

**HOW PERSONALITY MODULATES BRAIN  
RESPONSES TO EMOTION IN MUSIC:  
A REGIONS-OF-VARIANCE APPROACH**

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<p>Tiivistelmä – Abstract</p> <p><b>Background:</b> Personality is related to emotional tendencies, and emotion is an important part of musical experiences. In particular, the personality traits Extraversion and Neuroticism have been respectively related to positive and negative emotionality (Larsen &amp; Ketelaar, 1991) and to neural responses to positive and negative emotional stimuli (e.g., Canli et al., 2001). Openness to Experience is not characterized by affective tendencies, but it has been related aesthetic sensitivity (Costa Jr &amp; McCrae, 1992) and to the intensity of music-induced emotions (Vuoskoski &amp; Eerola, 2011a). Research on the role of Extraversion and Neuroticism in neural responses to emotion in music has given some null (Koelsch, Skouras, &amp; Jentschke, 2013) and unexpected findings (Park et al., 2013); this research may be extended with different methodological choices, particularly with a larger sample size and with a method of selecting Regions of Interest (ROIs) that is intended for investigating individual differences in brain function (Omura et al., 2005).</p> <p><b>Aims:</b> (1) To investigate the role of Extraversion, Neuroticism, and Openness to Experience in brain activations during implicit perception of emotions in music, and (2) to implement a data-driven method of selecting regions of interest as regions of variance (ROV; Omura et al., 2005).</p> <p><b>Hypotheses:</b> It was predicted that Extraversion and Neuroticism would be related to brain activity during perception of positively- and negatively-valenced musical stimuli, respectively. The investigation of Openness was exploratory as this trait is not characteristically related to affect. No specific hypotheses were tested with regards to brain areas, as the method for selecting regions of interest was data-driven.</p> <p><b>Methods:</b> Fifty-five participants were scanned using functional Magnetic Resonance Imaging while they listened to thirty, 4-second music excerpts portraying happiness, sadness, or fear, and they were asked to indicate the number of instruments following each excerpt. The Big Five Questionnaire (John &amp; Srivastava, 1999) was used to measure personality traits. Regions of interest were selected as clusters of voxels with higher between-subjects variance in activation, relative to the mean within-subjects residual variance in activation, and a whole-brain voxelwise analysis additionally run for comparison.</p> <p><b>Results:</b> In the ROV analysis, Neuroticism was positively related to activation during Sad music in the left supramarginal and angular gyri (<math>p &lt; .001</math>, corrected), and Openness was positively related to activation during Happy music in the region of the left superior temporal gyrus, extending into the temporal pole, middle temporal gyrus, Heschl's gyrus, postcentral gyrus, supramarginal gyrus, and rolandic operculum (<math>p &lt; .05</math>, corrected). In the whole-brain analysis, similar results were found for Neuroticism but not for Openness.</p> <p><b>Discussion:</b> These results support previous findings of trait-congruent links between personality and neural responses to emotional stimuli. Additionally, they indicate the usefulness of the ROV method for investigating individual differences; the ROV analysis was consistent with the robust whole-brain results and was additionally sensitive to clusters that did not survive whole-brain correction for multiple comparisons.</p>	
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# 1 INTRODUCTION AND PROBLEM STATEMENT

People often describe each other in terms of characteristics or traits. In academic research, there is interest in whether these individual differences are quantifiable, whether they are learned or innate, and whether they have biological bases. This was the case even as far back as the ancient Greeks, when the physician Galen (130-210 AD) developed a medical theory of individual differences, in which temperament was determined by the balance of different bodily fluids (Stelmack & Stalikas, 1991).

In the past century, several biological theories of personality have been proposed. The prominent personality theorist Hans Eysenck (1916-1997) suggested that Extraversion was based in cortical arousal and Neuroticism in bodily responses to emotion and stress (Eysenck, 1967). At the systems level, Jeffrey Allan Gray (1934-2004) proposed that differences in personality could be explained by activity in biologically-distinct systems relating to approach, inhibition, and avoidance behaviors (Gray, 1970; Gray & McNaughton, 2003; McNaughton & Corr, 2004). Alternatively, at the molecular level, Claude Robert Cloninger (1944-) proposed a model of personality related to neurotransmitter activity, that is, Novelty Seeking as related to dopamine activity, Harm Avoidance to serotonin, and Reward Dependence to norepinephrine (Cloninger, 2000).

Arguably the most prominent description of personality today is the Five-Factor Model (FFM) (Goldberg, 1981, 1993; McCrae & Costa Jr, 1985), whose factors have been named Extraversion, Neuroticism, Conscientiousness, Agreeableness, and Openness to Experience. The FFM has been inductively derived through factor analysis from multiple personality theories and questionnaires (John & Srivastava, 1999). It has been shown to be stable over time (Costa & McCrae, 1988), consistent between self- and others- ratings (McCrae, 1993), valid across large cross-cultural samples (McCrae, 2001; McCrae & Terracciano, 2005), and predictive of real-life outcomes (Cuijpers, van Straten, & Donker, 2005; Richard & Diener, 2009). Behavioral genetics studies indicate that the FFM is partially heritable (e.g., Bouchard Jr, 1994), which some researchers take as evidence for a biological basis for personality (McCrae, 2009), though it is not fully understood how genetics and environmental factors contribute to personality. Regardless of its cause,



personality as described by the FFM appears to be a meaningful source of individual differences.

Individual differences are often treated as noise in investigations of the neural correlates of behavior and cognition. This may be logical if the research goal is to investigate consistent responses across a population. However, it has been suggested that individual differences that are consistently associated with cognitive/behavioral outcomes may have neural underpinnings, and warrant neuroscientific investigation (Gold, Frank, Bogert, & Brattico, 2013; Hariri, 2009; Kanai & Rees, 2011; Quarto et al., 2017; Vuoskoski & Eerola, 2011b). Further, it has also been suggested that individual differences may account for discrepancies in the results of functional neuroimaging studies. This was argued by Eugene et al. (2003), who conducted two separate but identical studies of the neural underpinnings of transient sadness, and found that the results were significantly different between the two studies despite their being methodologically identical. They suggest that individual differences likely explain these discrepancies.

Interested in individual differences in brain structure and function can be seen in the growing body of individual-differences neuroscience research in the past two decades. Indeed, in a fairly recent review of the neural correlates of personality, Kennis, Rademaker, and Geuze (2013) discussed 76 studies done between 2001 and 2013. Many of these studies (75%) used emotional and/or rewarding stimuli; emotionality and reward-sensitivity are core features of several personality factors. Indeed, behavioral evidence suggests that Extraversion is related to a tendency to experience positive emotions (Larsen & Ketelaar, 1991) and to engage in rewarding situations (Lucas & Fujita, 2000), Neuroticism is related to a tendency to experience negative emotions (Larsen & Ketelaar, 1991), and Openness has been related to more intense aesthetic experiences (Costa Jr & McCrae, 1992; Nisbaum & Silvia, 2011; Silvia, Fayn, Nisbaum, & Beaty, 2015). These personality-related tendencies may be correlated with brain activity during emotional and artistic stimuli (Kennis et al., 2013).

However, in the field of music neuroscience, the neural correlates of personality differences have not received a great deal of attention. This is somewhat surprising, given that behavioral music research has found that personality plays a role in felt emotions during music listening both in experimental settings (Vuoskoski & Eerola, 2011a) and in everyday settings (Juslin, Liljeström, Västfjäll, Barradas, & Silva, 2008), and that personality plays a role in music preferences (Rawlings, Barrantes i Vidal, & Furnham, 2000; Rentfrow & Gosling, 2003; Vella & Mills, 2017; Vuoskoski & Eerola, 2011b). Findings in such studies

are sometimes weak or unexpectedly null, but even the trends seem congruent with the relation between personality and emotionality. Additionally, research in other fields such as visual aesthetics and emotion have also found such trait-congruent correlations (Abello & Bernáldez, 1986; Cleridou & Furnham, 2014; Fayn, MacCann, Tiliopoulos, & Silvia, 2015).

Thus, the present study will examine the of the role of personality in neural activity during music-emotion perception. Specifically, it investigates the roles of Extraversion, Neuroticism, and Openness to Experience in hemodynamic activity during implicit perception of Happy, Sad, and Fearful instrumental music.

There have been two previous studies (to our knowledge) addressing the role of Extraversion and Neuroticism in neural activity during music-emotion perception (i.e., Koelsch, Skouras, & Jentschke, 2013 and Park et al., 2013). However, there are several reasons for further research on this topic. Concern has been raised in the past few years regarding the reliability of neuroimaging research, particularly relating to

1. Publication bias in academia favoring non-null results (Ioannidis, Munafo, Fusar-Poli, Nosek, & David, 2014),
2. The difficulty found in replicating results in psychological sciences (Open Science Collaboration, 2015), and
3. The low statistical power in neuroimaging studies with small sample sizes (Button et al., 2013).

Further, it has been proposed that conventional methods for selecting regions of interest (ROIs) in neuroimaging studies may not be ideal when investigating individual differences (Omura et al., 2005).

With these concerns in mind, the present study can be seen to contribute to the scientific community in the following ways:

1. It addresses a topic that has received some previous attention (i.e., two studies, to our knowledge), but arguably not enough attention to establish reliable knowledge on the topic,
2. It uses a larger sample size than has been used by previous studies (this is especially relevant since individual differences generally have smaller than standard effect sizes; Gignac & Szodorai, 2016),

3. It uses a method for selecting regions of interest that may be more appropriate than some previous research for investigating a question relating to individual differences, namely, the regions-of-variance method (ROV; Omura et al., 2005), and
4. It investigates the role of the personality trait Openness to Experience, which was not investigated in the aforementioned two studies on this topic, in addition to Extraversion and Neuroticism, which were previously investigated.

These statements will be supported and described in more detail in later chapters.

With regards to applications of this research, this question is of interest for a number of reasons. As noted above, personality plays a role in processing emotional, rewarding, and aesthetic stimuli, and behavioral research indicates that music can be experienced as being emotional and rewarding. Such research also suggests that personality is involved in emotional experiences of music, and if this is reliably found to be reflected in neural activity, then future investigations involving music and the brain may benefit from controlling for the role of personality, or else directly investigating it. On a more pragmatic level, it is beneficial to better understand personality because it has been related to real-world outcomes; in particular, Extraversion and Neuroticism have been related to subjective well-being (Richard & Diener, 2009), happiness (Costa & McCrae, 1980), and mood disorders (Jylhä & Isometsä, 2006). A better understanding of relations between personality and musical experiences may also inform music therapy practices, for example, in informing therapists as they design individualized interventions. Additionally, this study may have methodological implications for the utility of the regions-of-variance method for selecting regions of interest, as it appears to be the second study that has utilized the method.

## 2 LITERATURE REVIEW

There are several questions that ought to be addressed in an investigation of the role of personality in the neural correlates of perceiving emotions in music:

1. Whether music can be considered an emotional stimulus,
2. Whether the five-factor model of personality measures meaningful individual differences,
3. Whether functional Magnetic Resonance Imaging is a suitable brain-imaging technique for addressing the research question, and
4. whether further research is warranted on the topic of the role of personality in brain function during perception of emotions in music.

### 2.1 Music as an emotional stimulus

In everyday contexts, music is used by listeners to experience and regulate their emotions (North, Hargreaves, & Hargreaves, 2004; Sloboda, O'Neill, & Ivaldi, 2001). Indeed, listeners report that music induces emotions approximately 55% of the time that they are listening (Juslin & Laukka, 2004). However, it is important to consider whether associations between music and emotion can be consistent between individuals, and whether music-evoked emotions resemble the everyday emotions that are associated with personality traits.

#### 2.1.1 Universal and learned associations between music and emotion

Cross-cultural and developmental studies can help to clarify the extent to which associations between music and emotion are learned or universal. In support of the idea of universal associations, several cross-cultural studies have found that listeners unfamiliar with the style of the musical stimuli made similar music-emotion associations as those familiar with the musical style, particularly for basic emotions (e.g., Balkwill & Thompson, 1999; Balkwill, Thompson, & Matsunaga, 2004; Fritz et al., 2009). However, one must keep in mind the indicators that there is some learning involved. For example, al-

though Balkwill and Thompson (1999) found that Western listeners were sensitive to joy, sadness, and anger in Hindustani ragas, Westerners were not able to recognize peace as an emotion in the stimuli. Also, a developmental study by Dalla Bella, Peretz, Rousseau, and Gosselin (2001) indicates that younger children (i.e., 3-4-year-olds) have trouble distinguishing emotions in music. Thus, research suggests that music can communicate some emotional meaning across cultures, but some degree of enculturation is involved in learning music-emotion associations, particularly for more complex emotions.

There are several theories as to why there are some universal music-emotion associations. One explanation points to the common features between music and affective prosody. There is evidence of similarities in vocal expression of emotion across languages and cultures (Scherer, 2005), and Juslin and Laukka (2003) suggest that music uses the features of vocal expression in speech to express emotion (though perhaps the directionality of this relationship is not so evident). Even more basic sound qualities like acoustical roughness, or consonance/dissonance, can influence music preferences (Zentner & Kagan, 1998) and categorization of musical emotions (Kim et al., 2010). Another possible explanation comes from the perspective of embodied music cognition (Leman, 2008) - for example, happiness is associated with faster musical tempi in listeners from Western (Gabrielsson & Juslin, 1996), African (Fritz et al., 2009), and Japanese (Balkwill et al., 2004) cultures.

### **2.1.2 Music-evoked emotions**

Although the studies mentioned above indicate that people perceive emotion in music in a manner that is to some degree universal, the question remains as to whether music can evoke the emotions it portrays. It is not always the case that the emotions induced by music are the same as those perceived in music. For example, music listeners may feel fear or surprise at a sudden loud sound in a piece perceived as portraying an emotion other than fear or surprise (Juslin, Harmat, & Eerola, 2014), they may feel emotions tied to autobiographical memories associated with the music rather than the emotions perceived in the music (Baumgartner, 1992), they may experience emotions associated with music as a result of a learned association with emotionally-valenced experiences (Blair & Shimp, 1992), and they may feel both sadness and pleasure while listening to sad music (Vuoskoski, Thompson, McIlwain, & Eerola, 2012). Despite these sources of inconsistencies between the emotions perceived in and evoked by music, evidence largely points to the notion that music can evoke the emotion it portrays (Vuoskoski & Eerola, 2011a).

### 2.1.3 Similarity between music-evoked emotions and everyday emotions

Another cause for disagreement regarding music and emotion is the question of whether music-evoked emotions are comparable to everyday emotions (Koelsch, 2014).

In considering this question, it is helpful to note what is involved in everyday emotions and compare this to music-evoked emotions. One prominent conceptualization of emotion is the Component Process Model proposed by Scherer (2005), in which multiple processes simultaneously contribute to emotion. Scherer's definitions of these components are as follows:

- *Body symptoms* are neurophysiological reactions associated with emotions,
- *Motor expressions* of emotion include facial and vocal expressions that communicate reactions and behavioral intentions,
- *Subjective feeling* is the personal emotional experience that allows the individual to monitor their internal state and their interaction with the environment,
- *Action tendencies* are the motivational components that prepare and direct actions relating to emotions, and
- *Cognitive appraisal* involves the evaluations of objects and occurrences.

Music research largely suggests that these components are also involved in music-evoked emotions. For example, with regards to motor expression and body symptoms, Lundqvist, Carlsson, Hilmersson, and Juslin (2009) found that perceived happiness in music was related to increased activity of the zygomatic (smile) muscle and higher skin conductance. Additionally, music can elicit the subjective feeling of emotion; people report that music influences their emotions over half of the time that they listen to music, and they indicate that the emotions felt during music listening can resemble emotions felt in everyday contexts (Juslin & Laukka, 2004). Furthermore, music can also involve emotion-related action tendencies, as seen in the finding that people dance differently depending on the emotion expressed in the music (Burger, Saarikallio, Luck, Thompson, & Toiviainen, 2013).

### 2.1.4 Neural correlates of music-evoked emotions

In support of the notion that emotions evoked by music are to analogous to everyday emotions, studies have found that the neural correlates of music-evoked emotions are similar to those for everyday emotions (Koelsch, 2014). Indeed, it has been argued that music's ability to evoke emotions makes it a useful tool for emotion research.

Different aspects of music processing are related to activity in various cortical and sub-cortical regions of the brain. In a meta-analysis of the neural correlates of music-evoked emotions, Koelsch (2014) notes that brain areas that are most associated include the bilateral amygdala, right nucleus accumbens, parahippocampal gyrus, cingulate cortex, orbitofrontal cortex, and the bilateral auditory cortices.

Of these areas, the amygdala, nucleus accumbens, parahippocampal gyrus, and the cingulate cortex are components of the limbic system, which is active even in newborn infants listening to music (Perani et al., 2010). This system is largely involved in emotion, learning, and memory-formation, among other functions. Individual areas contribute in different ways to these functions, and this is also reflected in research with emotional musical stimuli.

The amygdala plays a central role in affective music processing, especially the superficial and basolateral amygdala (Koelsch, 2014). The superficial amygdala has been shown to activate more strongly to joyful or pleasant music (Blood & Zatorre, 2001; Mueller et al., 2011), and to exhibit greater functional connectivity with each the nucleus accumbens and the mediodorsal thalamus during joy-evoking music, compared to fear-evoking music (Koelsch, Skouras, Fritz, et al., 2013). Indeed, the superficial amygdala is related to processing cues that are socially and affectively relevant, and it may function in a network with the mediodorsal thalamus and the nucleus accumbens to modulate approach and withdrawal behaviors in response to such cues (Koelsch, 2014). Music's communicative abilities (Cross & Morley, 2009) and its resemblance to emotional speech (Juslin & Laukka, 2003) supports this suggestion that music may be perceived as socially relevant (Koelsch, 2014).

