual cortex (Bear et al., 2016, ch. 9-10). T.D. processing refers to prior knowledge and expectation modifying the information transmitted by neurons, affecting how they respond to stimuli. As such, our interpretation of incoming sensory information is highly influenced by prior knowledge, experiences, and expectations and in relation to this paper emotional states and reactions (Mohanty & Sussman, 2013).

1.3.1.2. The Biased Competition Model of Attention

Attention can be defined as “the process by which certain information is selected for further processing and other information is discarded, i.e., the ability to focus on specific stimuli and locations” (Goldstein & Hooff, 2018, p. 83). As the processing capacity of the visual system is limited, directing your attention towards something comes at the cost of neglecting something else, creating a "competition" among stimuli for processing resources as described in *the biased competition model* developed by Desimone and Duncan (1995). According to their model, this competition for neural representation occurs within the visual cortex itself and can be biased in different ways via B.U. as well as T.D. influences (Desimone & Duncan, 1995). According to the model, attention serves to enhance response to relevant stimuli at the expense of irrelevant ones. The extent to which the unattended stimuli is being processed varies in different models (Lavie, 1995) but most studies do suggest that attention is a key factor in filtering the relevant information in visually cluttered scenes by enhancing neural response in the visual cortex (Pessoa & Ungerleider, 2004). This is compellingly illustrated in change blindness studies where people fail to detect changes in the environment because their attention is directed elsewhere (Rensink, 2002; Rensink et al., 1997; Simons & Levin, 1997).

1.3.1.3 Neural Substrates of Emotional Modulation: The Attention System

Research indicates that specific brain circuits serve to amplify neural response to emotional stimuli, a modulation similar to an attentional effect usually driven by endogenous goals (Vuilleumier & Huang, 2009). At the neural level, selective attention operates by increasing sensory responses through modulatory influences imposed on early cortical pathways by frontal and parietal areas (Pessoa & Ungerleider, 2004; Vuilleumier & Driver, 2007). Enhanced perceptual processing is hence thought to result from T.D. modulation of the sensory cortex by higher-level regions in the parietal and frontal cortex, which can both be driven by endogenous or exogenous factors (Vuilleumier, 2005). It's been found that attending to a stimulus will lead to enhanced sensory response for all areas of retinotopic visual cortex (Hopfinger et al., 2000; Ungerleider, 2000).

Emotionally relevant stimuli have the capability of producing similar enhancement of cortical processing (Vuilleumier & Huang, 2009). Emotional rather than neutral faces have been found to enhance activity in the fusiform face area, an area related to processing of faces located within the visual cortex (Vuilleumier, 2005). A study by Grandjean and colleagues (2005) similarly found greater activation in the auditory cortex in response to emotional voices compared to neutral voices (Grandjean et al., 2005). EEG recordings in humans also indicate potential analogies between emotion and attention effects on sensory responses. Several studies found a higher amplitude of visually evoked potentials for emotional versus neutral faces (Ashley et al., 2004; Eger et al., 2003; Eimer & Holmes, 2002; Pizzagalli et al., 2002).

These findings suggest that emotion can produce activations strikingly analogous to those due to selective attention, enhancing the representation of emotionally relevant, rather than strictly task relevant, stimuli in specific regions of sensory cortex (Vuilleumier et al., 2003; Vuilleumier & Driver, 2007). A potential mechanism for these effects could involve emotional influences on the frontoparietal attention networks which could then bias activation in sensory cortices (Vuilleumier & Huang, 2009). This is supported by findings by Armony and Dolan (2002) who found increased parietal activation in response to emotional stimuli (Armony et al., 1998).

1.3.2. Emotional Modulation as “Independent” from the Attentional System (EO)

The effects of emotional modulation seem similar to the modulatory effects of the attentional system. Nonetheless, some research suggest that they work at least partly independent from one another and that enhanced sensory responses to emotional stimuli do not seem to depend on frontoparietal attention systems (Vuilleumier, 2005; Vuilleumier & Huang, 2009). The literature suggests that, in several situations, emotional modulation can still arise from task irrelevant stimuli (Critchley et al., 2000; Keil et al., 2005; Pasley et al., 2004). This is furthermore supported by findings from a neuroimaging study by Vuilleumier (2005) in which patients with deficits in spatial attention due to parietal damage (neglect syndrome) still showed an advantage for the detection of emotional relative to neutral stimuli, together with increased activation in the visual cortex, even when emotional stimuli appeared on the "neglected" side of space where patients usually fail to direct attention (Vuilleumier, 2005).

1.3.2.1. Neural Substrate of Emotional Modulation: The Amygdala

As previously mentioned, several studies suggest that the influence of emotion on perception seem to be highly modulated by the amygdala. Amygdala not only receives sensory input from all modalities, it also sends projections to many cortical and subcortical regions and these re-entrant loop processes potentially allow it to influence perception and behaviour in multiple ways (Amaral et al., 2003; Holland & Gallagher, 1999). Neuroimaging studies show that amygdala activity correlates with enhanced responses to emotional stimuli in visual cortex (Morris et al., 1998; Pessoa & Ungerleider, 2004; Sabatinnelli et al., 2005) and connectivity analyses also reveal a greater coupling of amygdala with fusiform and primary visual cortex when seeing fearful compared to neutral faces (Morris et al., 1998; Pessoa & Ungerleider, 2004). In an fMRI study, Vuilleumier and colleagues (2004) tested whether the amygdala has modulatory influences on sensory processing in patients with medial temporal lobe sclerosis. Subjects saw faces (fearful or neutral) paired with houses and had to focus attention on one stimulus category only. Faces were always task irrelevant. In their study, enhanced neural responses to fearful faces normally seen in distant fusiform areas were found for both healthy controls and patients with sclerotic damage limited to the hippocampus. However, this enhanced neural response was not seen in patients with sclerotic damage to both the amygdala and the hippocampus. In other words, unlike healthy con-

trols, patients with amygdala damage no longer showed any differential increase to fearful versus neutral faces in visual areas. Their findings suggest that amygdala damage disrupts functional activation by emotional stimuli of distant, structurally intact but connected areas of the brain, notably the visual cortex. This suggests a functional influence of the amygdala on posterior sensory cortices and provides a mechanism for prioritised processing of emotional stimuli.

Some neuroimaging studies indicate that even though both neutral and emotional stimuli produce weaker signals when unattended rather than attended, sensory responses to the latter are still amplified even without selective attention (Vuilleumier, 2005). This persistent modulation of sensory response might produce a reflexive form of "emotional attention" that is dependent on amygdala signals and distinct from more voluntary components of attention mediated by fronto-parietal networks (Vuilleumier & Huang, 2009). Increased perceptual processing of emotional stimuli may therefore partly result from direct feedback signals imposed by amygdala on cortical pathways, potentially influencing other T.D. influences imposed by attentional systems in the frontal and parietal cortices (Vuilleumier, 2005).

1.3.2.2. Emotional Modulation in an Evolutionary Context

While these reviewed positions disagree on the mechanisms underlying the modulatory process of emotion, they all support the notion that emotional stimuli enhance activity in sensory areas. This has been suggested to result from the brain's evolutionary ability to recognise and respond to stimuli that hold significance to the individual (Minati et al., 2009). As previously mentioned, the human brain has a limited processing capacity and is thus not able to process all information equally. As such, emotional modulation could serve as a function to quickly filter out irrelevant information. The modulation also implies a faster and more accurate recognition of emotions which is suggested to be an important evolutionary aspect of social interaction (Lang et al., 1998). In a social context, it can help create a more harmonious environment and afford more effective communication and conflict avoidance. In sum, the modulatory process can help attract and focus attention on important elements of the environment, such as potential sources of food, potential danger, and potential mates and respond more quickly to social cues (Lang et al., 1998; Minati et al., 2009).

1.4. Words as Stimuli (SW)

The present study seeks to investigate the emotional information, i.e., the lexico-semantic representations of written words. When presenting words in the visual modality rather than read aloud, you avoid emotional information embedded in the prosody and intonation in speech from interfering with the lexico-semantic information (Pell et al., 2011). Although some studies have found emotional words to

elicit slightly weaker response than other emotional visual stimuli such as pictures, Citron (2012) provides evidence that manipulation of single words represents a suitable means to study emotion processing and that single words can elicit cortical or cerebral responses qualitatively comparable to the ones elicited by pictures and faces (Citron, 2012). Generally, emotional words have been found to be processed faster and more accurately (Kousta et al., 2009), elicit larger amplitudes of electrophysiological components associated with emotion processing (Kissler et al., 2007), and enhance neural activity in limbic brain regions (Kuchinke et al., 2005)

1.5. fMRI (SW)

Magnetic Resonance Imaging (MRI) is a non-invasive imaging technique that uses strong magnetic fields, magnetic field gradients, and radio waves to produce three dimensional detailed anatomical images (Sternberg et al., 2012). Functional MRI (fMRI) uses the same basic principles of atomic physics as MRI but whereas MRI measures brain anatomy, fMRI measures brain function. In fact, fMRI is one of the most widely applied neuroimaging techniques for determining neuronal activation during cognitive functioning in the human brain (Buxton, 2003) and is frequently applied in neuroscientific research as well as clinical settings. Although non-BOLD fMRI exists, most fMRI research, including the current study, exploits the blood-oxygenation-level dependent (BOLD) effect to localise changes in neuronal signal and relate those to experimental manipulation (Poldrack et al., 2011).

1.5.1 The Bold Effect (EO)

fMRI measures brain activity by detecting changes associated with cerebral blood flow (CBF) (Buxton, 2003, ch. 16). This makes fMRI an indirect measure of neuronal activity relying on the assumption that haemodynamics, i.e., the local control of blood flow and oxygenation, and neuronal activation are coupled (Heeger & Ress, 2002). Active neurons experience an increase in metabolism, demanding additional glucose and oxygen. This causes an increase in oxygenated blood flow (oxyhaemoglobin) in the active brain regions as the brain vasculature increases the local CBF. Oxyhaemoglobin and deoxyhaemoglobin each have different magnetic properties depending on the concentration of O_2 , producing different local magnetic fields. When haemoglobin is fully saturated with oxygen (oxyhaemoglobin) it behaves as a diamagnetic substance, meaning that when placed into a magnetic field (the MR scanner) it weakly repels the field, causing a small negative magnetic susceptibility. On the contrary, as oxygen is extracted from the blood (deoxyhaemoglobin) it becomes paramagnetic and works as a depressor of the MR signal by causing distortions in the magnetic field. FMRI exploits the fact that changes in blood oxygenation produces such measurable effects on MR images (Buxton, 2003) and within any particular imaging voxel the proportion of deoxyhaemoglobin relative to oxyhaemoglobin dictates how the MR signal will behave in a BOLD image. Areas with high concentration of oxyhaemoglobin give a higher signal (i.e., a brighter image) than areas with low concentration.

To sum up, interpretation of fMRI data is based on the assumption of neurovascular coupling, i.e., that blood is a correlate of neuronal activity (Iadecola, 2017). FMRI can therefore be used to measure the haemodynamic response and relate it to spatially and temporally coupled neuronal activity believed to reflect functional properties. FMRI data represents the BOLD signal in the brain across time as four-dimensional data files. A sequence of three-dimensional brain volumes constitutes the first three dimensions. Each brain volume is an MR image of the brain that can be decomposed into voxels, small three-dimensional units analogous to pixels in two-dimensional image data. The fourth dimension of fMRI data is time.

1.5.2. The Haemodynamic Response Function (EO)

The timing of stimulus processing and underlying neural activity are not exactly mirrored by the MR signal, i.e., the BOLD signal, elicited by instantaneous brain activity. Rather, the haemodynamic response function (HRF) is used as a measure of the BOLD signal response in the brain to a stimulus and is known to follow a particular shape that can be modelled with a Gamma Distribution, reflecting the fact that the BOLD response is in fact very slow. More specifically, the shape peaks around six seconds and returns to baseline over the next several seconds. The BOLD signal thus has a significant haemo delay relative to stimulus onset as well as onset of neural spiking in the order of 3-5 seconds (Poldrack, 2011). The term *canonical HRF* refers to a specific form of the gamma distribution that has been parameterised to best fit the BOLD response typically observed in fMRI studies (Jahn et al., 2022). The canonical HRF can be used as a reference or template for comparison of HRF across several subjects or brain regions in fMRI analysis and will be used in the current study. When the gamma distribution is applied to fMRI data, it's called a *basis function*. This refers to it constituting the basis for modelling the HRF, allowing researchers to estimate the expected BOLD response to a given stimulus and compare it to the measured time series data. Modelling the HRF is a critical step in fMRI studies of brain activity. In fMRI experiments, stimuli are often presented before the BOLD response for the previous stimulus has returned to baseline. In order to better understand our fMRI data, we can transform the measured BOLD signal into a function. If we can identify the canonical shape of the blood flow response to a brief stimulus, we can predict how it would appear in response to stimuli of different durations and combinations of stimuli presented over time. More specifically, utilising our knowledge about the canonical HRF allows us to sum together, or convolve, individual HRFs, creating a BOLD signal reflecting the moving average of individual HRFs (Jahn et al., 2022). Having the time course of the stimuli temporarily mapped to the BOLD signal is crucial for the analysis of fMRI data. Convolved time-series for different stimuli are used to account for variability in the recorded BOLD signal at each voxel location using statistical modelling.

1.5.3. Motivating the use of fMRI (SW)

fMRI is a flexible neuroimaging method compatible with a wide range of different experimental paradigms. fMRI can be used to study the brain's response to a variety of stimuli and task demands and allows the researcher to propose a wide range of possible research questions depending on the experimental paradigm applied. It is non-invasive and does not rely on the use of radiation inherent in other imaging methods such as CT or PET scans. fMRI is optimal for mapping complex cognitive functions in the brains of human volunteer subjects with a good combination of spatial and temporal resolution. The temporal resolution of fMRI is limited by the previously mentioned haemo delay causing a ~5s delay between initial neuronal spiking and BOLD signal peak, making it difficult to distinguish BOLD responses to distinct events occurring within a short time window. fMRI produces high spatial resolution images with a typical pixel size of 3-4 mm although higher field magnets (7T) can achieve a pixel size of up to 500 microns (Glover, 2011).