The basolateral amygdala, on the other hand, has shown activations to unpleasant or sad music (Koelsch, Fritz, v. Cramon, Müller, & Friederici, 2006; Mitterschiffthaler, Fu, Dalton, Andrew, & Williams, 2007) as well as to joyful music (Koelsch et al., 2006; Mueller et al., 2011). This area has been related to perception of both positive and negative nonmusical stimuli as well (LeDoux, 2000; Murray, 2007). The basolateral amygdala receives direct input from the primary auditory cortex (Koelsch, 2014), and is therefore involved in responding to emotionally-relevant sounds (Cross & Morley, 2009).

Another limbic structure related to music-evoked emotions is the nucleus accumbens, a component of the ventral striatum in the basal ganglia. It is functionally part of the dopaminergic mesolimbic reward pathway along with the ventral tegmental area, and is

implicated in highly rewarding behaviors like eating and sex as well as addictions (Purves et al., 2012). Pleasurable responses to music have also been associated with activations of the ventral striatum (Blood & Zatorre, 2001; Blood, Zatorre, Bermudez, & Evans, 1999; Salimpoor et al., 2013). Koelsch's (2014) meta-analysis indicated a cluster of activation in the right ventral striatum (nucleus accumbens) and the left dorsal striatum (caudate nucleus), and he notes that Sescousse, Caldú, Segura, and Dreher (2013)'s meta-analysis of the neural correlates of reward indicates the same co-activation is also shown in response to food, money, and sexual reward.

The hippocampal formation is also involved in music listening, as well as memory, learning, and spatial orientation. It also plays a role in emotion through its regulatory role regarding the stress response of the hypothalamus-pituitary-adrenal (HPA) axis (Jacobson & Sapolsky, 1991). This can be seen during music-induced positive emotional experiences in the connectivity between the hippocampus and the hypothalamus (Koelsch & Skouras, 2014). This area may also be related to emotional responses to unpleasant music; while most people find dissonant music unpleasant, patients with parahippocampal lesions find it pleasant (Gosselin et al., 2006). The involvement of the hippocampus in oxytocin regulation (Neumann & Landgraf, 2012) and observations that it is involved in attachment behaviors in animals (e.g., Kimble, Rogers, & Hendrickson, 1967) suggest that it may also be involved in social bonding - an important function of music. Indeed, Koelsch et al. (2015) proposed that affect-related emotions are based in a hippocampus-centered system. This social relevance of the hippocampus is supported by the finding of increased activity while synchronizing with a virtual partner (Fairhurst, Janata, & Keller, 2012).

Another limbic structure involved in music-evoked emotions is the cingulate cortex. This area is involved in emotions, memory, and learning, and has also been implicated in mood disorders (Drevets, Savitz, & Trimble, 2008). Koelsch (2014) notes that several subdivisions of the cingulate cortex - including the anterior cingulate cortex, middle cingulate cortex, and rostral cingulate zone - are a part of the pathway involved in autonomic and muscular reactions to music. Additionally, the pre-genual cingulate cortex has been implicated in pleasurable responses to music (Koelsch, 2014).

The orbitofrontal cortex is a region of the prefrontal cortex related to affect-generation (Koelsch, 2014) as well as to reward and decision-making regarding hedonic experiences (Kringelbach, 2005). It is involved in rewards relating to food, money, and sex (Sescousse et al., 2013) as well as music (Salimpoor et al., 2013).



In summary of this section on music as an emotional stimuli, emotion is an important feature of musical experiences, and the consistency in music-emotion associations across musical traditions suggests some degree of universality in perception of emotion in music. The emotions evoked by music can be inconsistent with those portrayed by the music, however, evidence from behavioral, physiological, and brain imaging studies largely suggests that music evokes the emotions it portrays and that these emotions bear resemblance to everyday emotions.

## **2.2 The five-factor model (FFM) as a measure of personality**

Now that it has been demonstrated that music can be considered an emotional stimulus, it is important to establish that the five-factor model (FFM) of personality functions in a reliable and valid manner as a measure of individual differences that are related to real-life outcomes, in order to justify a hypothesis that personality as measured by the FFM plays a role in neural responses to emotion in music. Thus, here there will be a brief outline the history of the FFM, its criticism, and its support.

### **2.2.1 History**

The five-factor model came out of the trait approach to personality. A trait can be defined as, “the tendency to act, think, and feel in a certain way - over time and across situations” (Schütz & Vater, 2007, p. 994-995). People have long used categories to describe recurring characteristics in others. However, more quantitative approaches to identifying traits developed in the past century.

One widely-accepted approach has been the application of factor analysis, which searches for covariance between the individual measured variables - which are traits or ‘facets’ - and tries to explain this covariance with overarching ‘factors’. These latent variables are thought to be ‘underlying’ the data; they are the broadest dimensions that each summarize a variety of traits (John & Srivastava, 1999). This approach was attractive to personality psychologists because it allows for an inductive model of personality, whereas many previous models had been based on observation and deduction.

Various models have emerged from using this factor analytic approach. Notable among these models is Raymond B. Cattell’s theory of 16 Personality Factors (16PF; Cattell, 1945) and Hans Eysenck’s theory of the Gigantic Three (Eysenck, 1947). However, general consensus has emerged around models with five factors (John & Srivastava, 1999). The factors that emerge from factor analysis are inductive, but researchers usually interpret the

factors and try to give them meaningful labels. The Big Five model (Goldberg, 1981, 1993; McCrae & Costa Jr, 1985) has become the predominant model in personality psychology, and its factors have been labeled Extraversion (E), Neuroticism (N), Conscientiousness (C), Agreeableness (A), and Openness to Experience (O).

### 2.2.2 Criticisms

Despite its widespread acceptance, the trait approach to personality and the FFM are not without criticisms. With regards to the trait approach in general, criticisms tend to point out that traits are insufficient to fully explain behavior and cognition in everyday situations. Mischel famously argued against the trait approach in the 1960s (Mischel, 1968), though he later tempered his outright rejection in support of an interactionist approach in which both traits and situations play a role behaviors (Mischel & Shoda, 1995). Others, in contrast, assert that the complexity involved in the psychology of an individual is better represented in a person-centered approach (Block & Block, 1980). Proponents of the five-factor model have considered the limits of the pure trait approach in a more recent description of the Five-Factor Theory (McCrae & Costa, 2008).

With regards to the FFM in particular, there is some disagreement as to the *number* of most basic factors. There are several objections along these lines from lexical studies that use the trait-related words in different languages as the basis of a factor analysis. For example, De Raad and Peabody (2005) found that a three-factor model better explained the trait-related words in Dutch, Italian, Czech, Hungarian, and Polish. The argument is that if a population has no word to describe a factor, or the facets thereof, then that personality factor cannot exist in the population, or at least, individuals cannot have a concept of the factor. However, this presupposes the notion that trait conceptions, and perhaps the traits themselves, are linguistically bound. Against this view, McCrae (1990) pointed out that the English language contains fewer words related to Openness.

Another argument against the FFM is that it does not exist at the ideal factor *level*; it has been proposed that two higher-level factors may provide a more stable solution for explaining variation in personality (e.g., DeYoung et al., 2010; Digman, 1997). However, correlations between questionnaire answers and these higher-level factors appear to be weaker than with the FFM factors (Deary, 2009), and it has been suggested that these ‘metatraits’ actually represent the negative or positive evaluation of one’s personality rather than personality itself (McCrae & Costa Jr, 1999).

### 2.2.3 Support

Despite the limitations of the trait approach and the Big Five model in particular, there are many findings that support the FFM.

The reliability of the FFM has been demonstrated in several ways. The FFM has been derived from variables arising from a number of different personality theories and questionnaires (John & Srivastava, 1999). Its reliability has been demonstrated with consistency between self- and others-ratings of personality, with correlations the range of .4 to .6 (Funder & Colvin, 1997; McCrae & Costa Jr, 1989). Additionally, the reliability of the FFM over longer periods of time was demonstrated by Costa and McCrae (1988) in a six-year longitudinal study that indicated high trait stability in adults over age 30, based on self-ratings and on ratings by spouses. With regards to the particular questionnaire used in the proposed study, the Big Five Questionnaire (BFQ), John and Srivastava (1999) found that the BFQ had a mean internal consistency of .83 in a sample of 462 American undergraduates.

The validity of the FFM has been demonstrated by cross-cultural research. McCrae (2001) found a similar five-factor personality structure across twenty-six cultures. McCrae and Terracciano (2005) replicated these results across fifty cultures, and additionally found a similar role for age and sex in personality, as well as consistency between other- and self-reported personality. With regards to predictive validity, traits are related to real-world outcomes, including success in school settings (Matthews, Zeidner, & Roberts, 2012) and work settings (Barrick & Mount, 1991), mood disorders (Cuijpers et al., 2005), and subjective well-being (Richard & Diener, 2009).

It has been suggested that the seeming universality of the FFM is due to its biological underpinnings (McCrae, 2009). Indirect evidence for this comes from studies of behavioral genetics. Twin studies show a greater correlation in personality scores between monozygotic twins than between dizygotic twins (e.g., Bouchard Jr, 1994), even in cross-cultural samples (Yamagata et al., 2006), suggesting that inherited factors account for 30-60 % of the variance in personality traits (Benjamin et al., 1996). More direct evidence of the role of genes may also be seen, for example, in the linking of Novelty Seeking/Extraversion to the DRD4 gene that encodes for a dopamine receptor (Ebstein et al., 1998) and between Neuroticism/Harm Avoidance and the SLC6A4 gene that codes for a serotonin transporter (Lesch et al., 1996). However, it should be noted that there are several confounders that get in the way of reaching consensus between studies attempting to replicate these results (Ebstein et al., 1998).

Therefore, for the most part there is consensus that the FFM functions in a reliable and valid way as a measure of individual differences across populations. Further, it correlates with real-world outcomes, and it may have biological correlates.

#### **2.2.4 Traits of interest for this study**

In the previous section, I attempted to justify using the FFM of personality as a measure of individual differences. However, the question remains as to why personality might be related to perception of emotional music stimuli, and why Extraversion, Neuroticism, and Openness in particular. In the following subsections, I will attempt to demonstrate how Extraversion and Neuroticism have been related to tendencies to experience positive and negative affect, respectively, and how Openness has been related aesthetic sensitivity and to experiences of emotion in music.

#### **Extraversion**

Extraversion is characterized by warmth, gregariousness, assertiveness, activity, excitement seeking, and positive emotions (Costa & McCrae, 1992). In experimental settings, Extraversion has been related to more-effective positive-mood induction (Larsen & Ketelaar, 1991). Additionally, in everyday situations, Extraversion has been related to higher positive mood (David, Green, Martin, & Suls, 1997) and higher subjective well-being (Pavot, Diener, & Fujita, 1990). Some might argue that these subjective happiness ratings could reflect temporary mood states, rather than stable happiness. However, in a longitudinal study, Costa and McCrae (1980) showed that Extraversion and Neuroticism could predict happiness and well-being ten years later.

Some doubt has been cast on the strength of the correlation between personality and emotion because the methodological differences between studies made it difficult to compare results. Therefore, Lucas and Fujita (2000) used structural equation modeling to assess the consensual results from various datasets using different personality and affect scales, and found a correlation of .59 between Extraversion and pleasant affect. They also did a meta-analysis of previous literature and found an average correlation of .37.

There is also some neuroscientific evidence of a link between Extraversion and perception of positive emotional stimuli. Extraversion has been positively related to activity in the ventral prefrontal cortex during perception of humorous cartoon pictures (Mobbs, Hagan,

Azim, Menon, & Reiss, 2005) and in the inferior frontal gyrus to positive words (Canli, Amin, Haas, Omura, & Constable, 2004) and positive pictures (Canli et al., 2001). Additionally, Extraversion was positively related to activity in the anterior cingulate cortex (ACC) during implicit perception of positively-valenced words (Canli et al., 2004; subgenual ACC - Haas, Omura, Amin, Constable, & Canli, 2006) and passive perception of positively-valenced pictures of people, animals, scenery, etc. (Canli et al., 2001), though the role of different subdivisions of the ACC is not clear with regards to personality (Kennis et al., 2013). Extraversion has also been related to greater amygdala activation to pictures of positive facial expressions (Canli et al., 2001), pleasant odours (Vaidya et al., 2007), and positively-valenced pictures of people, animals, scenery, etc. (Canli, Sivers, Whitfield, Gotlib, & Gabrieli, 2002). Thus, neuroscientific research supports a link between Extraversion and positive emotionality. However, it should be noted that there are relatively few studies on this topic and it appears that they have not been replicated, so interpretations should be cautious.

It has been proposed that Extraversion's relation to positive affect is a byproduct of Extraversion's relation to sociability. In support of this, Costa and McCrae (1980) found that sociability and activity were related to subjective ratings of happiness, Watson (1988) found that subjects' daily ratings of positive affect were related to social activity and exercise, and Côté and Moskowitz (1998) found that Extraversion was related to the interaction between agreeable behavior and positive affect in everyday situations. Alternatively, it has also been suggested that Extraversion's relation to positive affect and sociability are both byproducts of its relation to reward sensitivity (Gray, 1970). Lucas and Fujita (2000) used structural equation modeling on personality data from a cross-cultural sample of 6,469 college students from 39 nations and found that Extraversion facets loaded more strongly onto reward sensitivity than onto sociability. They therefore suggest that Extraversion facets such as sociability and positive affect both arise out of the propensity to engage in rewarding situations.

In the context of music, Extraversion has also been associated with positive affect. Rentfrow and Gosling (2003) found that Extraversion was related to preferences for musical genres that "emphasize positive emotions and are structurally simple" (p. 1241), as well as those that "are lively and often emphasize rhythm" (p. 1242). In line with this, Vuoskoski and Eerola (2011b) found that Extraversion was related to liking happy-sounding music. In the same study, the authors found Extraversion moderated the degree of congruence between current mood state and emotion ratings. In another study, Vuoskoski and Eerola (2011a) found Extraversion was related to higher felt emotions during music listening.

In everyday situations, Extraversion is related to more prevalent emotional experiences while listening to music (Juslin et al., 2008). This research suggests that the link between Extraversion and positive affect may also be present in relation to music.

## **Neuroticism**

Neuroticism is characterized by anxiety, hostility, depression, self-consciousness, impulsiveness, and vulnerability (Costa & McCrae, 1992), and has additionally been related to irritability, rumination, dysregulation of emotions, and state negative affect (Costa & McCrae, 1980; Costa Jr & McCrae, 1992; John, Naumann, & Soto, 2008).

Behaviorally, Neuroticism has been related to a tendency to experience negative emotions (Clark, Watson, et al., 2008; Larsen & Ketelaar, 1991; Robinson, Ode, Moeller, & Goetz, 2007). In line with this, Neuroticism has previously been associated with brain function during perception of negatively-valenced stimuli. In this research, positive correlations have been found in activation of the left middle temporal and middle frontal gyri (Canli et al., 2001) as well as the temporal pole (Jimura, Konishi, & Miyashita, 2009) and the medial prefrontal cortex (Haas, Constable, & Canli, 2008; Williams et al., 2006), and in connectivity between the right amygdala and dorsomedial prefrontal cortex (Cremers et al., 2010). Negative correlations have been found in activation of the right middle frontal gyrus (Canli et al., 2001) and in connectivity between the left amygdala and anterior cingulate cortex (Cremers et al., 2010). Further, in a study of brain structure, Kong et al. (2015) found that Neuroticism and Extraversion mediated the positive association between loneliness and gray-matter volume of the left dorsolateral prefrontal cortex. However, in a study more similar to the present study, Park et al. (2013) found against their expectations that Neuroticism was related to activations during perception of happy music, in the bilateral basal ganglia, insula and orbitofrontal cortex (this study will be discussed further in Section 2.4).

With regards to real-life outcomes, the link between Neuroticism and negative affective has been observed in diaries recording daily events and mood outside experimental settings (Bolger & Schilling, 1991; David et al., 1997; Marco & Suls, 1993). Additionally, it has been linked to mental health, being positively correlated with the likelihood of receiving care in the mental health sector (ten Have, Oldehinkel, Vollebergh, & Ormel, 2005) as well as diagnosis of and proneness to depression (Boyle et al., 2010; Saklofske, Kelly, & Janzen, 1995) and anxiety (Rusting & Larsen, 1998). In line with this, Costa and

McCrae (1992) found that Neuroticism was correlated with many clinical mental health measures, including including anxiety, depression, paranoia, aggression, suicidal ideation, and stress. Thus, a better understanding of this personality trait in particular could have clinical implications, and so Neuroticism has received more research than some other traits such as Openness, which is not as closely related to psychopathology (DeYoung & Gray, 2009).

In terms of behavioral music research, some attempts have been made to link Neuroticism to negative affect in music. Rentfrow and Gosling (2003) found that Neuroticism was positively correlated to liking for Reflective and Complex music, but this was a weak association ( $r = .08$ ), and it was only found in one of two samples. Ladinig and Schellenberg (2012) found that Neuroticism was related to higher felt sadness while listening to music; likewise Vuoskoski and Eerola (2011b) found that Neuroticism was positively related to ratings of sadness in music, however, this correlation became nonsignificant when current mood was controlled for. Additionally, Vuoskoski and Eerola (2011a) did not find any significant correlations between Neuroticism and music-evoked emotions, though there was a trait-congruent nonsignificant negative correlation between Neuroticism and liking for happy music. Thus the role of Neuroticism in music experiences may be trait-congruent with regards to negative affect, but the picture is less clear than it is for Extraversion due to nonsignificant and weak results.

### **Openness to Experience**

Openness to Experience is characterized by fantasy (imagination), aesthetic sensitivity, attention to subjective feelings, actions, ideas, and values (Costa & McCrae, 1992). Although Openness is not normally associated with tendencies to experience positive or negative affect, it is included in the present study because of its relation to aesthetic experiences, since music is an art form. Previous neuropsychological studies of the role of personality in perceiving emotional stimuli have used stimuli such as emotional faces (Canli et al., 2002), valenced smells (Vaidya et al., 2007), valenced pictures (Canli et al., 2001), and emotional words (Haas et al., 2006), but the current study used emotional music, which has an additional artistic element (Brattico & Pearce, 2013).

Much of the research on the neural correlates of Openness has focused on its putative link to intellectual abilities (e.g., DeYoung, Peterson, & Higgins, 2005; DeYoung, Shamosh, Green, Braver, & Gray, 2009), however, there has been some research on its relation to

aesthetic sensitivity. For example, Li et al. (2014) found that Openness mediated the association between trait creativity and the gray-matter volume of the right posterior medial temporal gyrus, Jung, Grazioplene, Caprihan, Chavez, and Haier (2010) found that Openness, when controlled for Intellect, was related to decreased integrity of white matter in the frontal lobes, and Li et al. (2014) found that Openness mediated the association between trait creativity and volume of the right posterior middle temporal gyrus. Functionally, Openness has also been related to increased connectivity in the default mode network (Adelstein et al., 2011; Beaty et al., 2014).

Regarding behavioral research, Openness has been related to musical experiences as well. In their study of the relation between personality and music preferences, Rentfrow and Gosling (2003) found that Openness had a positive correlations with preference for Reflective and Complex music and for Intense and Rebellious music, and it was negatively correlated with preference for Upbeat and Conventional music. Likewise, Openness has been linked to liking a greater variety of music outside mainstream genres (Dollinger, 1993). Regarding emotions in music, Openness has been related to greater liking for sad music (Vuoskoski & Eerola, 2011b; Vuoskoski et al., 2012) and fearful music (Vuoskoski & Eerola, 2011b), greater liking for music that induced sad feelings (Ladinig & Schellenberg, 2012), and the intensity of emotions induced while listening to tender and sad music (Vuoskoski & Eerola, 2011a). In line with the relation between Openness and aesthetic sensitivity, Openness is related to experiences of awe (Silvia et al., 2015) and chills (Colver & El-Alayli, 2016; Nusbaum & Silvia, 2011) while listening to music. Thus, although Openness is not typically related to emotional experiences, its association with artistic experiences and its links to music-emotional experiences make it of interest to this study.

In this section, I have shown why the traits investigated here are of interest. Extraversion and Neuroticism are associated with state positive and negative affect, respectively, and Openness to Experience is of interest due to its association with aesthetic experiences and emotional experiences of music. Conscientiousness and Agreeableness were not examined here because they are not characterized by emotional tendencies (Costa Jr & McCrae, 1992), nor was there another reason for their inclusion relating to music being the emotional stimulus - as was the case with Openness being related to aesthetic experiences (Costa Jr & McCrae, 1992) and to stronger emotional experiences of music (Vuoskoski & Eerola, 2011a).



## 2.3 fMRI as a measure of brain function

Now we turn to whether functional Magnetic Resonance Imaging (fMRI) is a suitable method for investigating the question at hand - the role of personality in neural responses to emotion in music. To address this, the following topics will be discussed:

1. What fMRI measures,
2. Its advantages and disadvantages for music research, and
3. The statistical analysis of fMRI images using a voxelwise general linear model.

### 2.3.1 What fMRI measures

fMRI has been a frequently-used functional brain imaging technique since its development in the early 1990's (Burunat & Brattico, 2018). It indirectly measures neural activity by measuring the hemodynamic response to neural metabolism; brain areas with increased neural activity will show increased cellular metabolism. fMRI tracks hemodynamic response by tracking the concentrations of oxyhemoglobin and deoxyhemoglobin. Hemoglobin is found in the blood stream, where it carries oxygen to tissues that need it for metabolism; oxyhemoglobin is hemoglobin with oxygen attached, and deoxyhemoglobin is hemoglobin without oxygen. When oxygen is removed from oxyhemoglobin to be used in metabolism, several electrons are freed, making deoxyhemoglobin strongly paramagnetic. Paramagnetic molecules distort magnetic fields, and so the location of deoxyhemoglobin can be tracked by measuring distortions in the strong homogeneous magnetic field emitted by the MRI apparatus. In this way, the fMRI signal results from a blood-oxygen-level-dependent (BOLD) contrast.

fMRI measurements are made in slices, and then three-dimensional images are constructed, made of tiny three-dimensional voxels. Voxels are analogous to pixels in a two-dimensional image, and are generally about  $2 \text{ cm}^3$ . For each voxel, there is a time course of the fMRI signal, indicating the level of hemodynamic response at each scan. Different things can then be measured using these voxelwise fMRI signals; this study used fMRI to measure activations. Neural activations are taken as areas where the BOLD signal is significantly related to a time-course regressor that indicates when events happened to the participants in the scanner, for example, when a certain type of music was playing.

### 2.3.2 Advantages and disadvantages of fMRI for music research

There are advantages and disadvantages of using fMRI, some more relevant in music research. The MRI apparatus can scan the entire brain in a noninvasive manner, and has been able to replicate neuroscientific findings with other methods. However, it is an indirect measure of neural activity, and it is not fully understood how neuronal activity relates to the fMRI signal (Burunat & Brattico, 2018). And although fMRI has better spatial resolution than some more direct measures of brain activity such as electroencephalography, a single voxel can contain millions of neurons (Huettel, Song, & McCarthy, 2009). Even if the signal does capture task-relevant neural activity, both the participant and the scanner create signal noise, which can only to some extent be removed through statistical techniques.

Another important limitation is the poor temporal resolution. This results from the 5-second delay of the hemodynamic response after nerve firing, and the fact that scans are taken every 2 seconds (with the apparatus used in this study). This disadvantage is particularly relevant to music research because music occurs in time. The temporal resolution can be slightly improved during data preprocessing, but this is one of the main criticisms of fMRI (Burunat & Brattico, 2018). In the present study, the stimuli last four seconds; this allows for two scans per stimulus.

One source of non-neural signal that is particularly notable in music research is the acoustic noise of the pulsing radiofrequency coils in the scanner; the noise is approximately 80 dB in newer scanner models (Burunat & Brattico, 2018). About 30 dB of noise attenuation can be achieved in the scanner with noise-canceling headphones and foam placed around the head in the scanner, and actual perception of the noise may be less problematic than it seems because it is thought that people tune out constant noise, or else any brain signal related to constant noise might be constant as well and so not be relevant to the stimulus.

The set-up required for fMRI can also be limiting for music research. The participant must lay still in order to avoid movement noise in the signal, and movement is often considered an essential part of musical experiences (Leman, 2008). Also, music is frequently experienced in social settings, and fMRI is not conducive to interpersonal interaction (though there have been some attempts at virtual interaction, e.g., Fairhurst et al., 2012).

Therefore, there are advantages and disadvantages to using fMRI; its poor temporal resolution, acoustic noise, and particular set-up are especially relevant in the context of music

research. Despite these limitations, fMRI has been frequently used in research on the neural correlates of music-evoked emotions (Koelsch, 2014), indeed, many of the personality studies described above use this brain-imaging method.

### 2.3.3 The statistical analysis of fMRI images using a voxelwise general linear model.

fMRI is not a very old technology, and younger still is the use of fMRI to investigate individual differences in brain function. Therefore, there does not appear to be a standard method for investigating individual differences at this time. However, based on the studies cited above in the literature review, the classical 2-level general linear model seems to be the most-frequently used. Here, I will describe this model and discuss the treatment of personality as a continuous or discrete variable.

Classical methods for modeling fMRI data involve a hierarchical statistical model, combining fixed effects within subjects and random effects between-subjects. Under most conditions, this hierarchical model is separable by subjects, and so it is computationally simpler to estimate it in two levels: 1) for each subject, a model of the BOLD signal with the stimulus regressors, and 2) for each condition, a between-subjects model of the level-1 parameter weights across the group, between groups, or across an individual difference. This “summary statistics” approach (Holmes & Friston, 1998) to fMRI modeling is outlined in Equations 1 and 2, and is often applied in a voxelwise manner.

$$\text{Level 1 : } Y_i = X_i\beta_i + \epsilon_i \quad (1)$$

$$\text{Level 2 : } \beta_c = Z\alpha_c + \varepsilon_c \quad (2)$$

Where for level 1,

- $i$  is the given participant,
- $Y_i$  is a  $n$ -by-1 vector of the preprocessed BOLD signal,
- $\beta_i$  is a  $p$ -by-1 vector of the the parameter-weight estimates (for the stimulus regressors),
- $X_i$  is a  $n$ -by- $p$  design matrix with the stimulus regressors,
- $\epsilon_i$  is a  $n$ -by-1 vector of a within-subjects residual,
- $n$  is the number of observations (i.e., scans), and
- $p$  is the number of parameters in the model (i.e., the number of stimulus regressors plus one for the constant).

And for level 2,

- $c$  is the given contrast (usually for a condition/stimulus type),
- $\beta_c$  is a  $m$ -by-1 vector of the contrasted beta estimates from level 1,
- $\alpha_c$  is a  $q$ -by-1 vector of the parameter-weight estimates (for the participant regressors),
- $Z$  is a  $m$ -by- $q$  matrix with the participant regressors,
- $\varepsilon_c$  is a  $m$ -by-1 vector of the between-subjects residual,
- $m$  is the number of observations (i.e., participants), and
- $q$  is the number of parameters in the model (i.e., the number of participant regressors plus one for the constant).

The first level is estimated in the same manner whether one is looking at activations across one or more groups, or at individual differences in activation. The difference comes in when defining the level-2 independent variable(s) (i.e.,  $Z$  in Eq 2). For looking at mean activation,  $Z$  will be a  $m$ -by-1 vector of ones (equivalent to a one-sample t-test). For comparing activation between groups, it could be a  $m$ -by-1 vector of ones and negative ones (2-sample t-test) or a  $m$ -by- $q$  set of binary vectors describing group membership (paired t-test or ANOVA), where in this case,  $q$  is the number of groups. For looking at an individual difference,  $Z$  is a  $m$ -by- $q$  vector of scores on the individual-difference measure (correlation or multiple regression), where  $q$  is the number of individual differences included in the model.

It is not uncommon to compare brain function between two groups, however, splitting participants into groups based on a continuous variable such as personality results in a loss of power equivalent to losing about a third of the sample size (J. Cohen, 1983; MacCallum, Zhang, Preacher, & Rucker, 2002). In any case, the personality scores in the present study had unimodal distributions (see Figure 10), so the data did not support splitting participants into groups. Therefore, personality was treated as a continuous variable in the present study.

### **The multiple-comparisons problem**

The models Equations 1 and 2 are often estimated in a *mass univariate* manner, meaning the same model with one dependent variable is estimated at every voxel. This raises a statistical problem because the number of false positives increases with the number

of tests done, and therefore the significance thresholds must be corrected for multiple comparisons.

In order to alleviate the multiple-comparisons problem, steps can be taken to reduce the number of independent tests. A simple way to do this is to select an anatomical or functional region, and take the average signal over the voxels in that region instead of considering each voxel separately. Alternatively, a more sophisticated method is to use a data-reduction method such as principal components analysis or independent components analysis to estimate a set of signals that capture most of the variance in the voxel time series across voxels. A common method that maintains voxelwise specificity is to focus the analysis on voxels in specific regions of the brain, that is, on regions of interest (ROIs). This is the method used in the present study.

### **Region-of-Interest (ROI) selection**

ROIs may be selected in different ways: a common method is to select regions based on previous research indicating that those regions were related to similar functions as the ones being studied, or alternatively ROIs may be selected from a whole-brain first-level analysis as those voxels that are most consistently activated across participants (Thirion, Varoquaux, Dohmatob, & Poline, 2014).

These methods of selecting ROIs may be problematic when examining individual differences in brain function, especially in the case where there is little existing literature investigating the question at hand (Omura et al., 2005). ROIs that are selected based on previous research of mean activation across participants may not show a large amount of variance related to the individual difference precisely because they had to have exhibited consistent activation between participants in order to have been statistically significant (Omura et al., 2005). The same problem arises if one selects ROIs based on common activation revealed in the first level of the analysis.

Omura et al. (2005) suggested an alternative approach for investigating the role of individual differences in functional neuroimaging: selecting regions with the greatest between-subjects variance in the level-1 parameter estimates, relative to the mean within-subjects residual variance. They refer to ROIs selected in this way as regions of variance (ROVs).

Therefore, for the present study, I considered four ways of selecting ROIs:

1. *A priori* based on previous research on emotion processing,
2. Functionally based on common activation across participants,
3. *A priori* based on previous research on the role of personality in neural responses to emotional stimuli, or
4. Functionally based on variation in activation across participants (ROV method)

Options 1 and 2 may not be ideal for studying individual differences, because they focus on areas commonly active across participants. Option 3 seems to avoid this potential problem, however, upon closer examination of the methods outlined in individual studies investigating the role of personality in neural responses to emotional stimuli, it appears that most of them selected ROIs using options 1 (Canli et al., 2002; Cremers et al., 2010; Williams et al., 2006) or 2 (Haas et al., 2008; Jimura et al., 2009; Mobbs et al., 2005; Park et al., 2013), with only one study employing a whole-brain analysis (Canli et al., 2001). Therefore, selecting option 3 could indirectly mean selecting options 1 or 2, unless the ROIs were selected based on the single whole-brain analysis study. Furthermore, it appears that the ROV method has not been used since its initial description in the paper by Omura and colleagues; thus, it may be beneficial for the field to examine its usefulness again.

For these reasons, the ROV method was used to select ROIs. An additional purpose of this study is to consider the usefulness of this method in this context, and so a whole-brain analysis was carried out in order to allow for a comparison of the results (note that this comparison was based on observation, and not a quantitative comparison/evaluation).

### **Avoiding circular analysis and ‘double dipping’**

Methods of functionally deriving ROIs run the risk of circularity; significance may be overestimated due to ‘double dipping’ when the same data is used to define regions of interest for an analysis and to perform the analysis (Kriegeskorte, Simmons, Bellgowan, & Baker, 2009). Such methods increase false positive rates by preferentially selecting noise that may be in line with the desired effect. This criticism has been made for the method of selecting ROIs functionally based on common activation across participants (i.e., option 2 listed on page 22): if you are looking for consistent neural activity across subjects, then selecting regions that are consistently activated across subjects will make it more likely that you find the hypothesized result by chance, as you are preferentially selecting noise that is more likely to be in line with any hypothesis of a significant mean

activation.

The relevant question here is whether functionally deriving ROIs as regions of *variance* runs the same risk of circularity. Here I argue that this is not the case. Selecting regions with similar activation between participants increases the likelihood of the mean activation being significant by chance, hence the ‘double dipping’. But in the context of the ROV method, selecting regions with high between-subjects variance (relative to within-subjects variance) could select noise that is by chance related to the behavioral individual difference of interest, however, it could also select noise that is highly variable between participants but is unrelated to the individual difference. One could even argue that there are more ways for noise to be randomly *unrelated* to a given individual difference than to be randomly related.

Therefore, functionally selecting regions of variance should not necessarily increase the false-positive rate. Perhaps future research could demonstrate this more convincingly using proofs and simulations. But in the present study, extra precaution was taken to avoid double-dipping by using a nonparametric method of significance estimation. This method involves building a distribution of null results using the data within the regions of variance, and so it controls for any potential increase in false positives resulting from the ROI-selection procedure.

## **2.4 Previous research on the role of personality in brain function during perception of emotions in music**

There has been some previous research on the role of personality in brain function during perception of emotions in music; we found two studies examining this topic.

Koelsch, Skouras, and Jentschke (2013) included an investigation of the role of personality in functional connectivity during perception of joyful, fearful, and neutral music. They did not find any significant relation between functional connectivity and Extraversion or Neuroticism, though they do report an uncorrected association between Neuroticism and connectivity in the rostral/caudal cingulate zone.

The other study, by Park et al. (2013), was more similar to the present study in that it also looked at neural activations rather than connectivity; they too examined the role of personality in activations during perception of happy, sad, and fearful music. As in the present study, they expected Extraversion-related activations during happy music

and Neuroticism-related activations during sad and fearful music. Contrary to these hypotheses, they found Neuroticism to be positively related to activation during happy music - in the bilateral insula, basal ganglia, and orbitofrontal cortex. They additionally found a marginally-significant negative association between Extraversion and activation during fearful music - in the right amygdala.

Further research such as the present study can help elucidate these null and unexpected results by extending methodological choices, particularly relating to ROI selection and sample size.

#### 2.4.1 ROI selection

The present study extends the methods of these previous studies using an alternative method for selecting ROIs that avoids limiting ROIs to areas where there was common activation across participants.

Park et al. (2013) used both functional and anatomical ROIs, and examined the average signal intensity within each ROI. They do not describe in detail how their ROI's were selected, but it appears that their choices correspond to options 1 and 2 as described in Section 2.3.3, namely, 1) *a priori* based on previous research on emotion processing (not looking at individual differences), and 2) functionally based on common activation across participants. As was pointed out in Section 2.3.3, these methods of selecting ROIs based on common activation across participants may not be ideal ROIs for investigating individual differences, or at least, it may not be ideal to limit ROIs to such areas.

Koelsch, Skouras, and Jentschke (2013) selected anatomical ROIs based on past research on the functional neural correlates of personality. As noted in Section 2.3.3, this method (option 3) may indirectly involve selecting regions with common activation across participants, as the original selection of these regions is often based on common activation in past studies or in the current study (i.e., options 1 or 2). Indeed, among the studies cited by Koelsch, Skouras, and Jentschke (2013) to justify their ROI selection, nearly all originally used option 1 (i.e., anatomical ROIs selected based on previous studies not looking at individual differences; Brück, Kreifelts, Kaza, Lotze, & Wildgruber, 2011; Canli et al., 2004, 2002; Eisenberger, Lieberman, & Satpute, 2005; Fischer, Wik, & Fredrikson, 1997; “Frontolimbic serotonin 2A receptor binding in healthy subjects is associated with personality risk factors for affective disorder”, 2008; Haas et al., 2006; Tauscher et al., 2001), two used option 2 (i.e., functional ROIs based on common activation across participants; M. X. Cohen, Young, Baek, Kessler, & Ranganath, 2005; Kumari, Williams, Gray, et al.,



2004), and one used a whole-brain analysis (Canli et al., 2001). Thus, aside from this single whole-brain analysis, the ROIs selected by Koelsch, Skouras, and Jentschke (2013) were originally selected based on common activation across participants.