1.5.4. fMRI and the Current Study (SW)

Previous studies have used BOLD fMRI to study the neural processing of emotional words based on the two-dimensional circumplex model of affect (Posner et al., 2009). It has been argued that fMRI provides a particularly well-suited means to study the processes involved in seeing words (Wandell, 2011). The relationship between the visual circuitry and reading has been focused on circuits within the ventral occipital-temporal cortex, an area with a spatial scale of around two square centimetres on the cortical surface. Additionally, the ability to safely repeat measurements on a single subject enables the use of sophisticated behavioural paradigms and the study of individual differences in brain activity. Overall, these factors make fMRI a valuable method for studying visual processing in the brain (Wandell, 2011).

1.6. Thesis Statement (EO, SW)

As presented in the preceding sections, affective neuroscience is a broad field with no single definition of the central concept "emotion" and with many neural underpinnings yet to be discovered. The present paper intends to investigate more specifically the concept of emotional modulation attempting to nuance the discussion and contribute to the knowledge we have about how emotions are being processed in the brain. Many studies on emotional modulation have used solely negative stimuli and have accordingly been interpreted as promoting adaptive behaviour in response to potential threats (Vuilleumier and Huang, 2009). However, the present study seeks to go beyond this and contrast emotional words (comprised of both positive and negative words) to neutral words. Using the two-dimensional circumplex model of affect, we will define emotionality based on a word's *valence* and *arousal* score following the procedure described in section 2.2.

The procedure and framework adopted in the current study are based on previously conducted experiments in the field (Citron et al., 2014; Herbert et al., 2009; Lewis et al., 2007). The analysis will be two-fold. In the first analysis (in subsequent sections referred to as A1), we will investigate the difference in brain activation between viewing a word compared to viewing a fixation cross. This allows us to make basic inferences about visual processing during the task and serves as a quality check of the data as it provides an indication of whether the words are being viewed and processed in the first place. In the second and main part of the analysis (in subsequent sections referred to as A2), we intend to study the concept of emotional modulation and investigate whether emotional nouns have the capability of enhancing response in the extrastriate cortex compared to neutral nouns. This has led to the formation of the following hypotheses:

1.6.1. Hypotheses

- H1: Contrasting a word and a fixation cross presented to the visual modality will result in significant clusters of increased activation in the striate and extrastriate cortices in response to words.*
- H2: Contrasting emotional and neutral nouns will reveal significant clusters of increased activation in the extrastriate cortex in response to emotional nouns.*

2. Methods (EO, SW)

2.1. Subjects (SW)

33 healthy subjects with no known history of psychiatric and neurological disorders participated in the study. Of these, three were excluded due to issues running the pre-processing pipeline. One additional subject was excluded due to file corruption in data processing, preventing it from being loaded and included in the second level analysis. Logfiles were reviewed and no repetitive lack of responses or any other behavioural indications of sleep or inattention during the scans was found. The final sample included 29 subjects (15 females, 14 males; mean age = 23.5 years, SD = 3.21, range = 18-31). All subjects were fluent in English, right-handed, and reported having normal or corrected-to-normal visual acuity and hearing.

2.2. Materials & Sentiment Classification (EO)

The stimuli in the present study consists of 303 nouns (293 unique, 10 randomly repeated nouns). The nouns were chosen based on the results of a previous studies where the 293 unique nouns were found to perform best in terms of predicting personality traits in a demonstrative choice task as well as a large-scale, online behavioural study using the nouns in a demonstrative choice task (Rocca and Wallentin, 2020). As the current study aims to investigate the neural correlates of processing neutral and emotional words, respectively, a sentiment classification procedure was applied to assign sentiment ratings and classifications to all the nouns presented to the subjects.

To classify the nouns according to their emotionality, the *Extended Affective Norms for English Words (XANEW)* lexicon developed by Warriner et al. (2013) was applied to the wordlist containing the experimental stimuli. XANEW is an extension of Bradley and Lang's (1998) *Affective Norms for English Words (ANEW)* lexicon which for long was the best practice lexicon used in studies investigating aspects of emotion using words of different emotional ratings. However, Warriner et al. developed XANEW as the number of words included in ANEW limited its usability in studies other than small-scale factorial experiments (Warriner et al., 2013). XANEW provides a set of normative emotional ratings for 13,915 English lemmas, i.e., the base form of words as they appear in dictionary entries. As with the *ANEW* lexicon, all words in the *XANEW* lexicon have been rated in terms of valence and arousal.

Following the procedure used by Lewis and colleagues (2007), all words used in the present study were categorised based on their emotional ratings specified by the *XANEW* lexicon. Words were categorised as emotional if they had an arousal rating > 5 and either a) a valence rating of < 3 or b) valence rating

> 6. This means that the emotional trial type contained both positive and negative words. Examples of the emotional positive words are: *vacation, happiness, fun, love, joke, kiss, humor, freedom, girlfriend, summer, goodness, wealth*. Examples of the emotional negative words are: *kill, death, hate, poverty, pain, victim, depression, torment, hell, jealousy, shame, deceit*. All of these words were contained in the same trial type, i.e., emotional. Examples of neutral words are: *package, semester, lawyer, carrot, situation, line, use, ham, shelf, shoulder, harp, and table*. Our distribution of valence and arousal ratings were found to satisfactorily reflect the trend in the XANEW dataset as seen in Appendix 1. All words contained in each trial type can be found in Appendix 2.

There were 10 nouns in the experiment that were not present in the XANEW lexicon. To obtain valence and arousal ratings of each of these 10 words, 19 coders were asked to independently provide ratings for each word following a coding scheme provided by the authors. An inter-coder reliability score was calculated. The score was calculated for each task (valence scoring and arousal scoring) using Krippendorff's α reliability coefficient, implemented in RStudio (v.2022.7.2.576; RStudio Team, 2022) using the packages *irr* (Gamer, 2015): valence ($\alpha = 0.511$), arousal ($\alpha = 0.275$). The obtained alpha for arousal indicates disagreement agreement among the coders, whereas the alpha for valence indicates moderate agreement. These trials were included following the same sentiment classification procedure as described above. The 10 trials with repeated words were excluded, resulting in the experiment consisting of 39 trials with emotional words and 254 trials with neutral words.

To account for a potential difference in neural responses in the two conditions being influenced by a low-level effect of word length, a Bayesian linear model was estimated using MCMC sampling to compare the mean word length of the emotional and neutral words, respectively. MCMC stands for Markov Chain Monte Carlo and is a simulation-based approach to Bayesian inference which uses a Markov Chain to sample from the posterior distribution of the model parameters. We used weakly informative priors (student_t, location = 1.5, scale = 2.5) for our model estimates and the model was estimated using MCMC sampling with 4 chains of 2000 iterations and a warmup of 1000. The MCMC algorithm is used to estimate the posterior distribution of the model parameters and the posterior predictive distribution of the word length. To assess quality of the model, prior and posterior predictive checks were performed. Additionally, model convergence was validated by visual inspection of trace plots and ranked Markov chains. R-hat and effective sample size (ESS) were inspected to assess convergence of the Bayesian sampling. R-hat = 1 (should be below 1.01 (Vehtari et al., 2021) and ESS = 4284 (should be greater than 1000 (Bürkner, 2017)), indicating that the estimation successfully converged. The model did not reveal any credible difference in the mean word length of emotional and neutral trials, respectively ($\beta = 0.29$, 95% CIs -0.36, 0.94). More information about the model and estimated parameters can be found in Appendix 3.

2.3. Procedure and Experimental Design (SW)

The data used in the present paper was collected as a part of Semantics of Depression, a neuroscientific study led by Line Kruse investigating linguistic representations and its relation to individual differences and depressive disorder. In contrast to the main study, which includes both healthy and depressed individuals, the present paper focuses solely on the healthy subject group.

The study was conducted at the Center for Functionally Integrative Neuroscience (CFIN) located at the Neuroradiology Research Unit at Aarhus University Hospital. After providing oral as well as written explanation of the experimental protocol and scanning procedure, written informed consent was obtained from all subjects in compliance with guidelines set by the Institutional Review Board guidelines at Aarhus University. The study was approved by the Institutional Review Board at Aarhus University and subjects were monetarily reimbursed with 200 DKK for their time spent participating.

The present paper uses the experimental paradigm called the Demonstrative Choice Task (DCT) introduced by Rocca and colleagues in 2019. It's a simple, new experimental paradigm where subjects are asked to match nouns with either the proximal *this* or distal *that* demonstrative without any further context and based solely on intuition (Rocca et al., 2019b). Subjects engaged in the DCT procedure with stimuli presented on an MRI-compatible 32-inch LCD display placed at the back of the MR bore. An MRI-compatible response pad was used to record responses as well as response times. A PsychoPy script (Peirce et al., 2019) programmed in PsychoPy3 was used to present stimuli and record subject responses. A structural image scan with a duration of 5 minutes was acquired prior to initiating the experiment. Each trial consisted of the presentation of a noun centred in the middle of the screen along with the proximal demonstrative *this* and the distal demonstrative *that*, presented just beneath the noun. The duration of each trial was 1 second. Thereafter, the noun was replaced by a central fixation cross visible for 5 seconds. The nouns were presented in the same order for all subjects. Subjects were instructed to couple each noun with either *this* or *that* using the response pad without further context. They were instructed to simply follow their intuition and choose the combination of demonstrative and word they thought fitted best.

The scanning procedure consisted of three runs, each of which lasted around 12 minutes. Trials were distributed evenly across runs and the researchers communicated with the subject in between trials. The full experiment lasted approximately 1.5 hours including preparation, structural scanning, around 45 minutes of functional scanning time, and debriefing.

2.4. MRI Data Acquisition (SW)

A 3T Prisma Fit MR scanner (software version Syngo MR E11) with a standard head coil was used to acquire both T2-weighted and echo-planar images (EPI) with Blood Oxygenation Level-Dependent (BOLD) contrast and T1 weighted structural images. 582 EPI volumes with BOLD contrast were acquired for each session per subject (resulting in 583 x 3 volumes per subject). The first five volumes were discarded to allow for effects of T1 equilibrium. Whole brain coverage was achieved using 80 axial slices of 1.80 mm slice thickness with an in-plane resolution of 1.79 x 1.79 mm in a 112 x 112 voxel matrix (FOV = 200.5 mm). Echo-planar images (EPI) were obtained with a TR of 1317 ms, a 29.6 ms TE and a 35° flip angle. A high-resolution 3D GR T1 anatomical scan was acquired for spatial processing of the fMRI data. It consisted of 256 x 256 x 192 voxels with a 0.90 mm x 0.90 mm x 0.90 mm voxel size, obtained with a TR of 2200 ms, a 2.51 ms TE and a 8° flip angle.

2.5. Image Preprocessing (EO, SW)

2.5.1. DICOM to BIDS and Image Preprocessing Software (EO)

The fMRI data used in the present study was organised according to the Brain Imaging Data Structure (BIDS) with the aim of making the current research project as accessible as possible, in accordance with the FAIR data principles (Findable, Accessible, Interoperable, and Re-usable). BIDS is an emerging community-driven standard for organising, annotating, and describing data collected during neuroimaging experiments. It is based on a formalised folder structure and JSON based metadata files with controlled vocabulary. This organisation of research data in a standardised way is aimed at increasing data sharing and usage and to facilitate reproducibility studies (Gorgolewski et al., 2016). In the present study, BIDScoin (v3.7.3) was used to convert source-level neuroimaging from DICOM format to nifty/json/tsv data-sets organised according to the BIDS standard. BIDScoin is a flexible open-source Python framework developed at the Donders Institute for Cognitive Neuroimaging at the Radboud University (Zwiers et al., 2022). All anatomical and functional images were preprocessed using the Nipype-based pipeline fMRIPrep (v22.0.2; Esteban et al., 2019) implemented in Python (v3.8.8; Van Rossum & Drake, 2009). A full boiler text containing in-depth explanations of all pre-processing steps automatically outputted by fMRIPrep can be found in Appendix 4.

2.5.1. Anatomical MR Data Preprocessing (SW)

The BIDS dataset contained one T1-weighted (T1w) image for each subject. T1w images were corrected for voxel intensity non-uniformity and used as T1w-reference throughout the subsequent preprocessing pipeline. For each subject, the T1w-reference was skull stripped and tissue segmentation of cerebrospinal fluid (CSF), white-matter (WM), and gray matter (GM) was performed on the brain-extracted T1w.

All T1w images were spatially normalised to the MNI (Montreal Neurological Institute) template, *MNI152NLin2009cAsym* (Fonov et al., 2009, 2011).

2.5.2. Functional MR Data Preprocessing (EO)

First, a reference volume and its skull stripped version was generated using a custom methodology of fMRIPrep. Then, head-motion parameters were estimated and BOLD runs were slice-time corrected to 0.625s (0.5 of slice acquisition range 0s-1.25s). The BOLD time-series were resampled into standard space generating a preprocessed BOLD run in MNI152NLin2009cAsym space and co-registered to a T1w reference using a boundary-based registration cost-function. Confounding time-series were calculated based on the preprocessed BOLD data, including framewise displacement (FD) and DVARS. The confound time series derived from head motion estimates and global signals were expanded with the inclusion of temporal derivatives and quadratic terms. Frames that exceeded a threshold of 0.5 mm FD or 1.5 standardised DVARS were annotated as motion outliers, and additional nuisance time-series were calculated using principal components analysis.

2.6. Analysis of Functional Imaging Data (EO)

Statistical whole-brain analysis of the fMRI data was based on the mass univariate general linear model (GLM) framework (Friston et al., 1994). We used the two-step GLM procedure (Worsley & Friston, 1995) implemented in Python using Nilearn, a Python package for flexible statistical analysis of neuroimaging data leveraging the scikit-learn Python toolbox for multivariate statistics (v0.9.2; Abraham et al., 2014). The GLM framework covers a broad class of models assuming that for each voxel i , a set of p regressors β_i (regressors of interest and nuisance regressors) is fitted against the voxel activation time course (i.e., BOLD response) Y_i over n time points, using an $n \times p$ design matrix X :

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_{1,1} & x_{1,2} & \dots & x_{1,p} \\ 1 & x_{2,1} & x_{2,2} & \dots & x_{2,p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n,1} & x_{n,2} & \dots & x_{n,p} \end{bmatrix} \times \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

Depiction of the GLM for a voxel with time-series Y predicted by a design matrix X including regressors of interest and nuisance regressors. Calculated weight factors corresponding to each regressor are placed in amplitude vector β while column vector e constraints calculated error terms (e_i) for the model corresponding to each time point i .

2.6.1. First Level Analysis (EO, SW)

2.6.1.1. Defining the First Level Model (SW)

The first step in our analysis was to specify a set of regressors, i.e., variables we wish to include in our model to explain our observed data. In addition to regressors modelling the experimental conditions of interest (i.e., the different regressors directly related to the research questions, each of which are time series representing the expected changes in neuronal activity associated with the corresponding condition), we also included nuisance regressors. As previously mentioned, various types of noise are embedded in the recorded fMRI data and the measured BOLD signal thus reflects a combination of fluctuations of both neuronal and non-neuronal origin. When dealing with fMRI data, the term nuisance regressors or confounds refers to variables that represent fluctuations with a potential non-neuronal origin (Esteban et al., 2019). These nuisance regressors are confounds to our data that we need to account for in our statistical model to avoid spurious results and minimise the risk of reporting false positives caused by physiological effects rather than neurological causes. Therefore, the removal of nuisance signals is a crucial step for carrying out statistical analysis of fMRI data.

2.6.1.1.1. Nuisance regression (EO)

There are various methods for filtering out noise from fMRI data to increase the signal-to-noise ratio ranging from principal component analysis (PCA) to various ways of conducting nuisance regression. By regressing confounding effects of non-neuronal signals out from the fMRI data or including them as nuisance regressors in the design matrix of the GLM, it is possible to minimise their confounding effects (Esteban et al., 2019). This process is known as *denoising* and is a widely applied method for dealing with confounds in fMRI data. Nonetheless, the choice of denoising strategy and which confounds to use in the analysis of fMRI data is a source of large debate in the neuroimaging community.

The current study employs a nuisance regression approach (Lund et al., 2006) based on the large array of confounding variables that are automatically calculated by the fMRIprep pipeline and stored in subject and run specific tabular files. Inspired by the Yeo 2011 pre-processing schema, the current paper includes the following confounding variables often used in analyses of neuroimaging data: the six standard rigid-body motion parameters (Friston et al., 1998, Lund et al., 2006), *csf*, and *white_matter*. The six rigid-body motion parameters, also known as the estimated head-motion parameters, are comprised by three translations (*trans_x*, *trans_y*, and *trans_z*) and three rotations (*rot_x*, *rot_y*, *rot_z*) estimated relative to a reference image. These nuisance regressors are also the common output of realignment (i.e., head-motion correction) of often used fMRI preprocessing software such as SPM or FSL (Esteban et al., 2019). These head motion regressors represent the motion in the x-, y-, and z-directions recorded

at each time point. The confound *csf* represents the average signal within anatomically derived eroded CSF images (Esteban et al., 2019). The confound *white_matter* represents the average signal within the anatomically derived eroded WM mask.

As opposed to Yeo and colleagues (2011), the *global_signal* confound was not included in the current analysis. The global signal represents the average signal across voxels in the brain and is thus a measure of the overall activity of the brain that can be highly variable across different scans and subjects. The relevance of global signal for various analyses purposes is highly debated, as it is less specific to individual brain regions and is more sensitive to differences in scanning parameters and subject characteristics (Liu et al., 2017). Global signal regression may remove important information about the overall brain activity during the task, potentially leading to inaccurate or misleading results, particularly if the global signal is correlated with the task conditions. Additionally, regressing out the global signal may decrease the statistical power of the study, making it more difficult to detect differences in brain activity between the two task conditions. This motivated our choice of not including *global_signal* as a confound in our analysis. CSF and white matter signals are often highly correlated with specific brain regions and can therefore cause spurious correlations in fMRI data if they are not properly accounted for. Additionally, CSF and white matter signals are typically considered more stable and consistent across different scans and subjects, making them more reliable confounds to include in fMRI preprocessing. Overall, including CSF and white matter confounds in fMRI preprocessing can help improve the reliability and interpretability of the resulting data. We constructed our first level model using the AR1 temporal variance model to account for temporal autocorrelations in the fMRI data.

2.6.1.2 Fitting First Level Model (SW)

For each subject, two separate first level analyses were conducted, analysis 1 (A1) and analysis 2 (A2), to investigate hypothesis 1 (H1) and hypothesis 2 (H2), respectively. After having specified the linear first level model, we fitted it for each of the 29 subjects using a cosine drift model for the design matrices.

The model was fitted to the data in an event-related design with the signal time-locked to the onset of stimuli. The haemodynamic response was modelled using a stick function convolved with the canonical haemodynamic response function (HRF), accounting for the delay in the haemodynamic response. The use of a stick function allowed for the creation of separate HRF-convolved regressors used to model each condition in A1 (word/fixation cross) and A2 (emotional/neutral), respectively.

A high-pass filter with a cut-off frequency of 0.01 Hz was used to remove low-frequency noise related to heart rate, breathing, and slow drifts in the fMRI signal, before being used in a multiple regression

analysis. We then proceeded to compute contrasts between the regressors of interest for each of the analyses. In the context of fMRI analysis, a contrast is the basic principle of the subtraction method for controlling for potential experimental confounds and refers to the difference in the measured neuronal activity between conditions of interest (Sternberg et al., 2012, ch. 2).

The subtraction method is based on the assumptions a) that measured brain activity during a particular condition can be separated into two components: a common component shared with other components and a unique component specific to that condition and b) that the unique component can be found by subtracting the common component from the measured activity in both conditions. Because BOLD fMRI is a relative and not absolute measure of brain activity, the subtraction method is a key aspect of experimental design (Goldstein & Hooff, 2018, ch. 2).

To assess the neuronal activity related to visual processing of a word rather than a fixation cross, A1 contained modelling onsets for the two types of trials (word/fixation cross) and computing within-subject first level contrasts between these (word > fixation cross). To assess the effects of emotional nouns compared to neutral nouns, A2 modelled onsets for the two conditions in trials where nouns were presented (emotional/neutral) and computed within-subject first level contrasts between these (emotional > neutral).

In both cases, contrasts were outputted as a z-score to allow for group-level statistical analysis. The uncorrected contrast images (z-maps) for three subjects are plotted in Fig. 1, with a threshold of $p < 0.001$ (Bonferroni corrected) in Fig. 1A (A1) and with a $p < 0.01$ (FDR corrected) in Fig. 1B (A2). Contrast images for all subjects can be found in Appendix 5. Fig. 1 below presents within-subject first level contrasts for three arbitrary subjects and demonstrates the between-subject variability in the first level contrast images before they are analysed at the group level. Visual inspection of the contrast images did not reveal any obvious issues that would necessitate the exclusion of any of the subjects from the study. This suggests that the brain activity was relatively consistent across subjects. Design matrices and contrasts used in A1 and A2 can be found in Appendix 6.

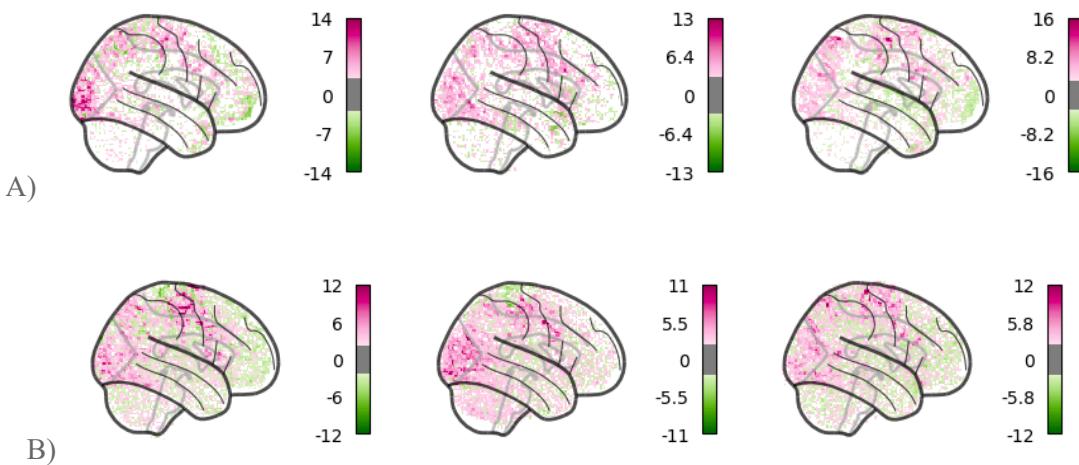


Fig. 1: Within-subject First Level Contrast Images for Three Individual subjects from Each Analysis
A) the contrast images for A1 (word > fixation cross). B) the contrast images for A2 (emotional > neutral). All images are uncorrected with a p-value of 0.001.

2.6.2. Second Level Analysis (EO)

A second level analysis was performed as a part of both A1 and A2. Spatial smoothing was done by applying a Gaussian smoothing kernel with a full-width at half-maximum of 8.0 mm to the data. Applying a Gaussian smoothing kernel implies replacing each data point by a weighted average of itself and its surrounding points, ultimately smoothing the data by reducing the impact of the individual data points and instead emphasising the overall patterns and trends in the data. This is another step taken in reducing the effects of noise and other sources of variability in the data with the aim of increasing the signal-to-noise ratio (Poldrack et al., 2011, ch. 3).

The second level model was fitted using the first level model objects as we were interested in an intercept-only group-level model, i.e., the average of a particular first-level contrast across subjects for each of our two first level analyses. Using the fitted second-level model, we computed the average group-level contrast using a one-sample t-test. When conducting mass univariate analysis to generate group-level contrast maps for fMRI data, there is an increased probability of false positives due to the high number of statistical tests being performed simultaneously. This is a common issue with high-dimensional data often referred to as *the problem of multiple comparison* (Poldrack et al., 2008). The term family-wise error rate (FWER) refers to the probability of making at least one false positive error in a set of statistical tests, and researchers must apply appropriate methods to control the FWER in fMRI analysis (Bender & Lange, 2001). For each of our analyses, the resulting z-map from our computed contrast (i.e., the performed one-sample t-test), was thresholded in order to perform statistical testing of our second-level analysis. Thresholding is a common step in fMRI data analysis that helps to identify

regions of the brain that are significantly active during the experimental condition. By setting a statistical significance level, we can exclude voxels that are likely to represent noise or random fluctuations in the data and focus on the voxels that are most likely to represent true brain activity.

For our first analysis (A1), whole-brain analysis was performed using a voxel-wise significance threshold set to $p < 0.001$ (Bonferroni corrected for multiple comparisons). Although Bonferroni correction may be overly conservative in the case of analyses of data from complex experimental design (Hollander et al., 2014), a conservative estimate of first statistical analysis is preferable since this analysis serves as a low-level quality check where genuine statistically significant difference is required to form the basis of the subsequent analysis (A2). In A2, whole-brain analysis was performed using a voxel-wise significance threshold set to $p < 0.01$ (FDR corrected for multiple comparisons). FDR was used as a correction method in this analysis for various reasons. FDR is more appropriate for handling complex designs, more lenient, allows for a larger degree of flexibility in the analysis, and performs more powerfully with smaller sample sizes (Poldrack et al., 2011, ch. 7). We used AtlasReader, a software tool for analysing and visualising fMRI data, to compute clusters in our fMRI data (v0.1.2; Notter et al., 2019). AtlasReader allows users to specify a range of parameters used as the basis of cluster formation. This includes a cluster extend parameter, which determines the minimum number of contiguous voxels needed to form a cluster. In both A1 and A2 we used a cluster extend parameter of 50 voxels. Furthermore, we used the Talairach atlas (Lancaster et al., 2000) as well as the Anatomical Automatic Labelling (AAL) (Collins & Korecki, 2022) atlas to associate cluster coordinates with labels of brain regions in both analyses.

2.6.3. Permutation Testing (SW)

For each of the analyses (A1 & A2), non-parametric permutation testing was done to assess the statistical significance of the results. In permutation testing, the data is randomly shuffled, and the analysis is repeated many times to create a null distribution of the statistic of interest (Poldrack et al., 2011, ch. 7). This null distribution is then used to evaluate the observed statistic and to determine the probability that it would have occurred by chance. In the current context, the permutation testing involved generating a null-distribution of cluster sizes and comparing these to the observed clusters. We used the negative log of the p-value, a common way of transforming the p-value to make it easier to interpret and compare with other measures, as it puts the p-value on a scale that ranges from 0 to infinity, with larger values indicating stronger evidence against the null hypothesis (Poldrack et al., 2011, ch. 7). We will use a negative $\log_{10} p$ threshold of 1, which corresponds to $p < 0.05$. This threshold indicates that there is less than 5% probability to make a single false discovery (95% chance that we make no false discovery at all). We will also cap the negative $\log_{10} p$ -values at 4, because this is the maximum observable value for the nonparametric tests, which were run with 10.000 permutations.

3. Results (EO, SW)

3.1. A1 - Word vs. Fixation Cross (EO)

Several brain regions were significantly activated for the contrast words > fixation cross. A total of 10 clusters of increased activation was found (see Table 1 for comprehensive overview of all 10 clusters and Fig. 2 for a visualisation of the clusters). The largest clusters were found in brain regions including the left postcentral gyrus, the left inferior parietal lobe, as well the occipital lobe in both hemispheres. These regions include the primary somatosensory cortex as well as striate and extrastriate cortex. All 10 clusters are visualised separately and can be found in Appendix 7.