The point of this discussion is not to say that the ROI-selection procedure in these studies was invalid. Rather, it is to say that it may be important to additionally use more exploratory methods with respect to brain areas when investigating individual differences, so that the field does not directly (through ROI-selection options 1 or 2) or indirectly (option 3) limit its investigations to areas of common activation across participants.

#### 2.4.2 Sample size

Another way to extend the methods of the previous studies on this topic is to increase the sample size. Calculating the ideal sample size for an fMRI study is a complex issue, and there are different methods and guidelines for doing so (e.g., Desmond & Glover, 2002; Murphy & Garavan, 2004; Zandbelt et al., 2008). Since the data used in the present study was collected as part of a larger study that was not designed specifically for the question at hand, the sample size used here was not chosen based on a power estimation. However, some general guidelines were put forward by Friston (2012) for determining the sample size needed to find the effect under investigation, without the need to do a power estimation. Friston uses a cost function that balances a) sensitivity to the size of the desired effect with b) sensitivity to trivial effects. For an expected large effect, this cost function indicates that the optimal sample size is around 16 participants, and for an expected medium effect it is around 50. For the topic at hand, it might be reasonable to expect a medium or small effect size, if there is an effect, given the following observations:

- The unexpected and null results in fMRI research on personality and brain function during perceptions of emotions in music (Koelsch, Skouras, & Jentschke, 2013; Park et al., 2013),
- Some null or weak results in behavioral research on personality and emotions in music (Rentfrow & Gosling, 2003; Vuoskoski & Eerola, 2011a, 2011b), and
- Research on the effect sizes in behavioral individual-differences research suggests that the normative effects in this field are smaller than standard definitions of small, medium, and large effect sizes (Gignac & Szodorai, 2016).

Thus, the present study arguably had a more appropriate sample size (55) than previous studies examining this topic (12 in Park et al., 2013, and 22 in Koelsch, Skouras, & Jentschke, 2013).

Therefore, the present study aims to extend past research on this topic with a more exploratory method of selecting regions of interest and with a larger sample size.

### 3 THE CURRENT STUDY

Literature from various fields of research suggests that personality might play a role in the neural correlates of perceptions of emotion in music. Here, music is considered an emotional stimulus due to universal emotion-music associations and music's ability to evoke emotions that resemble everyday emotions, which is reflected in activation of emotion-related areas during music listening. It has been suggested that individual differences play a role in neural activity, and the five-factor model of personality has been shown to be a valid and reliable measure of meaningful individual differences; therefore, investigation of the neural correlates of this personality model is warranted. Within the five-factor model, Extraversion, Neuroticism, and Openness to Experience are of particular interest when investigating music and emotions. Extraversion has been related to positive affect both in a behavioral tendency to experience positive emotions as well as in neural correlates of processing positive emotional stimuli and reward-related stimuli, and in musical preferences and behavioral responses to emotions in music. Alternately, Neuroticism has been related to negative affect in its association with negative affective states and emotion-related psychopathology, and some evidence indicates that Neuroticism is related to musical experiences in a way that is congruent with this link between Neuroticism and negative affect. Openness to Experience is not conventionally associated with state positive or negative affect, however, it is associated with an affinity for aesthetic experiences and more intense aesthetic experiences, and in particular has been associated with the music-evoked emotions. To this end, fMRI has been shown to be useful for measuring brain responses to music and emotional stimuli, but there is a need for additional research clarifying fMRI methods for investigating individual differences. Although previous studies have investigated the role of Extraversion and Neuroticism in neural responses to emotion in music (Koelsch, Skouras, & Jentschke, 2013; Park et al., 2013), further research would be beneficial for elucidating some of their null and unexpected findings. Here, we propose to do so by extending their methodological choices, and by additionally investigating the role of Openness to Experience.

### 3.1 Purpose

Therefore, the purpose of the proposed study is to investigate the roles of Extraversion, Neuroticism, and Openness to Experience in the neural correlates of implicit perception of emotion in music. A secondary aim is to explore the use of the Regions-of-Variance method for selecting regions of interest (Omura et al., 2005).

### 3.2 Hypotheses

It is hypothesized that Extraversion will be related to brain activity during perception of positively-valenced music, and Neuroticism during negatively-valenced music, because of their close associations with positive and negative affect, respectively. This study is more exploratory with regards to Openness because as a trait it is not characterized by particular affective states; rather, it is of interest because of its association with aesthetic experiences and the experience of emotions in music in particular.

There were no specific hypotheses made with regards to brain areas. While previous research has indicated that personality is related to neural responses to emotional stimuli, it seems that a consensual picture has not yet emerged with regards to which areas are strongly related to which traits, and most results have not been systematically replicated. Some of these studies selected regions of interest that had been previously related to the type of stimuli being used, for example, focusing on limbic regions when utilizing emotional stimuli. However, it should also be considered that areas that have in the past been found consistently active across participants might not be good candidate areas for investigating individual differences (Omura et al., 2005), or at least it might not be ideal to limit ROIs to such areas at this early stage of this field investigating the neural correlates of personality. Further, the use of a data-driven method for selecting regions of interest such as the ROV method precludes specific hypotheses with regards to brain areas that will be related to each trait.

### 3.3 Contribution to scientific knowledge

In the introduction, several reasons were given as to how the present study contributes to scientific knowledge of a topic that has received some research already, namely, these reasons are:

1. It addresses a topic that has received some previous attention (i.e., two studies, to

our knowledge), but arguably not enough attention to establish reliable knowledge on the topic,

2. It uses a larger sample size than has been used by previous studies (this is especially relevant since individual differences generally have smaller than standard effect sizes; Gignac & Szodorai, 2016),
3. It uses a method for selecting regions of interest that may be more appropriate than some previous research for investigating a question relating to individual differences, and
4. It investigates the role of the personality trait Openness to Experience, which was not investigated in the aforementioned two studies on this topic, in addition to Extraversion and Neuroticism, which were previously investigated.

## 4 METHODS

The data used in this study is a subset of a larger dataset, which has been previously examined in two published studies. Bogert et al. (2016) compared neural activity during explicit and implicit processing of emotions in music, and Carlson et al. (2015) related indicators of adaptive and maladaptive emotion regulation through music to activity in the medial prefrontal cortex.

The criteria for a participant in the larger dataset to be included in the present study was that a) the participant completed the personality survey and b) there were no reasons to exclude the participant's scans (such as radiological abnormalities or technical issues during data acquisitions).

### 4.1 Participants

Sixty-three subjects were recruited via email lists from the University of Helsinki (Helsinki, Finland) and Aalto University (Espoo, Finland). Potential participants were excluded if they had hearing or neurological problems, or if they were taking psychopharmacological medicine. Prior to scanning, participants were informed about the study, consented to participate, and completed an fMRI safety questionnaire. They were compensated for every half-hour of participation with a voucher for cultural and exercise activities. Seven subjects had to be excluded from analysis due to moving to much during scanning (3 subjects), neuroradiological abnormalities diagnosed by a radiologist (3), technical issues (1), and incomplete of personality data (1). Thus, 55 participants (20-53 years,  $M = 28.6$ ,  $SD = 7.98$ ; 23 males; three left-handed) were included the final sample.

Regarding musical experience, eleven participants reported playing an instrument for five or more years, and eight of those participants still played for at least two hours a week.

The paradigm used in this study, called the "MusEmo" paradigm, was one part of a larger experimental session that subjects completed. The "Tunteet project" that included paradigm received ethics approval from the "Koordinoiva" ethical committee of Helsinki

and Uusimaa Hospital District, and it was run according to the ethical guidelines of the Declaration of Helsinki.

## 4.2 Stimuli

The stimuli consisted of 30, 4-second instrumental music excerpts representing happiness, sadness, and fear (10 clips for each emotion). To select these stimuli, 81 excerpts were taken from a film-music database that had previously been perceptually validated as representing their emotional label (Eerola & Vuoskoski, 2011), and each excerpt was rated on nine emotions (happiness, sadness, fear, anger, tenderness, pleasure, disgust, surprise, unclear, or other emotion) by ten subjects who did not participate in the brain imaging study. The ten most representative excerpts for each Happy, Sad, and Fearful were selected as stimuli (30 total).

Adobe Audition was used to edit the stimuli so that they had equal loudness (average root mean square) and so that they lasted four seconds with fade-in and fade-out each lasting 500 ms.

The four-second duration was chosen for two main reasons. First, this data was intended to compare implicit and explicit processing of musical emotions (Bogert et al., 2016), and the authors wanted to have the stimulus duration comparable to other studies of implicit processing of emotional stimuli (e.g. Bach et al., 2008). Second, they also wanted to ensure that the stimuli were long enough to be comparable with neuroimaging studies of music and emotion (e.g., Koelsch et al., 2006) so that the music was long enough to robustly evoke emotion in the listener.

## 4.3 Apparatus

The apparatus used was a 3-T MAGNETOM Skyra whole-body scanner and a standard 20-channel head-neck coil (Siemens Healthcare, Erlangen, Germany), located in the Advanced Magnetic Imaging (AMI) Center at Aalto University, Espoo, Finland.

The functional images were obtained with interleaved gradient echoplanar imaging (EPI) with a 2-second repetition time (TR; i.e., the period of the radiofrequency pulse), a 2-millisecond echo time (i.e., the time between the radiofrequency pulse and the center of the echo). There were 33 4-millimeter slices taken at a flip angle of  $75^\circ$  (i.e., the slices are oblique), resulting in 3 x 3 x 4 millimeter voxels with 0 mm spacing. The field of view

was 192 x 192 mm, and the matrix 64 x 64 mm.

The structural images were taken following the fMRI task, and consisted of high-resolution anatomical T1-weighted MR images, with 176 slices, a 256 mm field of view, a 256 x 256 matrix, and 1 mm<sup>3</sup> voxels with 0 mm spacing.

## 4.4 Procedure

### 4.4.1 FMRI data collection

There were two blocks in the experimental design for fMRI data acquisition, shown in Figure 1. In the explicit block, participants were presented with the question “What emotion do you hear?” for 10 seconds, followed by a 4-second music clip, followed by a 5-second window in which they selected their response out of the options “sadness”, “happiness”, and “fear”. The implicit block was the same except that the question was, “How many instruments did you hear?”, and the options were “one”, “two”, or “many”. In order to familiarize the participants with the tasks, there was a short training session before the study stimuli were presented. The present study used the data from the implicit block.

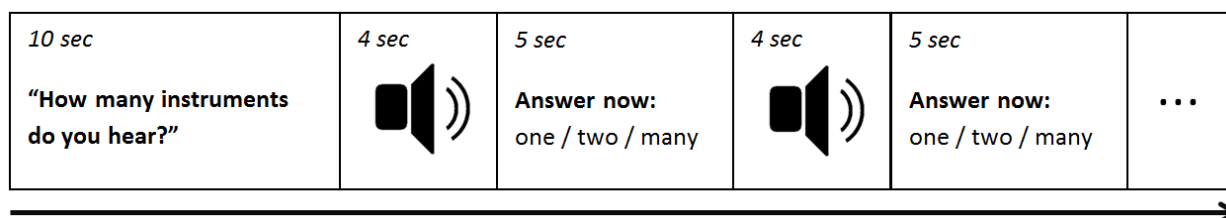


FIGURE 1. Stimulus presentation paradigm in the implicit emotion-processing block.

### 4.4.2 Questionnaire data collection

Self-rated Extraversion, Neuroticism, and Openness to Experience were measured using the Big Five Questionnaire (John & Srivastava, 1999). The questionnaire data were collected during a second session of data collection, which also included other brain measures, and in some cases, biological indicators drawn from blood samples. This second session took place on a separate day from the fMRI data collection, in the Biomag laboratory of the Helsinki University Central Hospital.



## 4.5 Preprocessing

Before fMRI data can be investigated for the question at hand, there are a number of data preprocessing steps that are taken to reduce the spatial and temporal variability in the data that is not related to the question.

fMRI scans are taken in slices, and so it is not possible to scan the entire brain at a given point in time. Thus, for example, the two scans that are furthest apart in space will be acquired about the TR time apart in time (in this case, 2 seconds). To correct for this, the data is interpolated between scans, and then resampled at the same time points throughout the brain; this is called slice-timing correction.

Individuals' brains vary anatomically, and so spatial preprocessing is needed to allow for spacial specificity when comparing brain function between participants. The first step in this process is to locate brain activity within a participant. To this end, during data acquisition a structural brain image is taken in addition to the functional images; then during preprocessing the functional images are co-registered with the structural image for each participant. Next, in order to compare activity in the the same location across individuals, the structural image and the co-registered functional images for each participant are warped to match a template brain, in this case the Montreal Neurological Institute (MNI) template. This spatial normalization makes voxels comparable between subjects, allowing for voxel-wise statistical tests. Slice-timing correction and spatial preprocessing were done in the Statistical Parametric Mapping (SPM) toolbox by a previous user of this dataset.

Preprocessing is also needed for the temporal aspect of the data. The fMRI signal contains three signals:

1. Neural signal that is related to the task,
2. Neural signal unrelated to the task, and
3. Non-neural signal

The goal of temporal preprocessing is to reduce the noise due to non-neural signal. To remove the noise caused by head movements, six parameters of the recorded head position (i.e., x, y, z, yaw, pitch, and roll) were used to predict the signal in multiple regression, and the residual was retained for further analysis. In order to remove long-term signal drift caused by the apparatus heating up, as well as slow changes in the signal caused by

heart beating and breathing, the data were detrended using spline interpolation with 5 anchor points. Additionally, the data were mean-centered within voxels. These temporal preprocessing steps were done in Matlab using custom codes and the fMRI Toolbox developed at the University of Jyväskylä, and are illustrate in Figure 2.

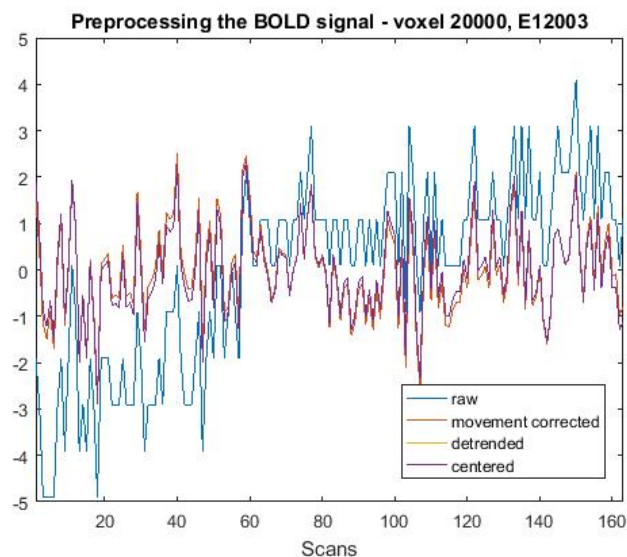


FIGURE 2. The BOLD signal before temporal preprocessing ('raw') and after each preprocessing step, for one voxel in one participant. Steps were done in the order they appear in the legend. Note that all lines are centered at 0 to allow for visual comparison, but mean-centering was done at the last step.

Regarding the noise generated by brain activity unrelated to the task, it is assumed that activity is task-relevant if its time course is related to that of the task. In order to eliminate irrelevant neural signal, brain activity during the task can be contrasted with brain activity during another task or with baseline activity. In the present study, there was no baseline condition, therefore, activity during each emotional condition will be contrasted with activity during the other two emotional conditions (e.g., Happy > Sad & Fear). This process is described in Section 4.6.3.

Additionally, having a larger sample size should reduce the influence of non-task-related neural signal as well as some non-neural physiological noise from the subject. These signals should vary between participants, and thus they should get canceled out in group analyses. The present study had 55 participants, which is a larger sample size than any of the studies noted earlier that have looked at the role of personality in the neural correlates of perception of emotional stimuli (ranging from 12-26 participants).

## 4.6 Analysis

The analysis followed the the summary-statistic approach to the two-level general linear model (Holmes & Friston, 1998). This involved the following steps:

1. *Preparing the level-1 design matrices* by creating regressors that capture the presentation timing of each stimulus;
2. *Level 1: Voxelwise within-subjects multiple regression*, in which the design matrix was used to predict the preprocessed BOLD data;
3. *Contrast estimation*, in which the level-1 parameter estimates for each stimulus type were contrasted against the other two stimulus types (e.g., Happy > Sad & Fear);
4. *Regions-of-Variance masking*, in which those regions with greater level-1 between-subjects variance (relative to within-subjects variance) were selected as regions of interest;
5. *Level 2: Voxelwise between-subjects partial correlation* between the contrasted beta weights for each stimulus and the scores for each personality trait, controlling for the other two personality traits; and
6. *Nonparametric significance testing* using permutation-derived null distributions of maximum cluster-size and -mass statistics.

Each of these steps will now be explained in more detail. These steps were carried out with custom codes in Matlab and the fMRIToolbox, which was developed at the University of Jyväskylä. A summary of the major components of the analysis pipeline can be seen in Figure 3.

Note that the voxels in the lower cerebellum (see Figure 4) were not scanned, and thus not included in these analyses.

### 4.6.1 Preparing level-1 design matrices

Each participant was presented with the stimuli in a random order, and so individual stimulus regressors needed to be created for each participant. To this end, stimulus onsets and offsets were read from the log files of the data acquisition sessions. A boxcar function was created for each stimulus such that the function was set to one for the time when the particular stimulus type was playing, and set to zero otherwise. See the top panel of Figure 5 for an example stimulus boxcar function.