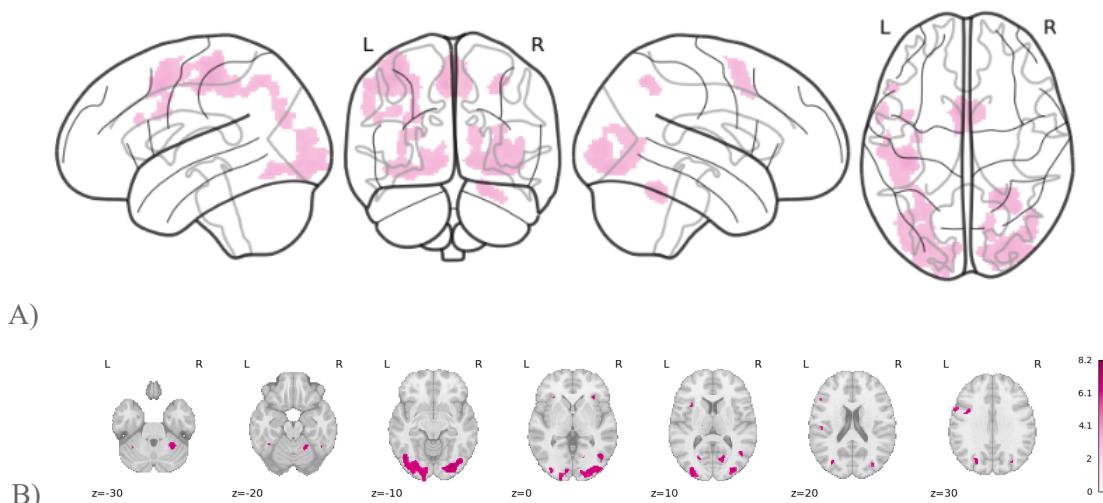


Fig 2: Cluster Visualisation (A1)

A) All 10 clusters visualised on a glass brain (Bonferroni corrected for FWER, $\alpha=0.001$). The cluster extent parameter was determined to 50. Visual inspection of the plot revealed clusters located primarily in the parietal and occipital lobes.
B) Group-level thresholded image (z -score ranging from 0-8.2) showing enhanced activation in the occipital lobe.

The results of the permutation test (see Fig. 3) showed that there was a significant difference in neuronal activity between words and fixation cross in areas including the occipital and parietal lobe. The negative log p-values are visualised. A p-value larger than 1 indicates significance.

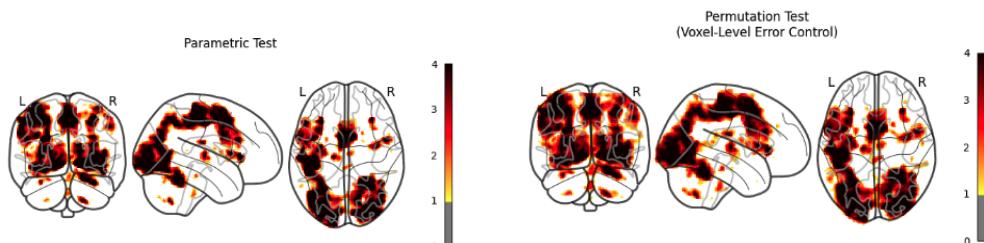


Fig 3: Permutation Test (A1)

Result of voxel-wise permutation test for the contrast: word > fixation cross. Significant activation ($p < 0.05$) after correction for multiple comparisons.

ID	H	Peak X, Y, Z, (MNI)	Peak Value	Peak (AAL2)	Cluster Size (mm)	Clu- ster Mean	Cluster Location (AAL2)	Cluster Location (talairach_ba)
1	L	-37.562, -25.340, 54.7	8.19	Postcentral	12183.7	6.440 45	42.70% Postcentral 22.86% Parietal_Inf 13.76% Precentral 10.37% Occipital_Mid 6.13% Parietal_Sup	60.23% BG; 10.46% BA 40; 7.59% BA 3; 5.66% BA 2
2	R	28.520, -84.278, -10.1	7.82	Fusiform	9640.2	6.451 89	28.83% Occipital_Inf 26.38% Occipital_Mid; 13.22% Lingual; 10.72% Calcarine; 9.83% Temporal_Mid; 6.08% Fusiform	64.74% BG; 21.20% BA 18; 8.52% BA 19
3	L	-26.846, -84.278, -11.9	7.35	Occipital_Inf	8928.24	6.335 95	31.13% Occipital_Inf; 29.58% Occipital_Mid; 13.57% Calcarine; 11.45% Lingual; 9.52% Fusiform	61.93% BG; 23.79% BA 18; 6.88% BA 17; 6.75% BA 19
4	L	-5.414, 8.594, 47.5	8.10	Supp_Motor_Area	5471.78	6.456 73	61.18% Supp_Motor_Area; 26.86% Supp_Motor_Area; 6.82% Cingulate_Mid	48.06% BG; 36.10% BA 6; 11.54% BA 32
5	R	21.376, -50.344, -24.5	7.72	Cerebellum	1940.67	6.529 43	68.93% Cerebellum_6; 31.07% Cerebellum_4_5	79.29% BG; 20.71% Dentate
6	R	16.018, -69.990, 7.9	6.69	Calcarine	1297.61	6.187 37	91.15% Calcarine; 7.52% Lingual	59.29% BG; 11.50% BA 23; 11.06% BA 18; 9.29% BA 17; 5.75% BA 30
7	R	33.878, -59.274, 51.1	7.36	Angular	1136.84	6.400 40	31.31% Angular; 28.79% Parietal_Inf; 20.71% noabel; 19.19% Parietal_Sup	65.66% BG; 33.84% BA 7
8	L	-60.780, 3.236, 40.3	6.81	No label	832.537	6.140 99	88.28% Precentral; 6.90% Frontal_Inf_Oper	55.17% BG; 27.59% BA 6; 17.24% BA 9
9	L	-37.562, 5.022, 29.5	6.49	Precentral	390.431	6.124 14	54.41% Precentral; 45.59% Frontal_Inf_Oper	77.94% BG; 13.24% BA 9; 8.82% BA 6
10	L	-50.064, 22.882, 25.9	6.74	Frontal_Inf_Tri	315.79	6.218 95	100.00% Frontal_Inf_Tri	60.00% BG; 27.27% BA 46; 7.27% BA 45; 5.45% BA 9

Table 1: Comprehensive Overview of Clusters (A1)

Regions showing significant BOLD signal change to words compared to fixation cross. ID: Significant cluster ID (with correction) ordered by cluster size in descending order; H (hemisphere): L=left, R=right; Peak X, Y, Z (MNI): Peak location in MNI stereotactic space coordinates; Peak Value: Activation value of peak; Peak (AAL2) anatomical label of peak location (Collins & Korecki, 2022); Cluster size is in mm.; Cluster Mean: Mean activation across the cluster; Cluster Location (AAL2): Anatomical labels of the areas covered by the cluster (Collins & Korecki, 2022); Cluster Location (talairach_ba): When identifiable, Brodmann areas (BA) were reported along with the cortical region, background label is denoted BG (Lancaster et al., 2000).

3.2. A2 - Emotional vs. Neutral (SW)

Several brain regions were significantly activated for the contrast emotional > neutral. A total of 6 clusters of increased activation was found (see Table 2 for comprehensive overview of all 10 clusters and Fig. 4 for a visualisation of the clusters). The largest clusters were found in brain regions including the supplementary motor area (SMA) as well as the superior occipital lobe and superior parietal lobe, both in the right hemisphere. All 6 clusters are visualised separately and can be found in Appendix 8.

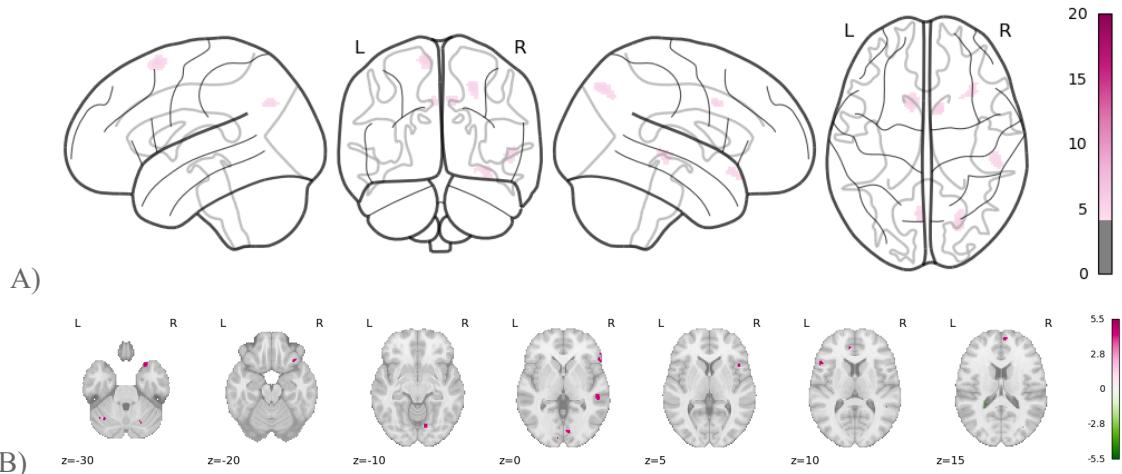


Fig 4: Cluster Visualisation (A2)

A) All 6 clusters visualised on a glass brain (FDR corrected for FWER, $\alpha=0.01$). The cluster extent parameter was determined to 50. B) Group-level thresholded image (z -score ranging from -5.5-5.5).

The results of the permutation test (see Fig. 5) showed that there was a significant difference in neuronal activity between emotional words and neutral words in areas including the parietal as well as the occipital lobe. The negative log p-values are visualised. A p-value larger than 1 indicates significance.

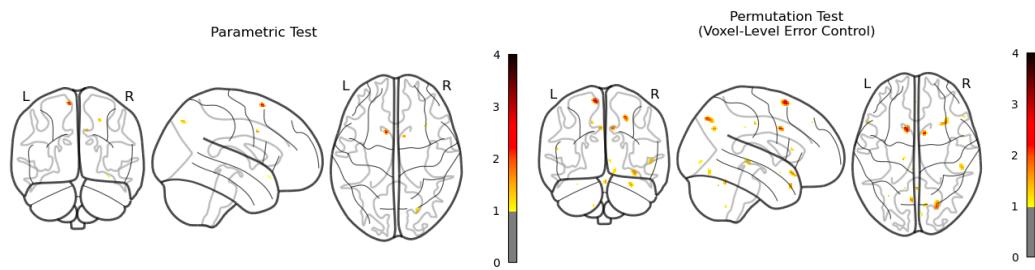


Fig 5: Permutation Test (A2)

Results of voxel-wise permutation test for the contrast: emotional > neutral. Significant activation ($p < 0.05$) after correction for multiple comparisons.

ID	H	Peak X, Y, Z (MNI)	Peak Value	Peak Location (AAL2)	Cluster Size (mm)	Cluster Mean	Cluster Location (AAL_2)	Brodmann Peak
1	L	-8.986, 12.166, 65.5	5.55	Supp_Motor_Area	757.895	4.61024	96.97% Supp_Motor_Area	59.85% BG; 40.15% BA 6
2	R	23.162, -75.348, 47.5	5.18	Parietal_Su	648.804	4.55505	60.18% Occipital_Sup 37.17% Parietal_Sup	55.75% BG; 43.36% BA 7
3	R	51.738, -30.698, -1.1	4.88	Temporal_Mid	533.972	4.44386	52.69% Temporal_Sup; 46.24% Temporal_Mid	83.87% BG; 12.90% BA 21
4	R	32.092, 1 9.310, -13.7	4.99	Insula	390.431	4.49624	60.29% Insula; 27.94% OFCpost; 7.35% no_label	95.59% BG
5	L	-5.414, -66.418, 34.9	4.99	Precuneus	321.531	4.43753	98.21% Precuneus	57.14% BA 7; 42.86% BG
6	R	10.660, 6.808, 34.9	5.24	Cingulate_Mid	298.56	4.58604	96.15% Cingulate_Mid_	36.54% BA 24; 34.62% BG; 28.

Table 2: Comprehensive Overview of Clusters (A2)

Regions showing significant BOLD signal change to words compared to fixation cross. ID: Significant cluster ID (with correction) ordered by cluster size in descending order; H (hemisphere): L=left, R=right; Peak X, Y, Z (MNI): Peak location in MNI stereotactic space coordinates; Peak Value: Activation value of peak; Peak (AAL2) anatomical label of peak location (Collins & Korecki, 2022); Cluster size is in mm.; Cluster Mean: Mean activation across the cluster; Cluster Location (ALL2): Anatomical labels of the areas covered by the cluster (Collins & Korecki, 2022); Cluster Location (talairach_ba): When identifiable, Brodmann areas (BA) were reported along with the cortical region, background label is denoted BG (Lancaster et al., 2000).

4. Discussion (EO, SW)

4.1. Summarise findings (EO)

Studies within the field of affective neuroscience have pointed towards the extrastriate cortex as a brain region particularly involved in the visual processing of words as well as their lexical and semantic aspects, including emotional connotations. The study used fMRI to measure BOLD response in subjects as they were presented a series of nouns characterised as either emotional or neutral in a demonstrative choice task. Building upon findings of neuroscientific studies investigating processing of visually presented emotional words, the aim of the current study was to two-fold. First, we conducted a simple analysis (A1) to confirm the hypothesised difference in visual cortex activation when subjects were presented with a word versus a fixation cross (H1). A total of 10 clusters of increased significant activation was found. In line with H1, the majority the clusters were located within the occipital lobe in areas covering parts of the visual system involved in extraction of low-level visual features as well as semantic information. Previous research findings indicate that the extrastriate cortex is involved in visual processing and particularly sensitive to the emotional content of words. Therefore, the second analysis (A2) and the main purpose of this study was to investigate the hypothesis that contrasting emotional and neutral words would show enhanced activity in the extrastriate cortex (H2). Results of A2 provided no support for H2 as no clusters of significant enhanced activation was found in the extrastriate cortex when contrasting emotional nouns to neutral nouns.

4.2. Methodological Limitations (EO)

One of the major methodological limitations of fMRI is its previously mentioned sensitivity to movement. Even very small physiological variations such as pulsation, respiration, or head movements introduce noise into the BOLD signal. More specifically, studies have found evidence that even small motion of 0.1 mm can systematically bias within- as well as between-group effects in the analysis of fMRI data (Power et al., 2012; Satterthwaite et al., 2013; Van Dijk et al., 2012). In order to compensate for this and improve the signal-to-noise ratio (SNR), fMRI studies are required to employ experimental paradigms with many repeated trials to acquire a sufficiently large amount of data to accurately assess brain activity. fMRI studies are therefore often long and tiresome for the subject. A long scanning time is likely to affect task performance as well as image quality, as it may result in the subject falling asleep or experiencing discomfort, resulting in movements. This emphasises the importance of carefully designing the experimental paradigm to maximise the amount of information that can be obtained from each scan, as well as selecting subjects who are able to remain comfortable and still for the duration of the experiment. However, even if the experimental paradigm employed in an fMRI study is carefully

designed to account for the above-mentioned, variance in the recorded fMRI signal will inevitably reflect several physiological influences apart from activity-coupled haemodynamic change. One must therefore be extremely careful when interpreting findings based on fMRI data, as several potential sources of error and bias may affect the reliability of the findings. For example, the relationship between brain activity and behaviour is complex, and different brain regions can be involved in a single cognitive process. Additionally, the statistical methods used to analyse fMRI data can be complex and affect the results. Moreover, fMRI data represents neuronal activity from a very large number of neurons, meaning that the same change in the fMRI signal could have been caused by small changes in the firing rates in a large subpopulation of neurons or large changes in the firing rates in a small subpopulation of neurons (Heeger & Ress, 2002; Scannell & Young, 1999).

4.3. A1 (word > fixation cross) (SW)

10 significant clusters of enhanced activity in the visual cortex in response to words as compared to fixations cross was found, providing support for H1. This finding is consistent with previous research which has shown that the visual cortex is involved in the perception and identification of visual stimuli, including words. Enhanced activity in the primary visual cortex suggests that subjects are in fact registering low-level visual features such as shape, colour, size etc. (Bear et al., 2016, ch. 10). We also found enhanced activity in the superior parietal lobe which is a part of the surrounding structures of the visual cortex located just above the occipital lobe, and also suggested to interact with the visual system (Johns, 2014). The majority of the two largest clusters were located within the occipital lobe, more specifically covering Brodmann Area 18 and 19. These areas are constituting the extrastriate cortex and as mentioned previously, it is an area particularly sensitive to word's lexical and semantic aspects. This finding may indicate that not only did the subjects register low-level visual features but they also interpreted the words and extracted their meaning. While this result is simple and hardly controversial, it is not superfluous knowledge as it serves as an important quality check for the subsequent analysis (A2) that assumes the processing and interpretation of the presented words. The enhanced activity in the visual area of the brain may also be partly attributable to attentional effects of subjects directing their attention towards the words they were explicitly told to evaluate. As explained in section 1.3, directing one's attention to a task-relevant stimulus is suggested to increase the activity within the sensory area responsible for the representation of that stimuli, i.e., directing your attention to a stimulus presented to a visual modality would result in increased activity in areas involved in visual processing.

4.4. A2 (emotional > neutral) (EO)

Contrary to what was hypothesised in H2, we found no clusters of enhanced activity in the extrastriate cortex in response to emotional words. 6 clusters of significant enhanced activation were found, none

of which were included in our hypothesis. The majority of the largest cluster was located in the supplementary motor area (SMA), a brain region associated with planning and control of voluntary movements (Bear et al., 2016, ch. 12-14) and the majority of the second largest cluster is located in the occipitoparietal region, Brodmann area 7 (BA7), a brain region associated with visuo-spatial coordination (Strotzer, 2009).

4.4.1 Discussion of Significant Clusters of Activation (A2) (SW)

The largest cluster found when comparing emotional to neutral stimuli was located in the left supplementary motor area (SMA). The SMA is a region of the brain that is involved in the planning and control of voluntary movements (Bear et al., 2016, ch. 12-14). It is located in the medial frontal lobe of the cerebral cortex, just in front of the primary motor cortex. The SMA is thought to play a key role in the coordination of complex movements, such as those involved in speaking or writing. It is also believed to be involved in the control of movements that require attention and intention, such as reaching for an object or making a conscious decision to move (Bear et al., 2016, ch. 12-14).

Enhanced activation in SMA in response to emotional words was not hypothesised. Nonetheless, it has been suggested that emotional processing can mobilise the body for action and that emotions can influence and interact with motor planning via this neural system (Rodigari & Oliveri, 2014). The idea that the SMA, specifically, may be sensitive to a word's emotional content is supported by evidence suggesting anatomical and functional connections between the limbic system and motor and premotor areas through prefrontal and cingulate cortical regions. The connection between emotion and action is thought to involve the amygdala, anterior cingulate cortex, and SMA, which are all part of the limbic system (Mogenson, Jones, & Yim, 1980). Further research is needed to formulate appropriate hypotheses regarding the relationship between emotional processing and the SMA.

The second largest cluster of significant increased activity is located in an area covering Brodmann Area 7 (Table 2). Anatomically, it includes the superior parietal lobule laterally and the precuneus medially and is predominantly involved in visuospatial processing, and episodic memory retrieval (Strotzer, 2009). Studies suggest that the precuneus plays a crucial role in self-processing tasks, possibly through the involvement of mental imagery strategies, as suggested by consistent anterior precuneus activation patterns (Cavanna & Trimble, 2006). A study by Ochsner and colleagues (2004) investigated emotional reflections. They found brain regions commonly activated by attribution of emotions to the self and others in the left precuneus, posterior cingulate, and prefrontal cortex (Ochsner et al., 2004).

While the literature does seem to suggest a potential link between emotional content and increased activation in these brain regions, explicit hypotheses on the relationship on a neural level are necessary for any conclusions to be drawn and are beyond the scope of this paper. However, given that the motor

cortex is involved in controlling movement, it is possible that the enhanced activity in the SMA observed in the emotional trials could be related to differences in behavioural measures such as slower response times in neutral trials. For example, if the enhanced activation in the SMA is associated with faster response times, this could suggest that this brain region plays a role in facilitating rapid responses during emotional trials. To better understand how the brain activity in the SMA potentially relates to behaviour during the scan, a simple Bayesian GLM was used to conduct an exploratory statistical analysis of the response time measurements. All trials in which no response was given were filtered out. The model was then fitted using the *brm()* function from the *brms* package (Bürkner, 2017) implemented using R Statistical Software (v4.0.3; R Core Team, 2020) in the RStudio software environment (v.2022.7.2.576; RStudio Team, 2022). The model predicted the response variable, *response time*, as a linear function of the categorical predictor variable, *trial type*, with an intercept and a slope coefficient. We used weakly informative priors (student_t, location = 1.6, scale = 2.5) for our model estimates and the model was estimated using MCMC sampling with 4 chains of 2000 iterations and a warmup of 1000. The MCMC algorithm is used to estimate the posterior distribution of the model parameters and the posterior predictive distribution of the response time. To assess quality of the model, prior and posterior predictive checks were performed. Additionally, model convergence was validated by visual inspection of trace plots and ranked Markov chains. R-hat and effective sample size (ESS) were inspected to assess convergence of the Bayesian sampling. R-hat = 1.001 (should be below 1.01 (Vehtari et al., 2021) and ESS = 3631, indicating that the estimation successfully converged. Nonetheless, the model's explanatory power is very weak ($R^2 = 3.65e-05$, 95% CI [4.95e-11,3.22e-04]) and the posterior mean estimate of the slope did not indicate any credible difference between response time in the two trial types, ($\beta = -0.03$ 95% CIs -0.03, 0.04). The results of this exploratory analysis did not provide any compelling evidence that the enhanced activity in the SMA observed in the emotional trials could be related to differences in the behavioural measure, response time.

4.4.2. Study Limitations (EO)

There are several confounding factors that might have resulted in our failure to confirm our second hypothesis (H2), some related to the choices made to simplify complex phenomena such as emotions and emotional processing. The following sections elaborates on potential sources of error and study limitations such as the binary sentiment classification procedure, linguistic features, and limitations of analytical choices.

The way in which the nouns were characterised as neutral or emotional forms the basis of our whole main analysis (A2). Therefore, the employed sentiment classification method is assumed to be important in explaining why no enhanced activation was found in the extrastriate cortex in response to emotional words. Classifying words in a binary fashion is a process of simplifying something complex and inher-

ently subjective into something binary that may not fully reflect all the semantic properties of the presented nouns. The characterisation of words as neutral or emotional may not accurately reflect the average way in which subjects perceive their emotional or semantic content. Individual differences in emotion word processing in healthy populations are expected and may be mediated by factors such as gender differences, emotional state, and trait variables such as motivation, mood, and personality traits or other covariates not accounted for in the analysis (Citron, 2012). As argued by Citron (2012), studies investigating emotional processing would benefit from obtaining ratings for the words employed by each subject taking part in the study, as this would allow for a better control of individual variability in the perception of specific words. If the study had to be re-done, researchers could consider implementing this as a manipulation check upon which the analysis could be conducted. That being said, the valence and arousal ratings were derived from the XANEW lexicon that has been widely applied in research on emotions. There is, however, no best-practice procedure of combining valence and arousal into a binary emotional classification. A different method could have been employed, considering research indicating that valence and arousal may interact (Citron, 2011).

There are two main reasons why we used a binary emotional/neutral classification rather than investigating interactions between different continuous ratings of arousal and valence. First, the question of how valence and arousal interact needs further investigation in order to build a strong hypothesis (Citron, 2012). Secondly, such an analysis would require a wider spread in terms of continuous valence and arousal ratings than what was present in the stimuli used in the present study.

Another potential source of error in our stimuli is the imbalance in the number of trials in the emotional and neutral conditions that consisted of 39 and 254 trials, respectively. This imbalance may lead to biased results with a better estimate of the neutral condition compared to the emotional condition, as estimations typically improve with an increase in the number of trials. Despite acknowledging that emotions are inherently subjective, studying a large group of subjects allows researchers to look at the averaged responses across the whole group of subjects. One potential limitation of the current study is the relatively small sample size of 29 subjects. Future replications of the study would benefit greatly from using a larger sample size to evaluate the findings more conclusively.

A general risk in fMRI studies is that enhanced activation observed in one or several brain regions might be caused by different levels of noise across regions, ultimately influencing the accuracy of the results. Higher levels of noise increase the likelihood of preventing an effect that actually exists to reach a statistical threshold, also known as type II errors (Hollander et al., 2014). FMRI studies with a small sample size are particularly prone to these error types as they are often underpowered.

Another way to improve the analysis would be to consider other linguistic features such as word length, the number of syllables in a word, or the presence or absence of certain sounds or phonemes in a word (Citron, 2012). Age of acquisition, referring to the age of which a word is typically learned (Hernandez and Li, 2007), may also be a factor impacting the results and could be considered in future analyses.

In the present paper, the canonical haemodynamic response function (HRF) was implemented in our statistical analyses. This HRF model is widely used because its parameters are based on the BOLD response observed in most empirical studies (Jahn et al., 2022). However, some brain regions or tasks may have atypical HRF properties which can lead to mismatches between the assumed HRF model and the actual data, resulting in mis-estimation of the model parameters (Cignetti et al., 2016). To address this issue, researchers have included temporal derivatives of the HRF function to accommodate variations in the haemodynamic response. Studies using visuo-motor tasks have shown that the haemodynamic response may be faster in visual areas and peaks a few milliseconds later in motor-related areas (Mohamed et al., 2003; Handwerker et al., 2004). However, it should be noted that including temporal derivatives increases the complexity of the HRF model, making it more difficult to interpret whilst not guaranteeing improved accuracy.

5. Conclusion (EO, SW)

This fMRI study aimed at investigating the neural correlates of emotional processing, focusing more specifically on the effect of emotional modulation. This was investigated by conducting a two-fold analysis. Results from the first analysis (A1) provide support for our first hypothesis (H1), namely that reading words as compared to viewing a fixation cross will enhance activation in areas covering the visual cortex. We found a total of 10 clusters of significant increased activation covering the post-central gyrus but with the majority of the clusters located within the occipital lobe. These areas cover parts of the visual system involved in extraction of low-level visual features as well as semantic information. Thus, these results may indicate that subjects both read and processed the words presented. The reviewed literature suggested that emotional content should affect the neural response in the extrastriate cortex. However, results from our second and main analysis (A2) provided no support for our second hypothesis (H2) as no enhanced activation was found in the extrastriate cortex when contrasting emotional nouns to neutral nouns. A potential cause of this finding could be related to the sentiment classification procedure that might have been too simplified to capture the nuanced and subjective aspect of emotionality. Additional measures could have been employed to improve the results including having a better balance of the number of emotional and neutral trials as well as including more linguistic features in the model. The second analysis revealed clusters of significant activation in areas suggested to be involved in planning and control of movement as well as areas suggested to play a crucial role in self-processing tasks. As activation in these areas were not hypothesised, inference

based on these results are out of the scope of this paper and is up for future research. In summary, our findings provide valuable insights into the processing of emotional words and shed light on aspects of emotional modulation.