A boxcar function does not resemble the fMRI signal and so it would be a poor model

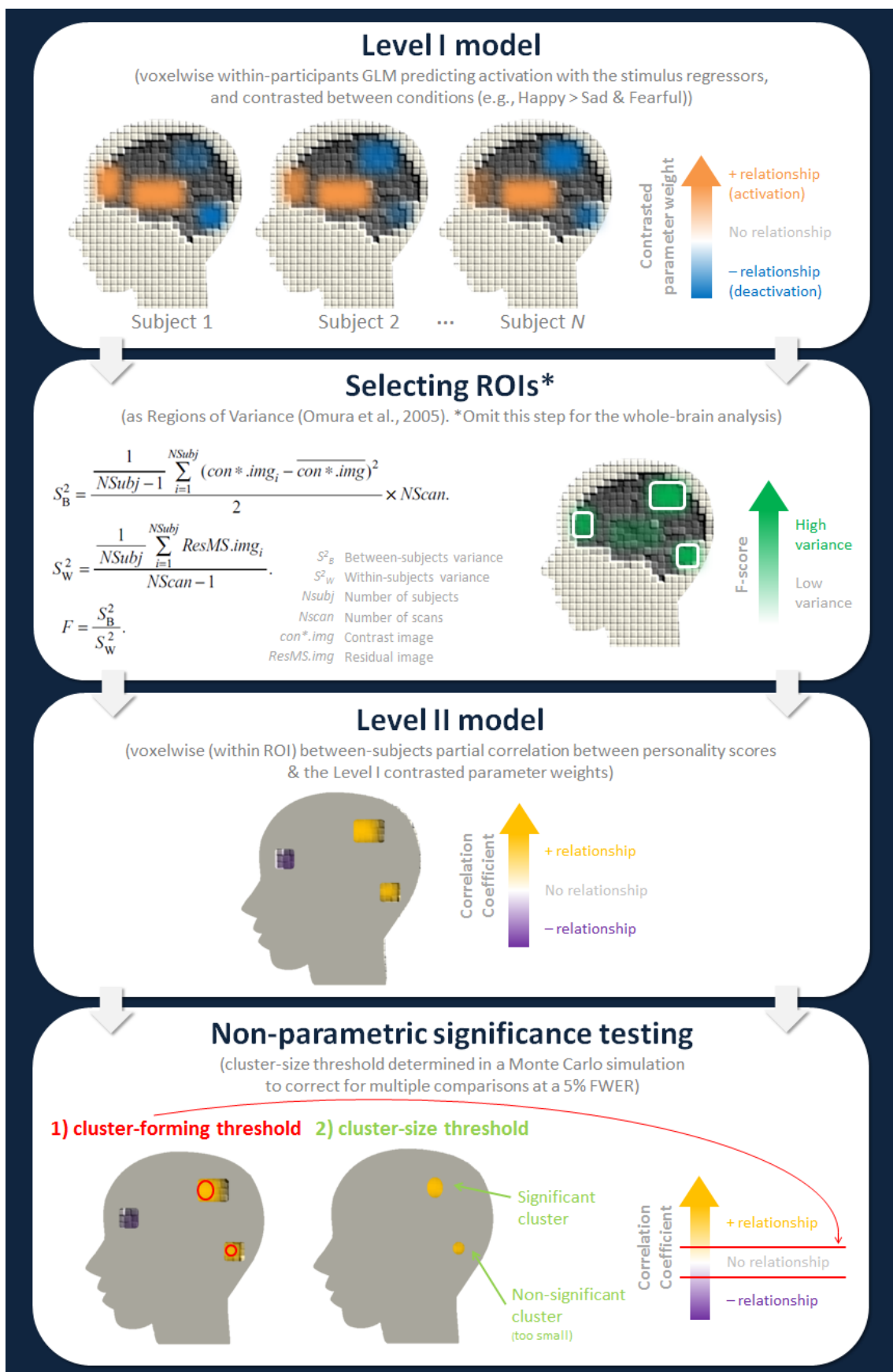


FIGURE 3. Illustration of the major components of the analysis pipeline.

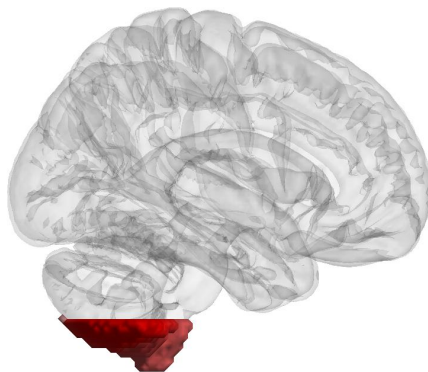


FIGURE 4. Voxels in the lower cerebellum that were not scanned and therefore were not included in the analyses.

of the signal. The hemodynamic response is delayed and smooth, and it has a particular shape and timing; thus, it is customary to convolve stimulus functions with a hemodynamic response function (HRF) so that they more closely resemble a potential BOLD response. A HRF has the shape of a typical hemodynamic response to an instant of neural activity, where the peak of the HRF occurs at about  $t = 5$  seconds because there is an approximate 5-second delay in the hemodynamic response to neural activity. Additionally, depending on the specific HRF, there is usually an undershoot after the peak returns to zero, reflecting the delay in the cessation of oxygen-delivery following cessation of neural activity. This study used a double-gamma HRF, generated using the `fmri_doublegamma` function in the `fMRIToolbox`.

The HRF was generated with a 25-second window with steps of  $1/10$  seconds (see the middle panel of Figure 5), and the stimulus boxcar functions were likewise upsampled by 10. This means that the stimulus functions were created in the deciseconds scale, allowing for smoother stimulus functions after convolution. If the functions were built in seconds, then the HRF and the boxcar would have two data points for each scan (because the TR for this study was 2 scans/second). But in a decisecond time scale there are 20 data points for each scan. A similar upsampling procedure is performed by the Statistical Parametric Mapping toolbox for analyzing fMRI data, with the default being 16 time bins per scan. In the textbook that describes the theory behind Statistical Parametric Mapping (SPM), a popular tool for analyzing fMRI data, Kiebel and Holmes (2007) describe the situation where the TR is 3.2 seconds, giving  $3.2/16 = 0.2$  seconds per time bin. In the present study, the repetition time (TR) was 2 seconds, and so the upsampling by 10 made 20 time bins per scan, giving  $2/20 = 0.1$  seconds per time bin. Kiebel and Holmes (2007) suggest that one does not gain temporal precision by choosing a smaller bin size due to

the low frequency band of the BOLD response, but there should not be a down side to a smaller bin size other than the slight increase in computational load; a smaller time bin was chosen here because it is simpler to conceptualize time in deciseconds than in  $1/8^{th}$  seconds (which is what the time scale would be with the SPM default settings of 16 time bins per scan).

After convolving the boxcar function with the HRF, the stimulus function was then down-sampled to have the same number of time points as the number of scans so that the stimulus function could be regressed against the imaging data. Since the TR for the fMRI image acquisition was 2 seconds and the sampling rate for generating the stimulus functions was 0.1 seconds, downsampling the stimulus functions to scans entailed selecting every  $20^{th}$  time point along the stimulus functions. See the bottom panel of Figure 5 for an example of an HRF-convolved stimulus function.

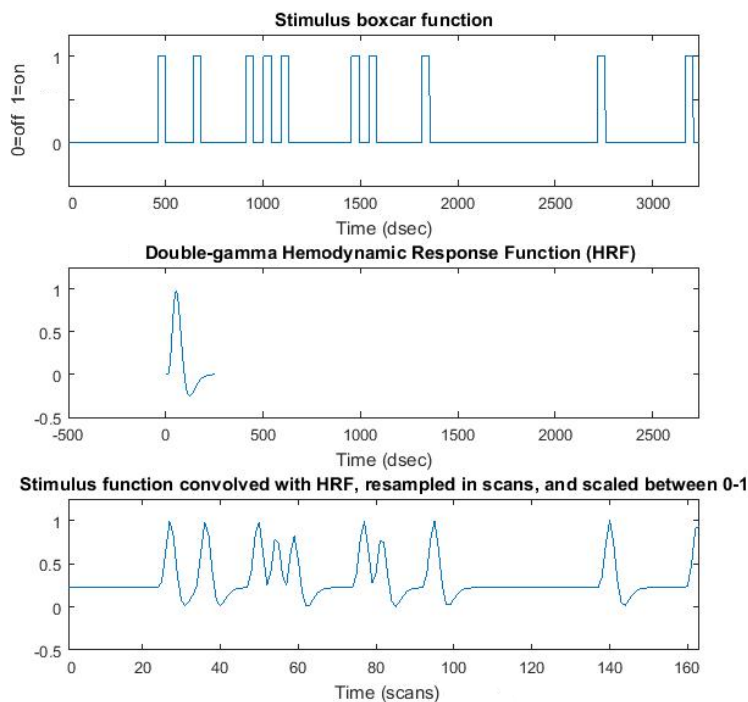


FIGURE 5. Steps involved in generating stimulus functions. The stimulus boxcar function (top) was convolved with the HRF (middle) to generate a stimulus function that more closely resembles a BOLD response (bottom)

One such function was generated for each the happy, sad, and fearful stimuli, as well as for the periods of silence. An additional constant regressor consisting of all ones was included along with the stimulus regressors. Because the BOLD signals were mean-centered during preprocessing, this constant regressor models the mean BOLD response across scans for the given voxel in the given participant. Thus, there were five regressors

generated for each participant: three stimulus regressors, one Silence regressor, and one Constant regressor. Together, these regressors are known as the design matrix ( $X$  in Eq. 1), since they describe the stimulus-presentation design of the study. In neuroimaging, the design matrix is typically viewed in graphical form, as illustrated in Figure 6.

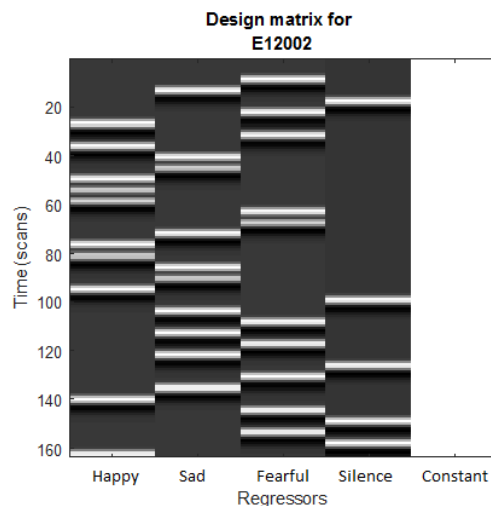


FIGURE 6. Graphical illustration of one participant's level-1 design matrix

In multiple regression, it is important that the columns of the design matrix are linearly independent, otherwise there is more than one solution to the regression equation. If a regressor (or a linear combination of multiple regressors) is highly similar to another regressor (or a linear combination of other regressors), then the model is overparametrized. In fMRI analysis, this is relevant in the context of modeling events/blocks that occurred during acquisition; if every moment is accounted for in some or other stimulus regressor, then the sum of some portion of the regressors will be highly and inversely related to the sum of the remaining regressors. This was the case when the design matrix included a regressor modeling the Answer period of the data acquisition paradigm (i.e., the 5-second periods between stimuli when participants answered the question, "How many instruments did you hear?"). This can be seen in the top panel of 7, in how every moment is captured in at least one regressor. In order to confirm that the design matrix was overparametrized with the inclusion of the Answer regressor, for each participant, the Answer regressor was correlated with the sum of the remaining regressors, and they were significantly and highly correlated ( $r_p = -.79$ ,  $p < .001$ ; see the lower panel in Figure 7 for an illustration of this correlation for one participant). Therefore, the Answer condition was not explicitly modeled in the design matrix.

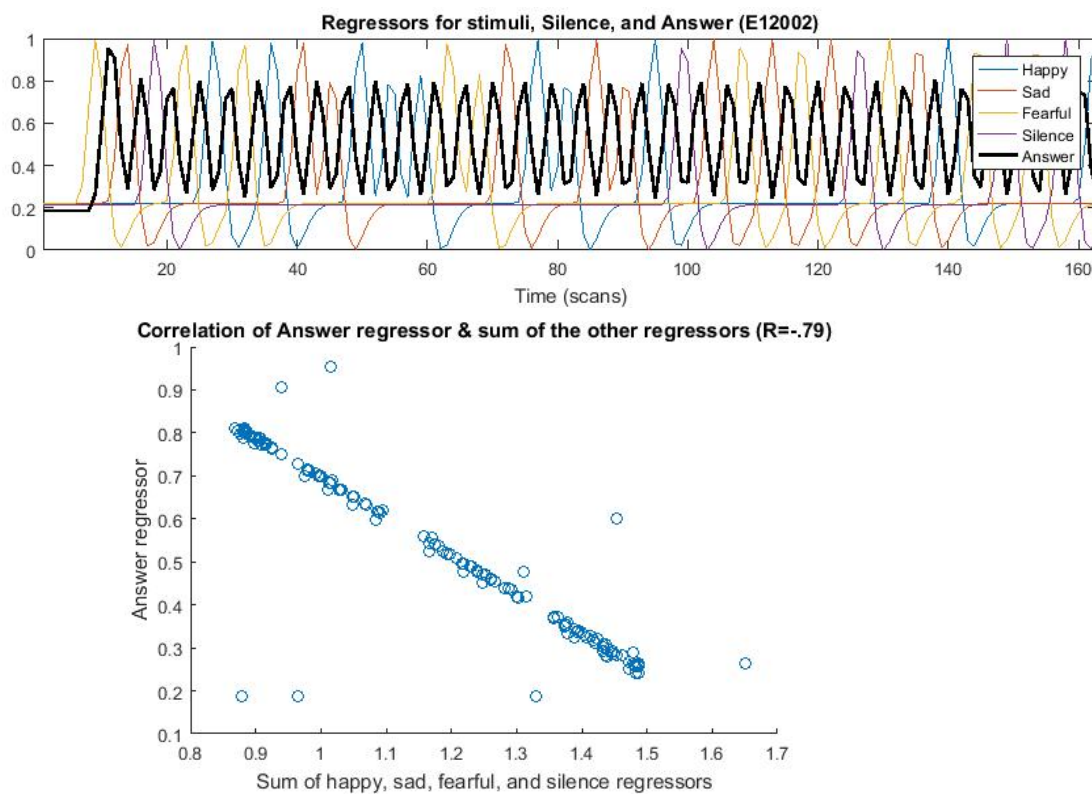


FIGURE 7. Figures showing how the inclusion of the Answer regressors results in over-parametrization of the design matrix. The upper panel shows that its inclusion means that every moment is accounted for in the design matrix. The lower panel shows the correlation between the Answer regressor and the sum of all the other regressors, that is, the linear dependence of the design-matrix columns. (Note that while the Pearson's correlation coefficient displayed is the mean across participants of this correlation, the data in the figure is only for one participant).



#### 4.6.2 Level 1: Voxelwise within-subjects multiple regression

For each participant and each voxel, the general linear model (GLM) was used to estimate how well the timing of the stimuli explained changes in the BOLD response. To this end, multiple regression was run with the design matrix as the predictor variables and the preprocessed BOLD data as the outcome variable. The result of this calculation is a set of beta estimates, one for each column in the design matrix. A standardized beta estimate for a given regressor describes the weight of that regressor in the model, that is, how much it contributes to the model. The general linear model can be described with the equation of a line, shown in Equation 1 in matrix form.

For this study, the level-1 GLM would be as follows:

$$y = \beta_{Happy}x_{Happy} + \beta_{Sad}x_{Sad} + \beta_{Fearful}x_{Fearful} + \beta_{Silence}x_{Silence} + \beta_{Constant}x_{Constant} + \epsilon \quad (3)$$

Where each stimulus regressor contributes to the overall regression model with a weight of  $\beta_{Regressor}$ . For mass-univariate modeling such as voxelwise modeling, ordinary least squares (OLS) estimates of the GLM can be efficiently computed on matrix form of this equation (Eq. 1) with the  $Y$  variable as an  $n$ -by- $v$  matrix, where  $n$  is the number of scans and  $v$  is the number of voxels. See Figure 8 for a graphical representation of the matrix form of the GLM for one voxel in one participant.

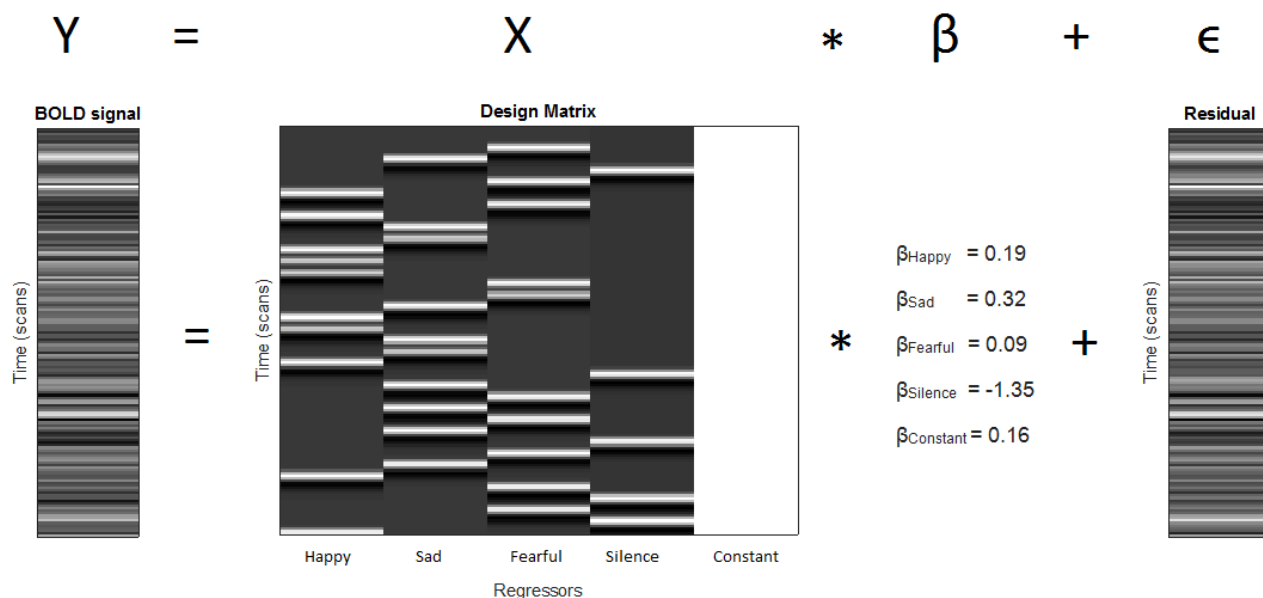


FIGURE 8. Regression equation in matrix form (top) and graphical representations of the equation for voxel 20000 in participant E12002 (bottom).

### 4.6.3 Contrast estimation

It is common in neuroimaging to use contrasts to investigate the neural activity related to one specific stimulus type, particularly for block and event-related designs. Since all of the stimuli were music, it would be expected that some brain areas would be comparably active during perception of all the stimuli. In order to highlight which areas contain activity related to a specific type of stimulus, a contrast is made by subtracting the conditions that are not of interest from the condition of interest. The idea is that if certain voxels are comparably active in all conditions, this contrast estimation will give those voxels a value near zero.

When using the GLM in matrix form, contrasts can be estimated by taking the dot product of the beta-estimate vector and a contrast vector. If one had a simple design matrix with condition A, condition B, and a constant, and one was interested in condition A, then the contrast vector would be [1 -1 0]. Basically this comes down to subtracting the betas for condition B from the betas for condition A. With three conditions, it is slightly more complicated. For a contrast to be valid, the contrast vector should sum to zero. In the present study, where there are beta weights for Happy, Sad, and Fearful stimuli, Silence, and a Constant, the contrast vector for each condition is as follows:

- [2 -1 -1 0 0] for the Happy condition,
- [-1 2 -1 0 0] for the Sad condition, and
- [-1 -1 2 0 0] for the Fearful condition

The contrast beta for the Happy condition, for example, would be calculated in the following way, for each voxel:

$$\beta_{HappyContrast} = \mathbf{2} * \beta_{Happy} - \mathbf{1} * \beta_{Sad} - \mathbf{1} * \beta_{Fearful} + \mathbf{0} * \beta_{Silence} + \mathbf{0} * \beta_{Constant} \quad (4)$$

It is also common to contrast conditions of interest against a baseline, emotionally “neutral” condition. Indeed, of the studies cited in the literature review that looked at personality with emotional stimuli in fMRI, most studies contrasted each emotional condition against a “neutral” condition (Canli et al., 2002; Cremers et al., 2010; Haas et al., 2008; Jimura et al., 2009; Mobbs et al., 2005; Park et al., 2013; Williams et al., 2006), with the exception of one study that used the individual beta estimates rather than a contrast (Canli et al., 2001). However, there was no neutral-music condition in this study.

Another option would be to contrast each condition against a “rest” condition. There were

five 4-second periods of silence that were included for another purpose, but this is not sufficient time relative to the cumulative length of the stimuli in order to be considered a rest condition. There was a 5-second Answer period following each stimulus in which there was no music (30 total), but arguably this was not a true rest condition because the participants were performing the task of indicating how many instruments they had heard in the previous musical excerpt.

Alternatively, directly contrasting emotions may be useful for distinguishing areas responding to the emotional content of the music as opposed to the music in general, and perhaps as well for distinguishing areas responding to the category of emotion as opposed to emotion in general. On the other hand, it could be argued that this follows a unrealistically compartmentalized view of brain function. With all of these considerations, the contrasts listed above were thought to be the ideal contrasts given the study paradigm.

In what follows, the results of the contrast estimation will be referred to as ‘contrast betas’.

#### **4.6.4 Regions-of-Variance (ROV) masking**

Regions-of-Variance (ROV) masking was used to isolate regions of interest (ROI) for the level-2 correlation between brain data and personality data. The motivation behind selecting ROIs rather than analyzing the whole brain is to alleviate the problem of multiple comparisons; by selecting fewer voxels, one reduces the number of independent tests, thus allowing for a more lenient significance threshold after correcting for multiple comparisons.

As the name implies, a regions-of-interest approach involves selecting regions that are of interest to the research question, and focusing the analyses on those regions. ROIs may be selected in different ways; a common method is to select regions based on previous research indicating that those regions were related to functions similar to the ones being studied, or alternatively, ROIs may be selected from a whole-brain first-level analysis as those voxels that are most consistently activated across participants (Thirion et al., 2014).

Omura et al. (2005) suggested an alternative approach for investigating the role of individual differences in functional neuroimaging: selecting regions with the greatest between-subjects variance, relative to within-subjects variance, in the level-1 results. Their equa-

tions for calculating the variance maps are as follows:

$$S_B^2 = \frac{\frac{1}{N_{subj}-1} \sum_{i=1}^{N_{subj}} (con * .img_i - \overline{con * .img})}{2} * N_{scan} \quad (5)$$

$$S_W^2 = \frac{\frac{1}{N_{subj}} \sum_{i=1}^{N_{subj}} ResMS.img_i}{N_{scan} - 1} \quad (6)$$

$$F = \frac{S_B^2}{S_W^2} \quad (7)$$

Where

- $S_B^2$  is the between-subjects variance,
- $S_W^2$  is the within-subjects variance,
- $F$  is the ratio of between- to within-subjects variance,
- $N_{subj}$  is the total number of subjects,
- $N_{scan}$  is the total number of scans,
- $con * .img_i$  is the contrast image for the given participant,
- $\overline{con * .img}$  is the mean contrast image (mean across participants), and
- $ResMs.img_i$  is the image of the mean squared residual (mean across time) for the given participant.

Essentially, for each voxel, an  $F$ -value is calculated, which is the ratio of the between-subjects variance in the level-1 parameter estimates ( $S_B^2$ ) to the mean within-subjects residual variance for that voxel (mean across participants;  $S_W^2$ ). These  $F$ -values make up the variance maps from which regions of variance are selected.

After calculating the  $F$ -maps, the next step is to isolate regions of variance by thresholding the  $F$ -values. To this end, we used a data-driven height threshold which is determined from the relative  $F$ -ratios. Voxels in the  $F$ -map were sorted in a vector according to their  $F$ -value, and then the ‘change point’ in the line was determined using the *findchangepts* algorithm in Matlab, with the *linear* statistic option. *Findchangepts* uses a parametric global method to find abrupt changes in a curve. The change point is the point at which the total residual error in the chosen statistic is at a minimum, the total residual error being the sum of a) the deviation of the left-side points from the left-side statistic (e.g., the mean) and b) the deviation of the right-side points from the right-side statistic (left-side and right-side referring to the signal on either side of the change point). The *linear* statistic option uses a statistic describing both the mean and the slope of the line. The

sorted  $F$ -voxel-values for each condition and the respective change point for each line is shown in Figure 9.

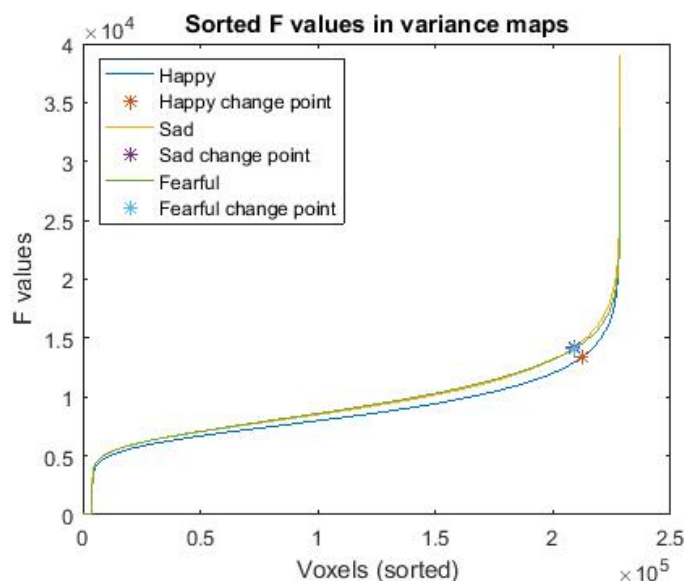


FIGURE 9. Sorted  $F$ -values in variance maps for each condition, and change point in each line (\*), which is used as the cluster-forming threshold for the respective condition's variance map.

The ROV maps were height-thresholded at the voxel level using this 'change-point' as the threshold. The maps were then subjected to an arbitrary cluster-size threshold of 15 voxels and were binarized in order to be used as masks the first-level contrast betas.

Note that the choice of height and extent thresholds for the ROV maps was not considered to be of great importance because the conservativeness of the level-2 significance threshold would be inversely related to the conservativeness of these ROV thresholds. For example, using *more-conservative* thresholds for creating the ROV masks would result in maps with fewer unmasked voxels; this means that the level-2 analysis would be performed on fewer voxels and there would be fewer comparisons to correct for when correcting for multiple comparisons, resulting in a *less-conservative* level-2 significance test. That being said, it is not known whether this relationship is linear, so there may in fact be ideal cluster-height and -extent thresholds for the ROV maps that optimally balance Type I and Type II errors in the level-2 results. This was not investigated in the present study, and could be investigated in future research should the ROV method prove useful.

See Appendix A for the regions-of-variance maps for each condition.

#### 4.6.5 Level 2: Voxelwise between-subjects partial correlation

The purpose of the level-2 analysis was to relate the personality trait scores to the level of activation during the different musical-emotion conditions. This was done in a voxelwise manner, following the summary-statistic approach described in Section 2.3.3.

The personality traits were significantly correlated with each other (see Section 5.1). Thus, in order to investigate the role of each personality trait, partial correlation was used on each combination of personality trait and type contrast beta, controlling for the other two traits.

For each combination of trait and condition, the partial correlation was calculated between the given trait ( $x$ ) and the contrast betas for the given condition ( $y$ ), controlling for the remaining traits ( $z$ ). This amounts to removing the effect of  $z$  from  $x$  and  $y$ , and then correlating  $x$  and  $y$ . Here, this was done by correlating the residual from a multiple regression modeling  $x$  with  $z$  with the residual from a multiple regression modeling  $y$  with  $z$  - in the context of the 2-level model described in Equations 1 and 2 these two residuals would be  $Z$  and  $\beta_c$ , respectively. With 3 personality traits of interest (Extraversion, Neuroticism, and Openness) and 3 emotional conditions for the musical stimuli (Happy, Sad, and Fearful), this entailed 9 pairwise partial correlations.

This resulted in a map of correlation coefficients for each combination of trait and condition. The sampling distribution of these values was normalized by converting the values to Z-scores using Fisher's transformation (Fisher, 1915), so that a parametric cluster-forming height threshold (i.e., a p-value) could be applied. For the ROV analysis, the ROV mask for the given condition was applied to each Z-map prior to significance testing. The cluster-forming threshold and significance tests are described further in the next section.

#### 4.6.6 Nonparametric significance testing

The analyses described above are *mass univariate* analyses, because they involve many tests (*mass*) with one dependent variable (*univariate*) - one test per voxel. This raises a statistical problem because the number of false positives increases with the number of tests done using the same data (in this case, the 'same data' is the same independent variables used for every tested voxel).

One intuitive way to correct for multiple comparisons is the Bonferroni correction, where

the significance threshold is divided by the number of tests. This controls for the probability of making a family-wise error (FWE), that is, the probability of having one false positive across the entire ‘family’ of tests. The logic is that if a  $p$ -threshold of .05 for one test means that there is a 5% chance that a result is a false positive, then dividing this  $p$ -threshold by the number of tests means that there is a 5% chance that any one of the results from the family of tests is a false positive, so the family-wise error rate (FWER) is 5%. In fMRI, this would equate to having at least one falsely-positive voxel in 20 studies using voxelwise inference, or at least one falsely-positive cluster in 20 studies using clusterwise inference.

However, Bonferroni correction does not work well for fMRI data. There are two reasons for this: 1) there are so many voxels (and consequently, tests) that dividing the significance threshold by the number of voxels would make the threshold too conservative, and 2) the Bonferroni correction is not actually valid in this setting because voxels are not independent; they are spatially autocorrelated (due to the nature of the hemodynamic response, brain structure, and because various preprocessing steps result in spatial smoothing, including explicit spatial smoothing).

In order to account for this spatial autocorrelation, it is common to consider groups of voxels rather than individual voxels. This can be done by applying a cluster-level threshold after the voxel-level threshold. Most commonly, this is a cluster-size threshold ( $k$ ). In a 2012 survey of reported fMRI methods, Carp found that under 60% of surveyed studies corrected for multiple comparisons, and that a common method of thresholding was to combine a more-conservative height threshold (e.g.,  $p < .001$ ) with an arbitrary extent threshold (e.g., 240 mm<sup>2</sup>). However, this method can lead to high Type I error; Eklund, Nichols, and Knutsson (2016) analyzed resting state data with arbitrary designs and showed that using height and extent thresholds of  $p < .001$  (uncorrected) and  $k = 80$  mm<sup>3</sup> (i.e., 10 2x2x2 cm voxels) leads to FWERs up to 60-90%. Alternatively, they found that nonparametric permutation tests of significance maintained the desired FWER.

Therefore, in the present study, a Monte Carlo simulation was carried out on the Z-maps, in order to find a cluster-level threshold that corrected for multiple comparisons at a FWER of 5%. In order to control for FWE in a nonparametric manner, one needs to build a null distribution of maximum values of the statistic being used (e.g., voxel  $p$ -values or cluster sizes/masses), and then select the  $n^{\text{th}}$  statistic in the distribution as the threshold,  $n$  being  $\lfloor (1 - FWER) * \text{NumberOfPermutations} \rfloor$  ( $\lfloor \rfloor$  means rounded down). In other words, if you want to control for FWER at 5%, and you have run 10000 permutations,

then the cluster-statistic threshold is the 9500<sup>th</sup> number in the ascending-sorted list of statistics.

The reason why one stores only the maximum statistic from each permutation, and not all of the statistics, is that FWE occurs when at least *one* voxel/cluster statistic is a false positive. If two statistics are over the FWER threshold, those two statistics will be the maximum and next-to-maximum statistics. If one statistic is over the threshold, it will be the maximum statistic. If no statistics are over the threshold, then the maximum is not over the threshold. Thus, the FWER threshold is derived from a distribution of maximum statistics.

Nichols and Holmes (2002) outlined the steps for performing a permutation test for significance testing in neuroimaging. Here are the steps and how they were carried out in the present study:

1. *Null Hypothesis*: The null hypothesis is that there is no correlation between the given personality trait and the set of contrast betas from the given condition.
2. *Exchangeability*: Under the null hypothesis, participants are exchangeable; if there is no correlation, then exchanging individual participants' data should not make a difference to the results. Therefore, participants' data can be randomized in order to build a null distribution of cluster statistics.
3. *Statistic*: Permutations were run for three different voxel-level cluster-forming thresholds:  $p < .05$ ,  $.01$ , and  $.001$ . The reason for using multiple thresholds is that there is not a clear answer as to which threshold is ideal. Two types of summary statistic were calculated for each cluster: a) cluster size, which is the number of voxels in the cluster, and b) cluster mass, which is the sum of the Z-values in the cluster. The reason for calculating both types of summary statistics is that cluster size is a more conventional measure, and cluster mass may be more intuitive because it can equate a lowly-activated large cluster with a highly-activated small cluster.
4. *Relabeling*: Ideally, one would do a permutation for every possible relabeling of the participants, but with 55 participants the  $1.27 \times 10^{73}$  possible permutations is not computationally realistic. When there are too many possible labellings, a subset can be used (Dwass, 1957; Edgington, 1969), in what is known as an approximate test, Monte-Carlo permutation test, or random permutation test. In this case, 10000 permutations were used.
5. *Permutation Distribution*: For each of the 10000 permutations, the sets of 3 trait scores for each participant were randomized across participants (i.e., participant



labels were randomized). In order to ensure that each randomization was unique, the `rng('shuffle')` Matlab command was called before the parallelized permutation loop. For each combination of personality trait and emotional condition, the level-2 partial correlation was calculated between the given trait and the contrast betas for the given condition, controlling for the remaining traits. The correlation coefficients were normalized using the Fisher transform. For the regions-of-variance analysis, the Z-maps were masked with the ROV map corresponding to the given condition (previously calculated with the real level-1 data). No masking was applied for the whole-brain analysis. For each height threshold ( $p < .05$ ,  $.01$ , and  $.001$ ), the maps were thresholded with a voxelwise cluster-forming threshold at the the corresponding 2-tailed Z-value (i.e.,  $Z = 1.96$ ,  $2.58$ , and  $3.29$ ). For two voxels to be in the same cluster, they needed to have one side, edge, or corner touching. For every cluster passing the threshold, the cluster size and mass was calculated, and then the maximum size and mass across clusters was saved. In this way, a null distribution of maximum statistics was built for every combination of trait, condition, and height threshold, for both the ROV and whole-brain analyses and for both the cluster-size and -mass statistics (i.e.,  $3 \times 3 \times 3 \times 2 \times 2 = 108$  distributions).

6. *Significance*: For each distribution, the 10000 values were sorted in ascending order. Then the cluster-statistic threshold was selected as the 9500<sup>th</sup> number, corresponding to a FWER of 5%. Each threshold was then applied to the corresponding map of the real data.

See Table 2 in Appendix B for the cluster-size and -mass thresholds.