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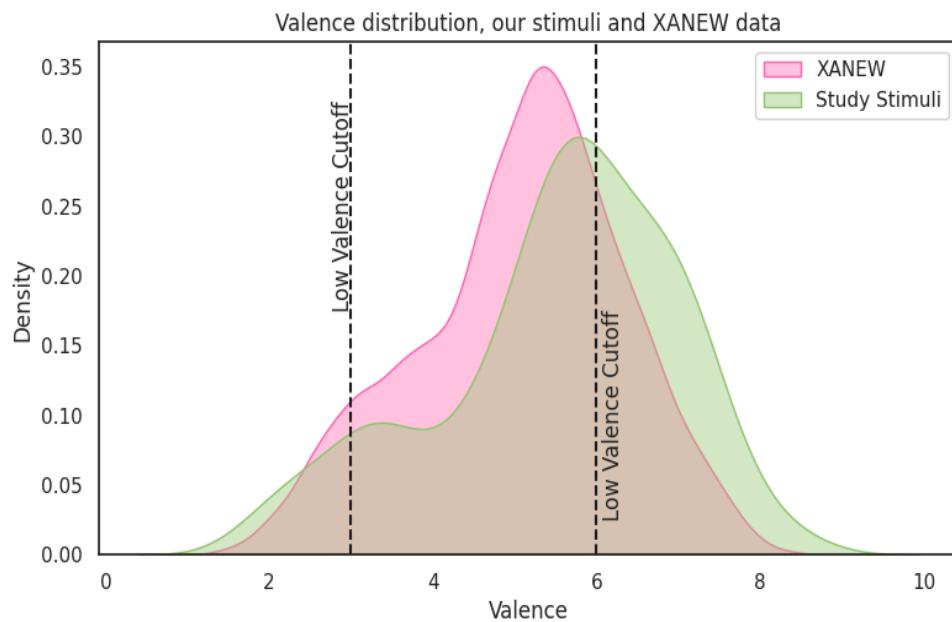
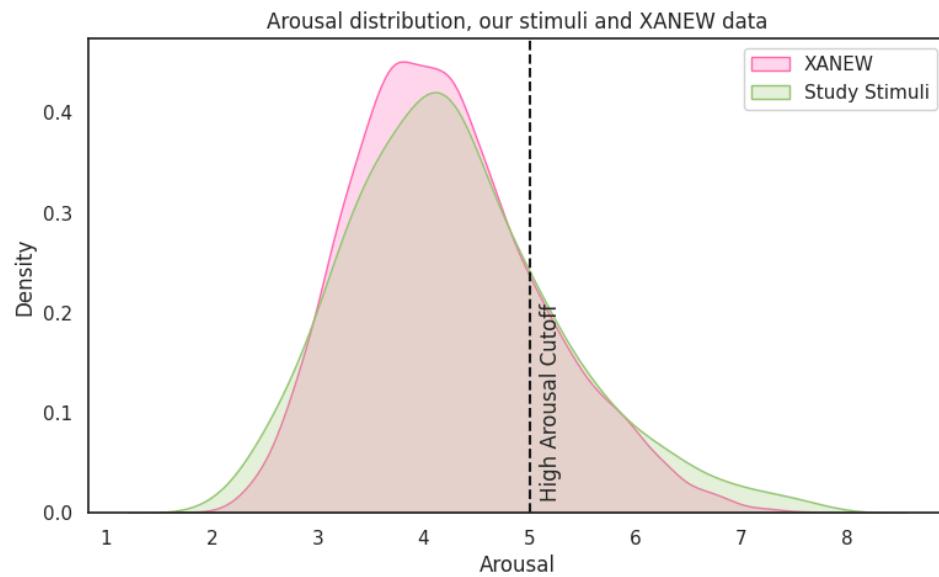
Yeo, B. T., Krienen, F. M., Sepulcre, J., Sabuncu, M. R., Lashkari, D., Hollinshead, M., ... & Buckner, R. L. (2011). The organization of the human cerebral cortex estimated by intrinsic functional connectivity. *Journal of neurophysiology*. doi: 10.1152/jn.00338.2011.

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Appendix

Appendix 1: Distribution of valence and arousal ratings

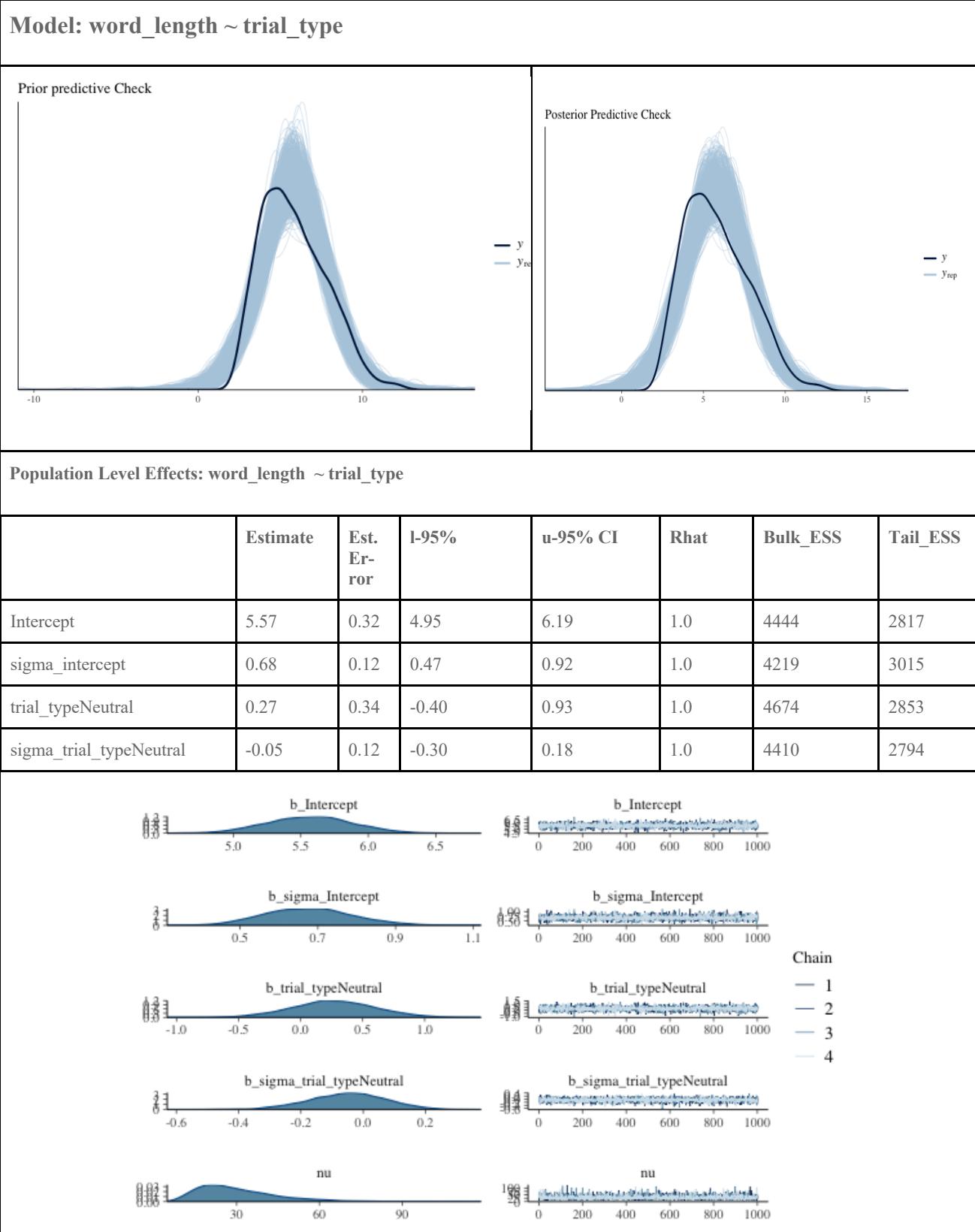


Appendix 2: Words used in the experiment in each trial type

Emotional (39): love, vacation, joke, kiss, life, friday, sex, whiteness, money, jealousy, party, death, torment, fun, joviality, girlfriend, wealth, freedom, coffee, hate, game, football, humor, deceit, depression, kill, hell, summer, shame, win, goodness, drink, beach, victim, poverty, zoo, happiness, pain, dog

Neutral (254): window, meeting, engineer, society, ease, voter, ham, right, noise, dress, debate, businessman, belief, health, rent, woe, stapler, complaint, woman, hospital, strategy, stupidity, hair, scare, artist, human, interest, guilt, toothbrush, cloud, cabinet, journalist, battle, thirst, bar, satire, question, friend, part, abyss, crib, conversation, comment, family, high, table, clue, minister, lamp, wonder, step, distraction, pencil, couple, man, perjury, class, envy, faucet, excuse, testimony, month, dread, dime, luck, advantage, chair, thought, type, feeling, paper, cost, awe, firework, number, optimism, shoulder, use, color, line, loner, care, home, loan, day, squeal, shoe, someone, election, routine, chicken, tourist, turtle, sport, harp, stampede, cyclone, group, darkness, arm, analogy, bribe, boy, hygiene, foot, plant, basketball, tribute, subway, lawyer, volcano, top, irony, rake, act, worker, greatness, patient, pie, jungle, snake, cathedral, car, storm, place, paradox, store, scream, speech, pilot, sense, sickness, honey, sand, bee, tennis, trumpet, cab, tornado, rose, delirium, room, mystery, army, faith, drug, carrot, area, monkey, choir, truck, damage, radio, homesickness, eye, refusal, religion, coolness, problem, ketchup, island, giant, pumpkin, ball, bonfire, van, era, nose, sight, motive, guard, hierarchy, brightness, carriage, scientist, actor, burden, dinner, hotel, flower, team, band, system, shelf, court, doctor, truth, sleep, lemonade, lake, elm, cup, accordion, riot, computer, emptiness, kitchen, legality, diplomat, knowledge, situation, beer, egg, field, hall, accident, need, avoidance, screen, crap, office, fate, hunger, stone, animal, play, semester, highway, company, finger, movie, law, boyfriend, trust, cooking, boat, duck, college, change, sweeteness, cafeteria, plot, plea, soldier, study, fish, world, reading, grief, door, shit, denial, sin, pineapple, garden, goal, package, relaxation, camera, thing, criminal, eggplant, mountain, addition

Appendix 3: Bayesian model, word length and trial type



Appendix 4: fMRIPrep Boiler Text

Results included in this manuscript come from preprocessing performed using *fMRIPrep* 22.0.2 (Esteban, Markiewicz, et al. (2018); Esteban, Blair, et al. (2018); RRID:SCR_016216), which is based on *Nipype* 1.8.5 (K. Gorgolewski et al. (2011); K. J. Gorgolewski et al. (2018); RRID:SCR_002502).00

Anatomical MR data preprocessing

A total of 1 T1-weighted (T1w) images were found for each subject within the input BIDS dataset. The T1-weighted (T1w) image was corrected for intensity non-uniformity (INU) with `N4BiasFieldCorrection` (Tustison et al., 2010), distributed with ANTs 2.3.3 (Avants et al., 2008), and used as T1w-reference throughout the workflow. The T1w-reference was then skull-stripped with a *Nipype* implementation of the `ants-BrainExtraction.sh` workflow (from ANTs), using OASIS30ANTS as target template. Brain tissue segmentation of cerebrospinal fluid (CSF), white-matter (WM) and gray-matter (GM) was performed on the brain-extracted T1w using `fast` (FSL 6.0.5.1:57b01774, RRID:SCR_002823, (Zhang et al., 2001)). Volume-based spatial normalization to one standard space (MNI152NLin2009cAsym) was performed through nonlinear registration with `antsRegistration` (ANTs 2.3.3), using brain-extracted versions of both T1w reference and the T1w template. The following template was selected for spatial normalization: *ICBM 152 Nonlinear Assymetrical template version 2009c* ((Fonov et al., 2009)RRID:SCR_008796; TemplateFlow ID: MNI152NLin2009cAsym).

Functional MR data preprocessing

For each of the 3 BOLD runs found per subject, the following preprocessing was performed. First, a reference volume and its skull-stripped version were generated using a custom methodology of fMRIPrep. Head-motion parameters with respect to the BOLD reference (transformation matrices, and six corresponding rotation and translation parameters) are estimated before any spatiotemporal filtering using `mcflirt` (Jenkinson & Smith, 2001). BOLD runs were slice-time corrected to 0.625s (0.5 of slice acquisition range 0s-1.25s) using `2dTshift` from AFNI (Cox & Hyde, 1997). The BOLD time-series (including slice-timing correction when applied) were resampled onto their original, native space by applying the transforms to correct for head-motion. These resampled BOLD time-series will be referred to as preprocessed BOLD in original space, or just preprocessed BOLD. The BOLD reference was then co-registered to the T1w reference using `mri_coreg` (Free-Surfer) followed by `flirt` (Jenkinson & Smith, 2001) with the boundary-based registration (Greve & Fischl, 2009) cost-function. Co-registration was configured with six degrees of freedom. Several confounding time-series were calculated based on the preprocessed BOLD: framewise displacement (FD), DVARS and three region-wise global signals. FD was computed using two formulations following Power (absolute sum of relative motions, Power et al. (2014)) and Jenkinson (relative root mean square displacement between affines, (Jenkinson et al., 2002)).

FD and DVARS are calculated for each functional run, both using their implementations in *Nipype* (following the definitions by Power et al. 2014). The three global signals are extracted within the CSF, the WM, and the whole-brain masks. Additionally, a set of physiological regressors were extracted to allow for component-based noise correction (Behzadi et al., 2007). Principal components are estimated after high-pass filtering the *preprocessed BOLD* time-series (using a discrete cosine filter with 128s cut-off) for the two *CompCor* variants: temporal (tCompCor) and anatomical (aCompCor). tCompCor components are then calculated from the top 2% variable voxels within the brain mask. For aCompCor, three probabilistic masks (CSF, WM and combined CSF+WM) are generated in anatomical space. The implementation differs from that of Behzadi et al. in that instead of eroding the masks by 2 pixels on BOLD space, a mask of pixels that likely contain a volume fraction of GM is subtracted from the aCompCor masks. This mask is obtained by thresholding the corresponding partial volume map at 0.05, and it ensures components are not extracted from voxels containing a minimal fraction of GM. Finally, these masks are resampled into BOLD space and binarized by thresholding at 0.99 (as in the original implementation). Components are also calculated separately within the WM and CSF masks. For each CompCor decomposition, the k components with the largest singular values are retained, such that the retained components' time series are sufficient to explain 50 percent of variance across the nuisance mask (CSF, WM, combined, or temporal). The remaining components are dropped from consideration. The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. The confound time series derived from head motion estimates and global signals were expanded with the inclusion of temporal derivatives and quadratic terms for each (Satterthwaite et al., 2013). Frames that exceeded a threshold of 0.5 mm FD or 1.5 standardized DVARS were annotated as motion outliers. Additional nuisance timeseries are calculated by means of principal components analysis of the signal found within a thin band (crown) of voxels around the edge of the brain, as proposed by (Patriat et al., 2017). The BOLD time-series were resampled into standard space, generating a *preprocessed BOLD run in MNI152NLin2009cAsym space*. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep*. All resamplings can be performed with *a single interpolation step* by composing all the pertinent transformations (i.e. head-motion transform matrices, susceptibility distortion correction when available, and co-registrations to anatomical and output spaces). Gridded (volumetric) resamplings were performed using `antsApplyTransforms` (ANTs), configured with Lanczos interpolation to minimise the smoothing effects of other kernels (Lanczos, 1964). Non-gridded (surface) resamplings were performed using `mri_vol2surf` (FreeSurfer).