## 5 RESULTS

### 5.1 Personality scores

BFQ scores ranged from -12 to 34 for Extraversion ( $M = 9.23$ ,  $SD = 9.22$ ), from -33 to 17 for Neuroticism ( $M = -11.33$ ,  $SD = 10.15$ ), and from -7 to 35 for Openness to Experience ( $M = 20.13$ ,  $SD = 9.49$ ). Extraversion and Neuroticism were negatively correlated (Spearman's  $r = -.42$ ,  $p = .001$ ). Extraversion and Openness were positively correlated (Spearman's  $r = .45$ ,  $p = .0005$ ). Neuroticism and Openness were negatively correlated (Spearman's  $r = -.37$ ,  $p = .005$ ). See Figure 10 for an illustration of these correlations and a histogram for each trait.

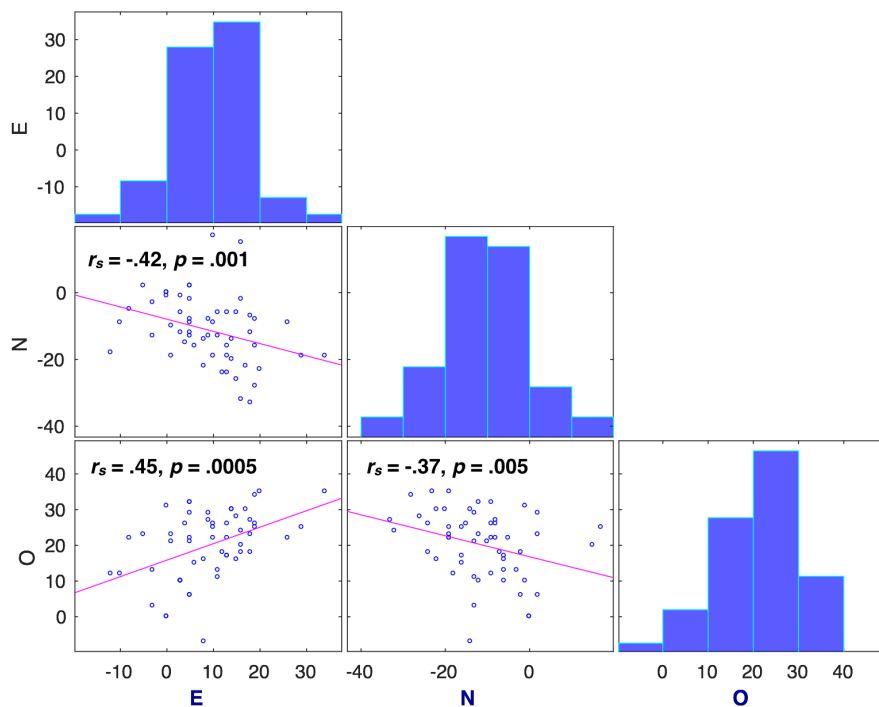


FIGURE 10. Histograms for each personality trait, and correlations between traits.

E = Extraversion,

N = Neuroticism,

O = Openness to Experience

$r_s$  = Spearman's correlation coefficient

## 5.2 fMRI results

Neuroticism was positively related to activation during Sad music in the left inferior parietal lobe, with voxels primarily in the supramarginal gyrus (BA 40) and angular gyrus (BA 39), with a cluster-forming threshold of  $p < .001$ , corrected at 5% FWER. The whole-brain analysis revealed a larger cluster in a similar location, additionally with voxels in the postcentral gyrus (BA 2). All voxels in the cluster found with the ROV analysis were included in the cluster found with the whole-brain analysis. See Table 1 for details and Figures 11 and 12 for orthographic views of the statistical maps of these results.

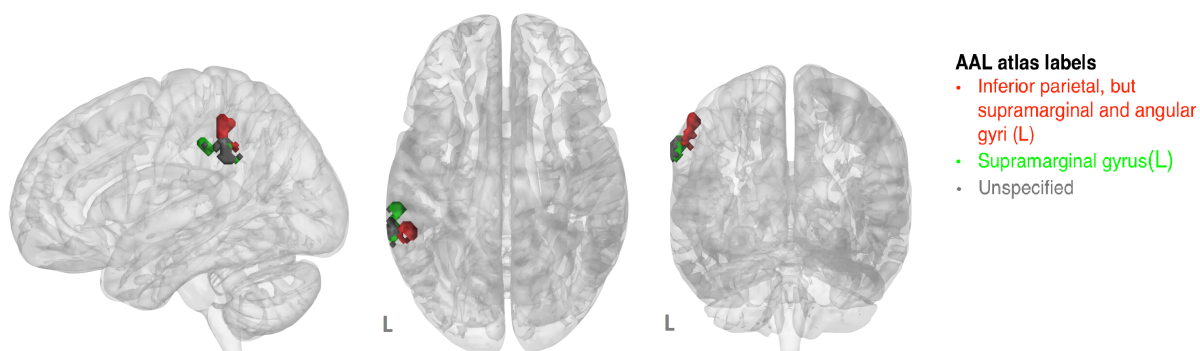


FIGURE 11. Significant cluster for the positive correlation between Neuroticism & activation during Sad music (ROV analysis). This result was found with a cluster-forming threshold of  $p < .001$ , corrected at 5% FWER using non-parametric cluster-size and -mass thresholds, which were  $k = 68$  voxels and  $Z = 248.49$ , respectively.

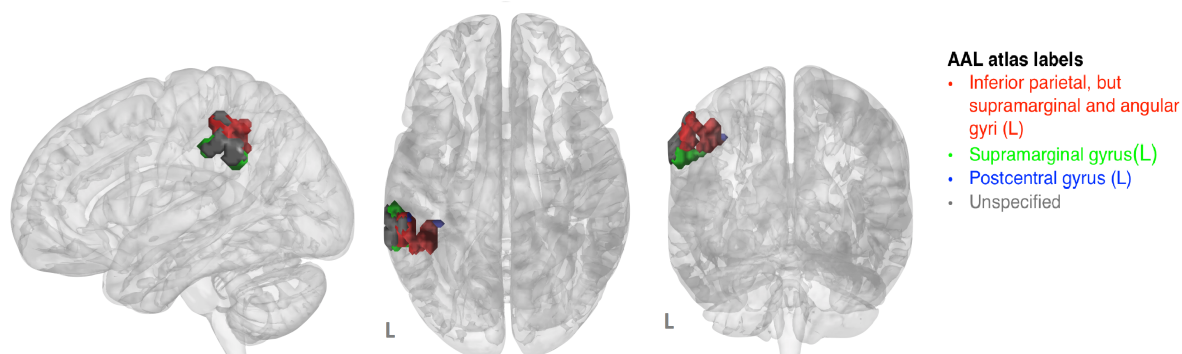


FIGURE 12. Significant cluster for the positive correlation between Neuroticism & activation during Sad music (whole-brain analysis). This result was found with a cluster-forming threshold of  $p < .001$ , corrected at 5% FWER using non-parametric cluster-size and -mass thresholds, which were  $k = 207$  voxels and  $Z = 760.68$ , respectively.

Openness was significantly and positively related to activation during Happy music in an extended cluster in the region of the left superior temporal lobe, and primarily included voxels in Heschl's gyrus (BA 42) and the superior temporal gyrus (BA 22), extending into the temporo-polar area (BA 38), middle temporal gyrus (BA 21), postcentral gyrus (BA 2), supramarginal gyrus (BA 40), and the rolandic operculum. This cluster was significant with a cluster-forming threshold of  $p < .05$ , corrected at 5% FWER. This cluster did not pass the FWE-correction threshold in the whole-brain analysis. See Table 1 for details and Figure 13 for orthographic views of the statistical map of this results.

The results were the same after cluster-size and -mass thresholding, suggesting that for this dataset, cluster size and mass are monotonically related at the high end of their distributions.

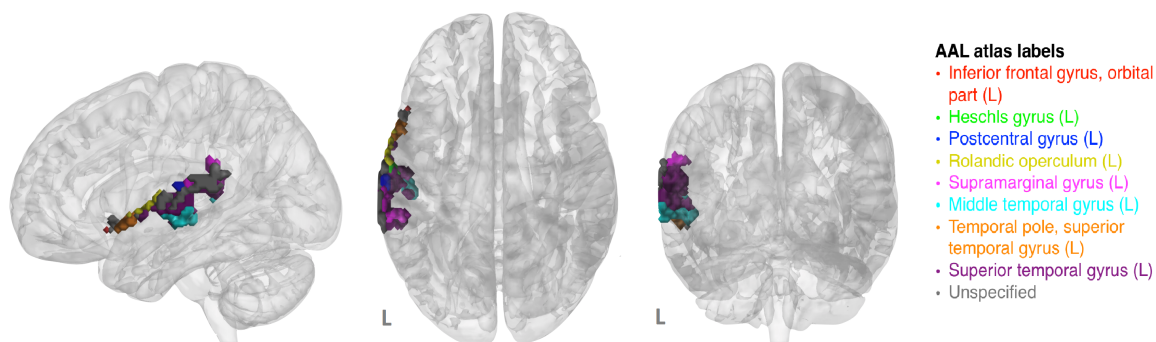


FIGURE 13. Significant cluster for the positive correlation between Openness to Experience & activation during Happy music (ROV analysis). This result was found with a cluster-forming threshold of  $p < .05$ , corrected at 5% FWER using non-parametric cluster-size and -mass thresholds, which were  $k = 507$  voxels and  $Z = 1295.28$ , respectively.

There were no results that passed correction for multiple comparisons for any other combination of trait and emotional condition. See Appendix C for maps of the non-significant results for the combinations of trait and condition that were expected to have a result and did not (i.e., Extraversion & activation during Happy music, and Neuroticism & activation during Fearful music).

TABLE 1. Significant results. All results passed correction for multiple comparisons at a 5% FWER, using cluster-size and cluster-mass thresholds determined in a nonparametric permutation test for each combination of trait and emotion contrast. Thus, entire clusters were accepted/rejected in an omnibus test, and it should be noted that while the component regions and their peak-value locations are listed in this table for the purpose of illustrating cluster extent, corrected significance was not estimated for individual voxels.

Region = region label, from the Automatic Anatomic Labeling (AAL) atlas.

BA = Brodmann area corresponding to the region.

L/R = left/right hemisphere.

Size = number of voxels in the cluster, each being 2 mm<sup>3</sup>.

Mass = mass of the cluster, which is the sum of the Z-values.

$x, y, z$  = MNI coordinates of the peak voxel in the given region.

	Region	BA	L/R	Size	Mass	$x$	$y$	$z$
<b>Regions-of-Variance analysis</b>								
<i>Neuroticism</i>								
<i>Sad &gt; Happy &amp; Fearful</i>								
	***(Entire cluster)		L	95	361.98			
	Inferior parietal, but supramarginal and angular gyri	40, 39	L	39	141.24	-66	-44	32
	Supramarginal gyrus	40	L	34	136.44	-56	-38	48
<i>Openness</i>								
<i>Happy &gt; Sad &amp; Fearful</i>								
	*(Entire cluster)		L	576	1363.94			
	Heschl's gyrus	42	L	11	27.14	-66	-10	6
	Superior temporal gyrus	22	L	307	53.63	-66	-30	18
	Temporal pole, superior temporal gyrus	38	L	24	53.63	-58	10	-2
	Middle temporal gyrus	21	L	95	227.52	-64	-10	8
	Inferior frontal gyrus, orbital part	47	L	1	1.98	-52	20	-8
	Postcentral gyrus	2	L	10	22.56	-66	-18	16
	Supramarginal gyrus	40	L	36	78.31	-64	-18	0
	Rolandic operculum		L	13	30.28	-60	8	0
<b>Whole-brain analysis</b>								
<i>Neuroticism</i>								
<i>Sad &gt; Happy &amp; Fearful</i>								
	***(Entire cluster)		L	466	1790.39			
	Inferior parietal, but supramarginal and angular gyri	40, 39	L	268	1001.18	-66	-44	32
	Supramarginal gyrus	40	L	126	512.64	-40	-36	42
	Postcentral gyrus	2	L	5	17.82	-42	-38	42

\* $p < .05$ , corrected

\*\*\* $p < .001$ , corrected

## 6 DISCUSSION

This study investigated the role of personality in the neural correlates of perceiving emotions in music. Specifically, it looked at activations associated with Extraversion, Neuroticism, and Openness to Experience during implicit perception of Happy, Sad, and Fearful emotions portrayed by instrumental music.

Extraversion and Neuroticism are characterized by tendencies to experience positive and negative emotional states (e.g., Larsen & Ketelaar, 1991, and have been related to brain function during perception of positive and negative emotional stimuli, respectively (e.g., Canli et al., 2002, 2001; Haas et al., 2008). Thus, it was expected that Extraversion would be related to the hemodynamic activity during perception of Happy music, and Neuroticism during Sad or Fearful music. There were no significant clusters that passed the correction for multiple comparisons for Extraversion & Happy or for Neuroticism & Fearful, but there was one robustly significant cluster in the left inferior parietal lobe for Neuroticism & Sad.

The inclusion of Openness to Experience as a personality trait of interest was more exploratory; while Openness is not normally characterized by emotional tendencies, it is related to higher engagement in artistic experiences (John & Srivastava, 1999), and it has been related to enjoyment of sad music in particular (Vuoskoski et al., 2012). Thus, Openness was also of interest, but in a more exploratory way with regards to specific emotions. Openness was positively related to activation during Happy music, in a cluster including auditory association cortex, temporopolar area, medial temporal lobe, and some extension into the middle temporal gyrus, and postcentral gyrus.

These findings will now be considered in the context of previous research in order to posit possible explanations. However, these remain speculative due to the exploratory nature of the hypotheses and methods with regards to brain localization, and due to the nature of the analysis as correlational.

## 6.1 Neuroticism & Sad

Neuroticism was positively related to activation in a cluster in the left inferior parietal lobe (IPL). This was the most robust finding; a similar cluster was found in both the ROV analysis and the whole-brain analysis, in both cases at the most conservative level of significance ( $p < .001$ , corrected for FWER at  $p = .05$ , see Table 1 and Figures 11 and 12 for details).

IPL function has previously been associated with musical emotions. Taruffi, Pehrs, Skouras, and Koelsch (2017) found that listening to sad music (in contrast to happy music) is related to mind wandering and to related activity in the default mode network, including the left posterior IPL. In a study that used data from same larger dataset as the present study, Bogert et al. (2016) looked at common activation across participants, and found the bilateral IPL to be active during sad music. It is interesting that the present study found Neuroticism to be related to activity only on the *left* side during sad music.

Neuroticism has been related to brain activations and connectivity during perception of negative emotional stimuli, in areas including the middle temporal and frontal gyri, temporal pole, amygdala, medial prefrontal cortex, anterior cingulate (Canli et al., 2001; Cremers et al., 2010; Haas et al., 2008; Jimura et al., 2009; Williams et al., 2006). However, it seems that few studies have reported results in the region of the cluster found here. This might be partially due to its exclusion from ROIs, which are often regions more traditionally associated with subjective emotions (e.g., Cremers et al., 2010), or are functionally derived as areas commonly activated across participants (e.g., Park et al., 2013). Indeed, some studies have explicitly excluded regions related to higher-level cognition, as they expect that such regions would not be related to Neuroticism; in their study on the the associations between the Big Five and gray-matter volume, DeYoung et al. (2010) said this in their hypotheses: “...Extraversion and Neuroticism, which appear to reflect basic affective systems, are not likely to be associated with the areas of lateral cortex that are involved in top-down control...” (p. 822). However, some studies did not exclude higher-level cognitive processing areas, and yet measures from the parietal areas were not related to Neuroticism (Canli et al., 2001; Kong et al., 2015).

That being said, a few studies have found associations between IPL function and Neuroticism. Servaas, Riese, Ormel, and Aleman (2014) investigated brain activity and connectivity during reading of worrisome versus neutral sentences, and found activations in the bilateral IPL as well as Neuroticism-related connectivity between the retrosplenial

cingulate cortex and the right IPL. In line with this finding, Sander et al. (2005) found that Behavioral Inhibition System scores (BIS, measuring harm-avoidance motivation) were positively correlated with activity in the right IPL during perception of angrily-spoken nonsense words, and that Behavioral Activating System scores (BAS, measuring reward-approach motivation) scores were positively correlated with activity in the left IPL. This is relevant because BIS scores are positively related to Neuroticism (Jorm et al., 1998). This study suggests that the IPL activity is related to individual tendencies to reward/approach behaviors, but it is notable that the present findings were in the *left* IPL, which Sander and colleagues found to be related to the BAS, not the Neuroticism-related BIS.

Indeed, other research has suggested that the left and right hemispheres are respectively associated with positive and negative affect (Ekman, Davidson, & Friesen, 1990; Wheeler, Davidson, & Tomarken, 1993), approach and avoidance behaviors (Davidson, Ekman, Saron, Senulis, & Friesen, 1990), and individual BAS and BIS scores (Sutton & Davidson, 1997, for a review, see Rutherford & Lindell, 2011). However, some later research only found associations between left-lateralized activity and BAS scores, with no lateralization evident for the BIS (Coan & Allen, 2003; Harmon-Jones & Allen, 1997). Additionally, it has been suggested that a behavioral activation/inhibition concept of lateralization is more useful than approach/avoidance, because some emotions such as anger result in left-lateralized activation whether the response behavior is approach or avoidance, and both behaviors are active responses (e.g., Wacker, Chavanon, Leue, & Stemmler, 2008). Based on this activation/inhibition theory, one might speculate that in the present study, sadness in music evoked a more active response in individuals with Neuroticism due to their increased susceptibility to negative affect (Larsen & Ketelaar, 1991). Alternatively, considering that most of the aforementioned studies examined asymmetry in frontal areas, it may be that lateralization is different in more posterior areas. Thus the present finding is consistent with previous research with regards to the IPL and Neuroticism, but it is perhaps less consistent with regards to lateralization.