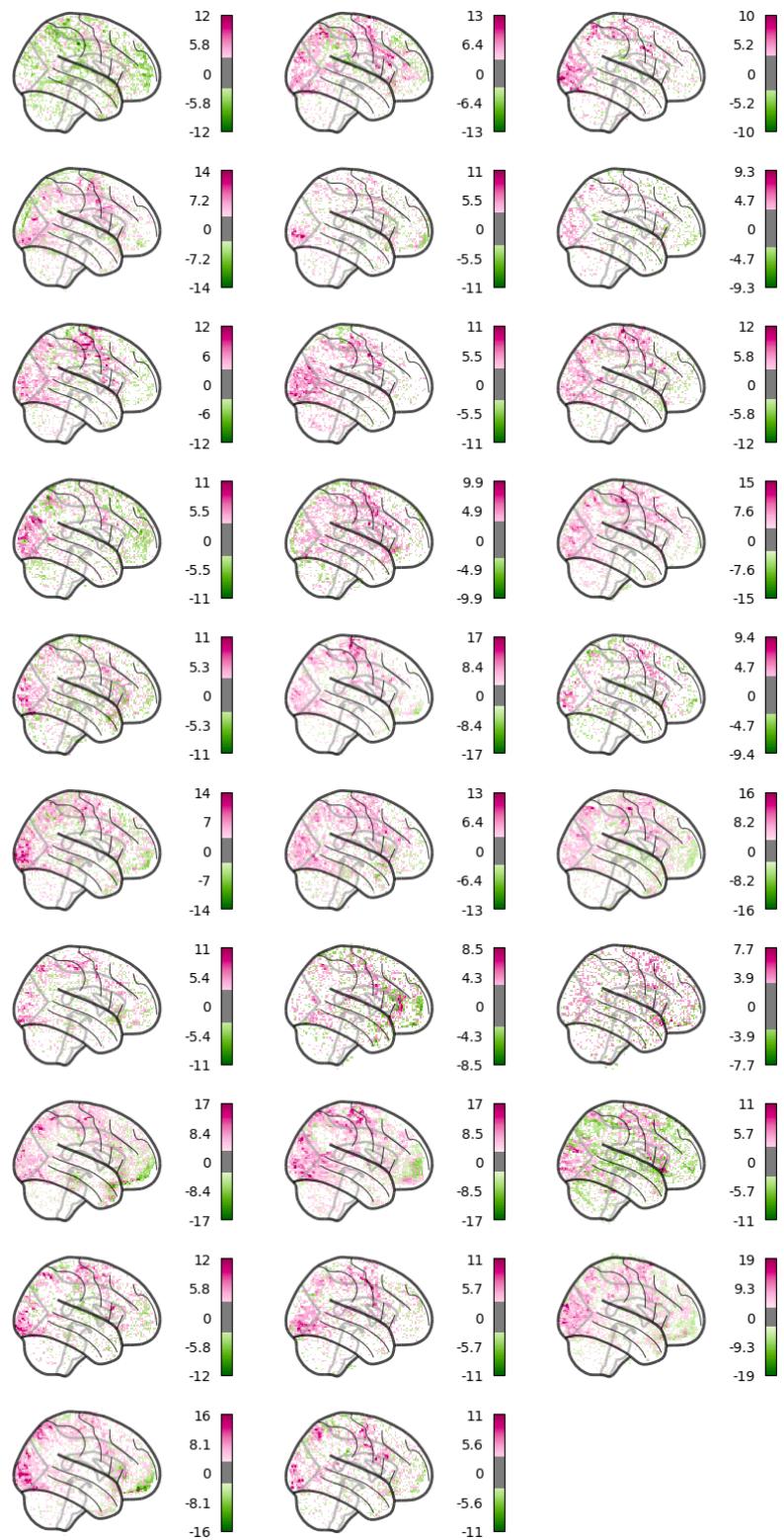
Many internal operations of *fMRIPrep* use Nilearn 0.9.1 (Abraham et al., 2014) RRID:SCR_001362), mostly within the functional processing workflow. For more details of the pipeline, see [the section corresponding to workflows in fMRIPrep's documentation](#).

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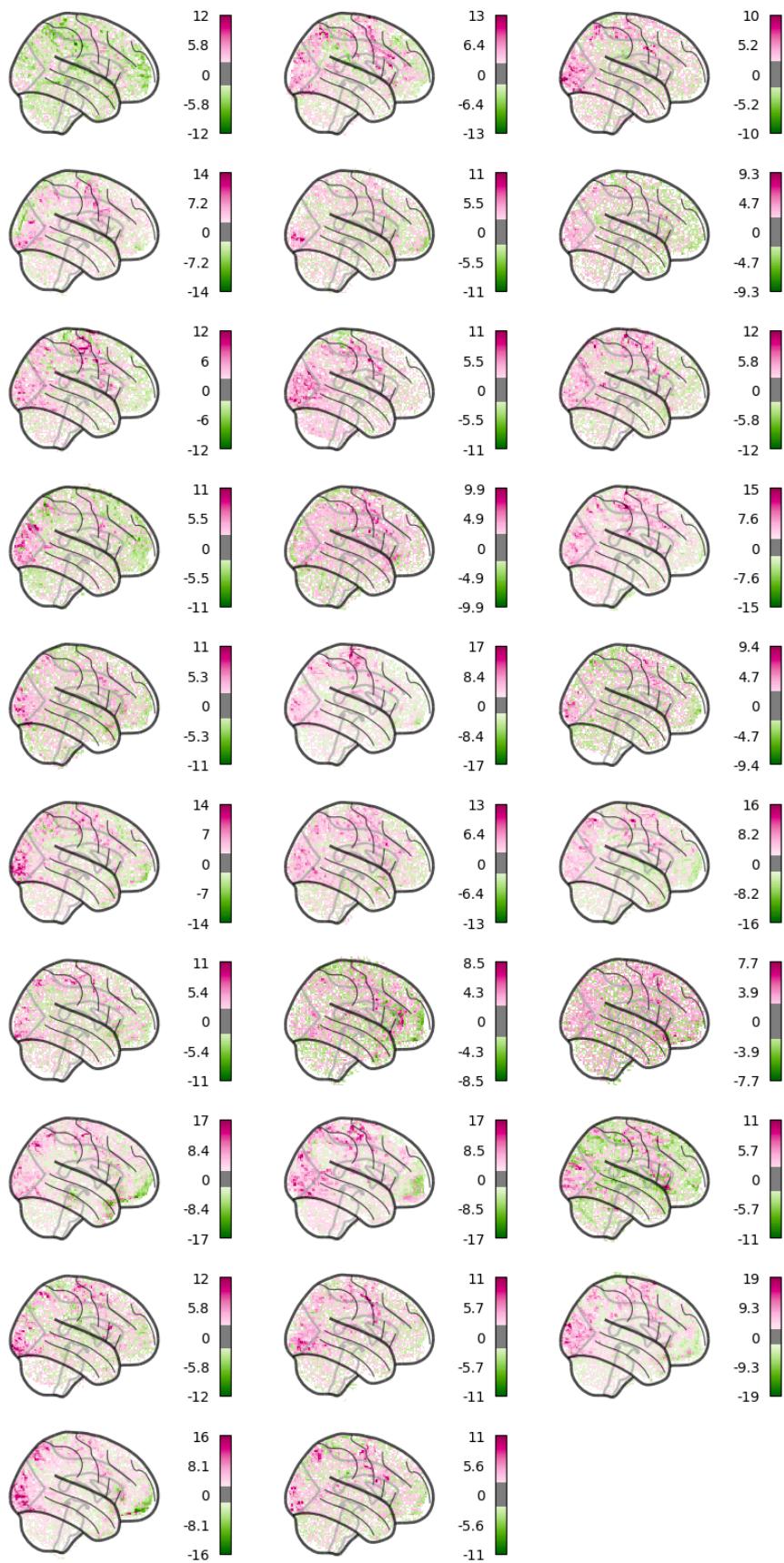
The above boilerplate text was not written by us but automatically generated by fMRIPrep. It was included in the appendix since the authors of fMRIPrep explicitly express that users should copy and paste this text into their manuscripts unchanged. It is released under the [CC0](#) licence.

Appendix 5: Within-Subject First Level Contrast images for all subjects

A5.1: Contrast Images for A1 (Word vs. Fixation Cross, unc p < 0.001)



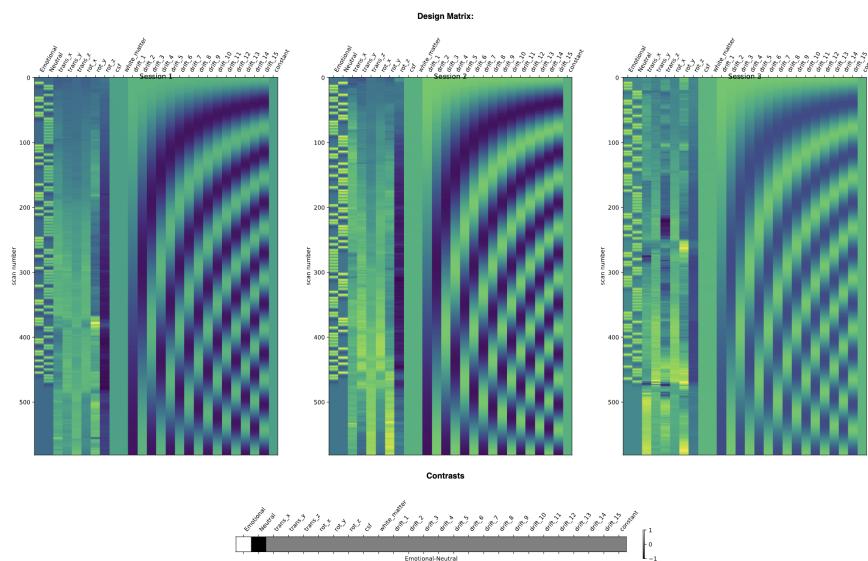
A5.2: Contrast Images for A2 (Emotional vs. Neutral, unc p < 0.01)



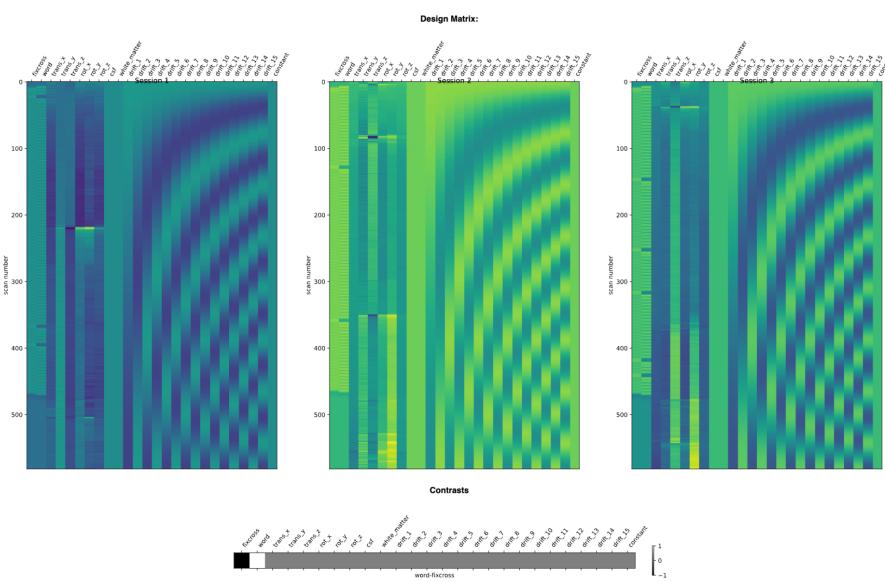
Appendix 6: GLM Design Matrices & Contrasts

In the design matrices below, rows represent time series and columns contain the predictors.

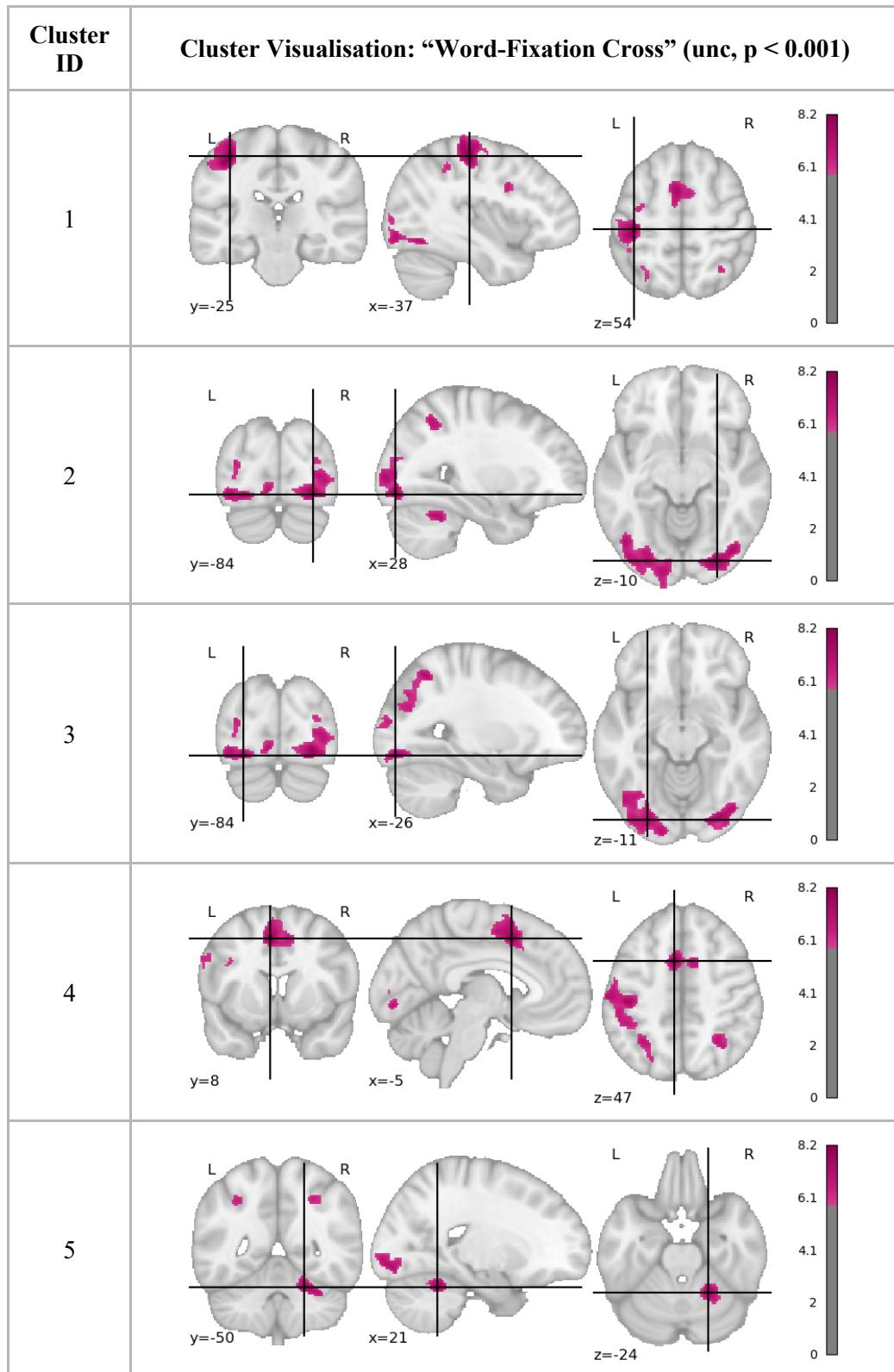
A6.1: Design Matrix for A1 (for one subject and three runs)

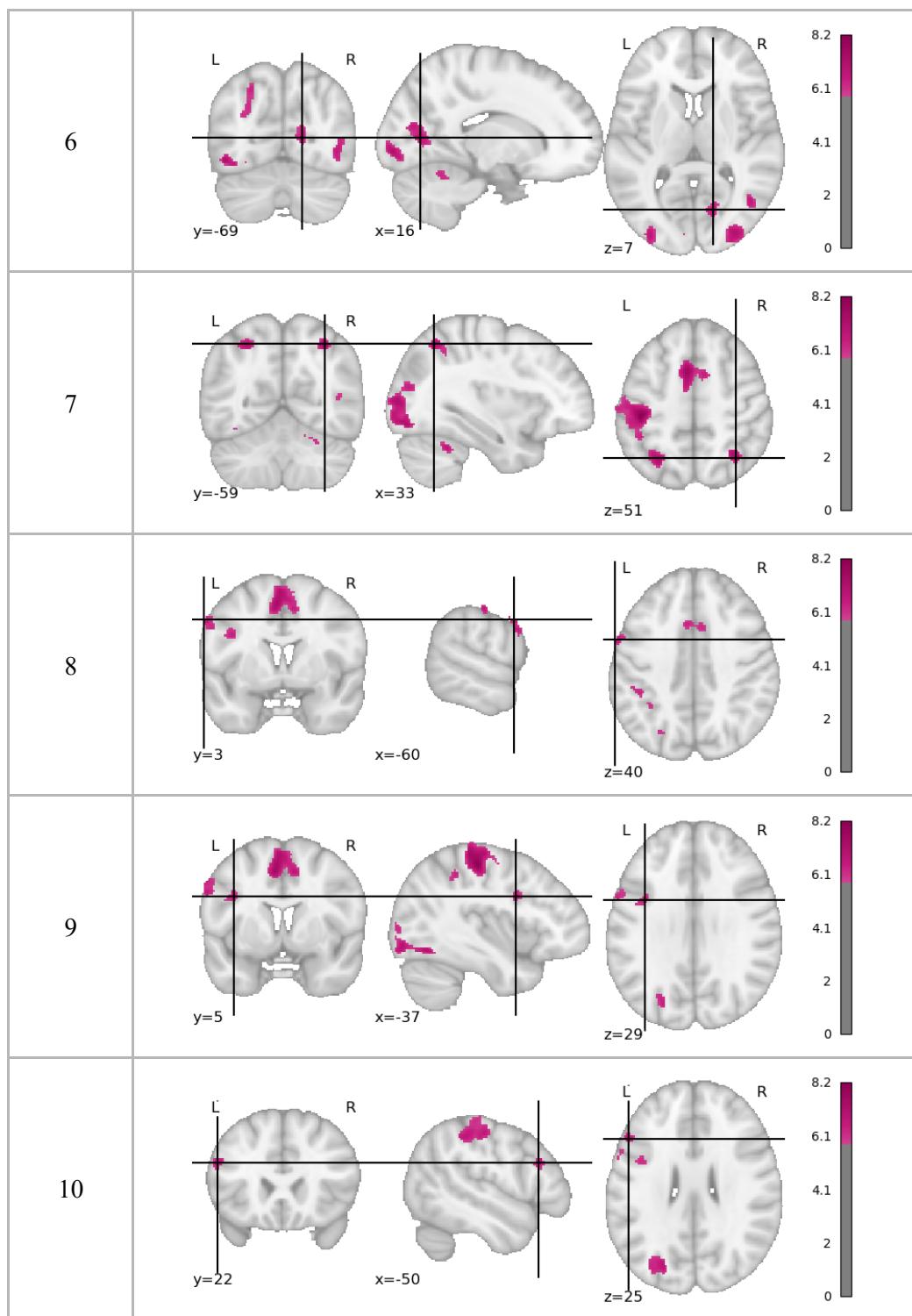


A6.2: Design Matrix for A2 (for one subject and three runs)

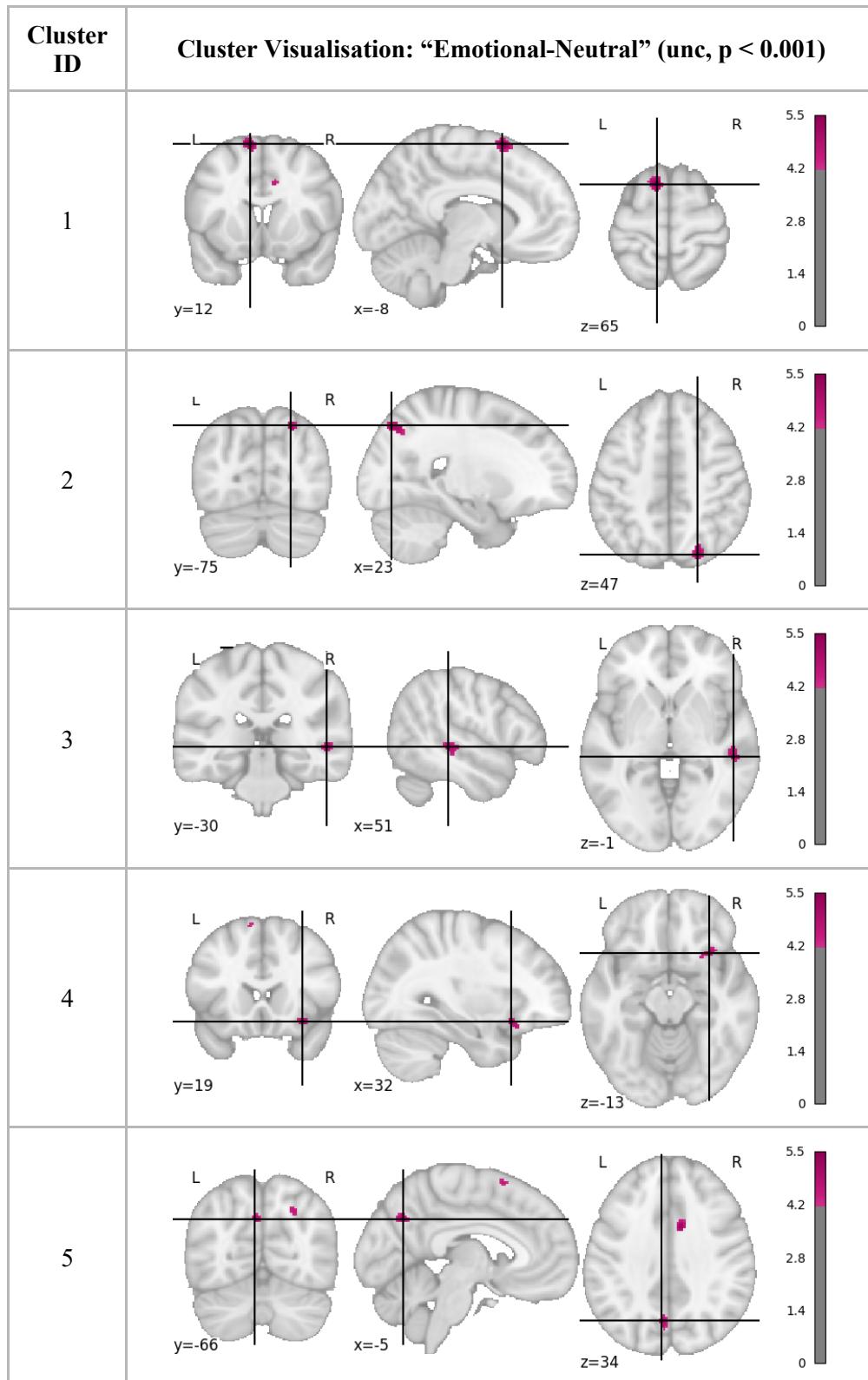


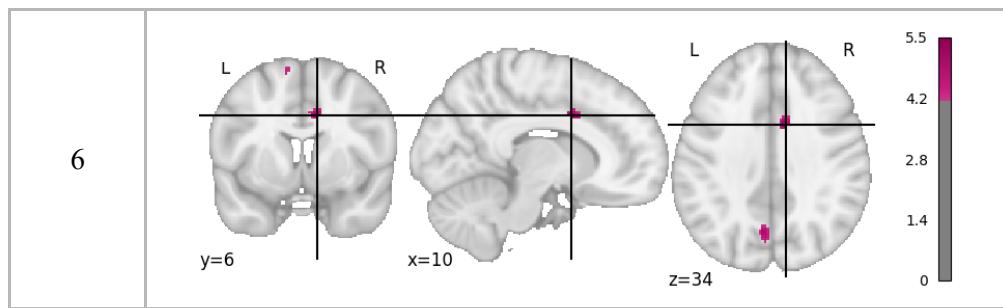
Appendix 7: A1 Clusters





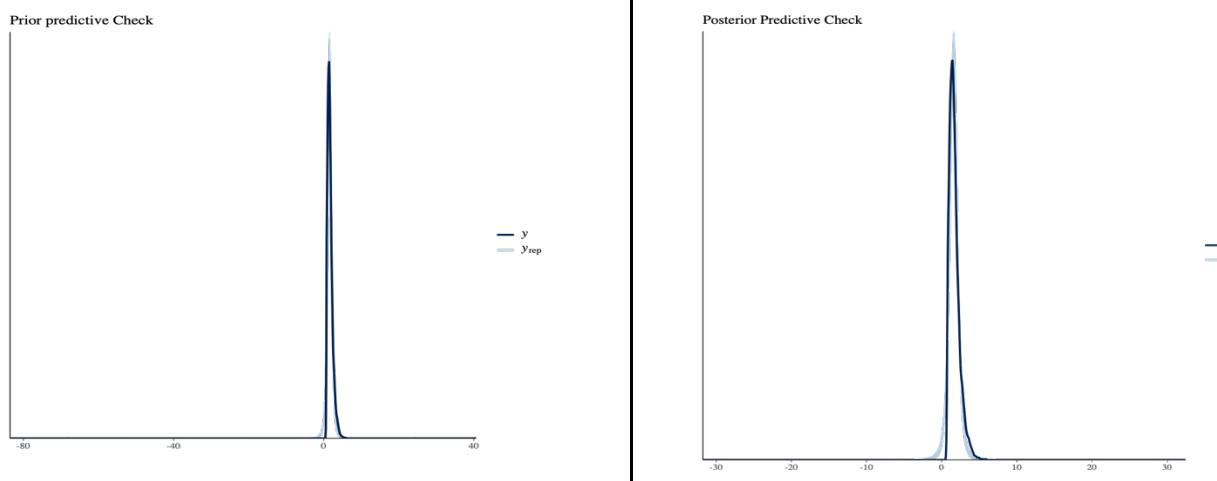
Appendix 8: A2 Clusters





Appendix 9: Exploratory Response Time Analysis

Model: rt ~ trial_type



Population Level Effects: rt ~ trial_type

	Estimate	Est.Error	l-95%	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
Intercept	1.58	0.02	1.55	1.62	1.00	4556	2771
sigma_intercept	-0.64	0.03	-0.69	-0.59	1.001	3631	2970
trial_typeNeutral	0.00	0.02	-0.03	0.04	1.001	4628s	2890
sigma_trial_typeNeutral	-0.03	0.03	-0.08	0.02	.99	3834	2793