The IPL has many functions, but notable for this context is its associated with cognitive emotional processes. The temporoparietal junction (TPJ), which includes the supramarginal and angular gyri, has been related to cognitive empathy (the understanding of others' emotional states; Schnell, Bluschke, Konradt, & Walter, 2011) and reasoning about others' minds and beliefs (Samson, Apperly, Chiavarino, & Humphreys, 2004; Saxe & Kanwisher, 2003). The TPJ is thought to be a part of a larger mentalizing network (Frith & Frith, 2006), along with the medial prefrontal cortex and the precuneus/posterior



cingulate cortex (e.g., Atique, Erb, Gharabaghi, Grodd, & Anders, 2011). It has been suggested that the mentalizing functions of the TPJ are implicit or automated (Decety & Lamm, 2007; Frith & Frith, 2006; Schnell et al., 2011), evidenced by the developmental shift in activations during perspective-taking tasks from frontal areas to the left inferior parietal cortex (Dosch, Loenneker, Bucher, Martin, & Klaver, 2010). Indeed, the right IPL has been associated with implicit processing of speech prosody (Bach et al., 2008) and emotional faces (Scheuerecker et al., 2007). This is relevant to the present study because the subjects were implicitly processing the different emotional music clips, as they were asked to indicate how many instruments they heard in the music, but again the lateralization is perhaps opposite of what might be expected.

The inferior parietal lobe has also been associated with emotional regulation, another emotional cognitive process. Particularly, the left IPL is associated with suppression as a method of negative-emotion regulation (Goldin, McRae, Ramel, & Gross, 2008). This may be relevant here because sadness is a negatively-valenced emotion, but some research has suggested that Neuroticism is not related to suppression as an emotion-regulation strategy, but rather to reappraisal (Gross & John, 2003; Wang, Shi, & Li, 2009). Recalling the theory of left-lateralized active responses (Wacker et al., 2008), it is interesting to note that reappraisal could be thought of as a more active emotion-regulation strategy.

The IPL has also been associated with higher-level auditory perceptions, consistent with its activation here to music. The right IPL plays a role in perception of pitch in music (Zatorre, Evans, & Meyer, 1994) and detection of emotion in speech (Buchanan et al., 2000; Wildgruber, Pihan, Ackermann, Erb, & Grodd, 2002), and the left IPL has been associated with phonological processing (Vallar & Papagno, 1995; Zatorre, Evans, Meyer, & Gjedde, 1992). Damage to the right IPL (among other areas) has also been associated with expressive instrumental amusia, which is the loss of ability to perform music (McFarland & Fortin, 1982), and a reduced ability to process music and experience aesthetic pleasure from music (Mazzoni et al., 1993). In multisubject functional-imaging studies, the IPL has been associated with processing of musical timbre (Alluri et al., 2012), musical performance and imagery (Meister et al., 2004), and perception of melodies versus random tones (BA 40) and of harmonized versus unharmonized melodies in musicians (BA 39; Schmithorst & Holland, 2003).

It seems that the IPL is not commonly associated with perceptions of emotions in music; for example, it was not mentioned in Koelsch's (2014) meta-analysis of the neural correlates of music-evoked emotion. However, functional neuroimaging studies have found the

right IPL to be active while subjects listened to pleasant-exciting music versus pleasant-relaxing music (Flores-Gutiérrez et al., 2007) and during perception of more expressive musical performances (Chapin, Jantzen, Kelso, Steinberg, & Large, 2010). Most relevantly, Omar et al. (2011) found that dementia-related gray-matter loss in a network including the right IPL resulted in impaired recognition of emotions in music, and Satoh, Nakase, Nagata, and Tomimoto (2011) reported a case where damage specifically to the right IPL resulted in a loss of music-induced emotions. However, the observation of music-emotion deficits following damage to the right IPL and sparing of the left may actually suggest that the left IPL does not play a crucial role in music-emotion functions because its sparing does not allow for maintained function.

Thus, although the inferior parietal area is not part of the limbic system, the network traditionally associated with the experience of emotion, it has been related to emotional cognitive processes, processing of pitch and speech sounds associated with emotion, and in processing musical emotion. It is interesting that most of the research described here has found relevant results for the *right* IPL, and the picture is less clear on the left. It could be proposed that the left IPL was more active in individuals scoring higher on Neuroticism because their sensitivity to sadness as a negative emotion elicited a higher empathic reaction and more-active emotion regulation. However, further research would be needed to support this interpretation.

## 6.2 Openness & Happy

Openness was positively related to activation in an extended cluster in the area of the left superior temporal lobe, primarily including voxels in Heschl's gyrus (BA 42), the superior temporal gyrus (STG; BA 22), and the medial temporal lobe (BA 48), with some extension into the ventral postcentral gyrus (BA 2), posterior superior temporopolar area (BA 38), middle temporal gyrus (BA 21), and the rolandic operculum (BA 47;  $p < .05$ , corrected for FWER at  $p = .05$ , see Figure 13 and Table 1 for details). This finding was less robust than the finding for Neuroticism & Sad, being found only in the regions-of-variance analysis and not in the whole-brain analysis, and only at the least-conservative cluster-forming threshold. Although there appears to be little functional brain research on Openness with emotional stimuli, this finding is interesting in light of previous research on music and emotion.

With regards to music research, the left superior temporal gyrus has been related to activation during happy music in contrast to sad music (Brattico et al., 2011, 2016; Mit-

terschiffthaler et al., 2007), and to disliked music in contrast to liked music (Brattico et al., 2016). It is perhaps notable that Openness is negatively related to preferences for Upbeat and Conventional music (Rentfrow & Gosling, 2003), which are terms that could be used to describe happy music. In the future it would be interesting to consider whether such Openness-associated activations are related to a combination of preference and emotional quality of the music, or perhaps with aesthetic/evaluative emotions induced by the music.

Emotion processing in other domains has been associated with function of regions in this cluster, including the temporopolar area and the rolandic operculum. The functions of temporopolar area (TP) are not well understood, but the left TP has been linked to complex perceptions with emotional responses (Olson, Plotzker, & Ezzyat, 2007) and to judgments of affective semantics (Ethofer et al., 2006). Koelsch et al. (2006) reported that perception of pleasant music is related to activity in the *right* TP, but activity in the left did not reach significance. There was also some extension of the cluster into the left rolandic operculum, which has been associated with perception of pleasant music (Koelsch et al., 2006) as well as perceptions of emotion in speech (Kotz et al., 2003). Although the cluster found in the present study did not extend far into the left middle temporal gyrus, there has been a previous association between Openness and this area on the right side; Li et al. (2014) found that Openness mediated the association between trait creativity and volume of the right posterior middle temporal gyrus.

Thus, the regions related to Openness & Happy in the present study have previously been associated with emotional processing, both in music and other modalities. In order to elucidate the brain correlates of role of Openness in perceiving music, future research may benefit by using longer musical stimuli to allow for higher engagement with the music, as well as physiological and/or verbal measures of engagement and emotional experience including aesthetic emotions.

### 6.3 Null results

Contrary to the hypotheses, Extraversion was not related to activations during Happy music, nor was Neuroticism related to activations during Fearful music. These hypotheses were based on the behavioral association between these traits and positive and negative emotionality, respectively (Larsen & Ketelaar, 1991), and additionally on some past neuroimaging research with trait-emotion congruent results (Canli et al., 2004, 2002, 2001; Cremers et al., 2010; Haas et al., 2008; Jimura et al., 2009; Mobbs et al., 2005; Williams et al., 2006). See Appendix C for the uncorrected results for these two hypothesized

relationships.

The null results in the present study may be due to a failure to detect an effect or to the absence of an effect. In support of the first possibility, associations between personality traits and brain activity during perception of emotional stimuli may have smaller effect sizes than mean activations to emotional stimuli. Thus, the expected effects may be difficult to detect with fMRI, which has a low signal-to-noise ratio (Logothetis, Pauls, Augath, Trinath, & Oeltermann, 2001), even despite the effort made here to reduce false negatives by using the ROV method and to increase statistical power using a large sample size. Indeed, Gignac and Szodorai (2016) did a review of effect sizes in individual-differences research, and suggested the normative guidelines defining small, medium, and large effect sizes should be smaller in this field than the standard guidelines (although this analysis was done on the results of behavioral studies, not neuroimaging studies, it is still notable here in the absence of such an analysis with neuroimaging results).

Alternatively, the null results may reflect the absence of an effect. When an expected effect size is on the smaller side, it can be especially challenging to distinguish between a failure to detect the effect and the absence of an effect because of the publication bias towards significant results. Thus, although there have been past associations between Extraversion and activation during perception of positive stimuli (Canli et al., 2002), and between Neuroticism and fearful stimuli (Cremers et al., 2010; Williams et al., 2006), there may be more-numerous unpublished null results for such associations. On the other hand, there may truly be no effect due to differences in the modality of the emotional stimulus; for example, perhaps happy faces but not happy music elicits higher activation in subjects with higher Extraversion. Or perhaps the separation of fearful and sad stimuli is important; some studies found that Neuroticism was related to brain activity during negative stimuli, but this category included sad and fearful stimuli (e.g., Canli et al., 2001).

Thus, the null results found here may be due to the true absence of an effect, or to insufficient statistical power to detect a true effect.

## 6.4 The Regions-of-Variance method

The purpose of the ROV method is to isolate regions of interest in which to investigate individual differences. Although the present study was not a systematic investigation of the effectiveness of this method, the results suggest that it can be a useful tool. First

of all, the cluster that was significant for Neuroticism & Sad in the whole-brain analysis was also significant in the ROV analysis; it would be worrisome if the ROV method had not found this result, since it was strong enough to be found in the more-conservative whole-brain analysis. Second, while the result for Openness & Happy did not pass the stringent cluster-size threshold for the whole-brain analysis, it did pass the threshold for the ROV analysis; this suggests that the ROV method may be useful for improving the power of the statistical tests to see results that cannot be seen in the more-conservative whole-brain analysis, while still using a data-driven ROI-selecting method. Therefore, in this study, the ROV method proved to be a useful tool for investigating individual differences.

## 7 CONCLUSIONS

In summary, this study investigated the role of the personality traits Extraversion, Neuroticism, and Openness to Experience in neural responses to implicitly-perceived emotion in music. In recent years, researchers have noted the importance of investigating individual differences in brain function rather than treating the differences as noise (Eugene et al., 2003; Plomin & Kosslyn, 2001). The five-factor model of personality has been shown to be a reliable (Funder & Colvin, 1997; John & Srivastava, 1999; McCrae & Costa Jr, 1989) and valid (McCrae, 2001; McCrae & Terracciano, 2005) measure of meaningful individual differences with real-world outcomes (Barrick & Mount, 1991; Matthews et al., 2012), warranting an investigations of its potential neural correlates.

Extraversion and Neuroticism have been related to positive and negative affect, respectively, in behavioral measures as well as neural activity (e.g., Canli et al., 2001; Larsen & Ketelaar, 1991). Thus, it was expected that these traits would be related to neural activation during positively- and negatively-valenced emotions in music. In line with this, Neuroticism was positively related to activations during Sad music in the inferior parietal lobe (IPL), perhaps reflecting the roles of the IPL in mentalizing and emotional regulation.

Openness is not characteristically related to particular affective states, however, it was of interest in this study because the stimuli were music. Openness has been related to more experiences of awe and chills while listening to music (Nusbaum & Silvia, 2011; Silvia et al., 2015), and more intense music-evoked emotions (Vuoskoski & Eerola, 2011a). Thus, it was thought that Openness may be involved, but there were no specific hypotheses regarding specific emotions. Openness was positively related to activations during Happy music in the region of the superior temporal gyrus, extending into the temporal pole, Heschl's gyrus, rolandic operculum, supramarginal gyrus, postcentral gyrus, and middle temporal gyrus. This region has previously been associated with positive emotions in music (Koelsch et al., 2006), and this finding perhaps reflects the more intense behavioral experience of emotions in music in individuals scoring high on Openness, but this remains speculative at this point.

The trait-congruent findings of the present study are in line with previous research suggesting that the behavioral associations between traits and emotional experiences are also reflected in brain function. Additionally they support the notion that music - even short clips of implicitly-perceived music - is an emotionally-relevant stimulus. Such research on personality and processing of emotional stimuli could have therapeutic implications, especially regarding Neuroticism, which has been linked to well-being (Richard & Diener, 2009) and emotional mental disorders (Costa Jr & McCrae, 1992; Cuijpers et al., 2005). Particularly, it could be notable for music-therapy practice that Neuroticism is related to activations during perception of sad music, though interpretations remain speculative as to why this is.

Further, this study demonstrates the usefulness of the regions-of-variance method in reducing false negative results, compared to a whole-brain analysis. Future research should more systematically evaluate this method.

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## LIST OF ABBREVIATIONS

AAL: Automated Anatomical Labeling

BOLD: Blood-Oxygenation-Level Dependent

E: Extraversion

fMRI: functional Magnetic Resonance Imaging

FWER: Family-Wise Error Rate

FWE: Family-Wise Error

GLM: General Linear Model

HRF: Hemodynamic Response Function

IPL: Inferior Parietal Lobe

N: Neuroticism

O: Openness to Experience

OLS: Ordinary Least Squares

ROI: Region of Interest

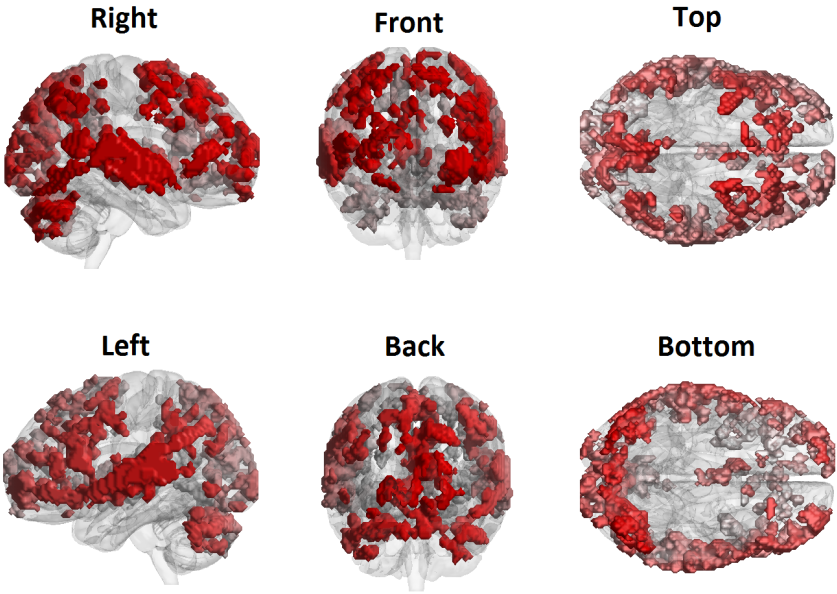
ROV: Region of Variance

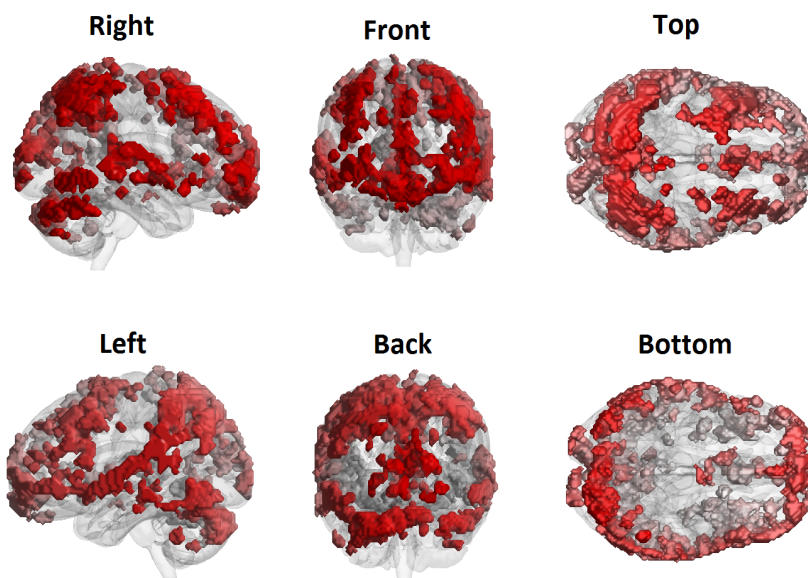
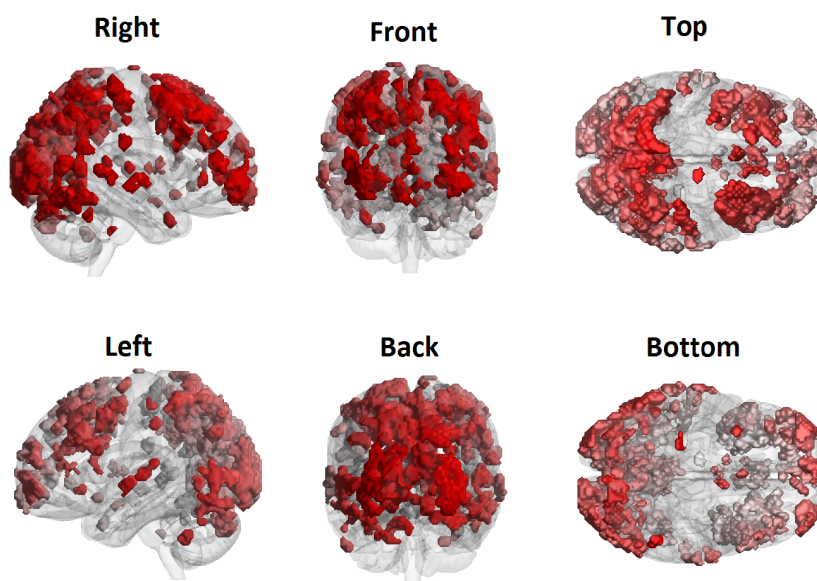
SPM: Statistical Parametric Mapping (a Matlab toolbox for analyzing brain data).

TR: Repetition Time

A REGIONS-OF-VARIANCE (ROV) MAPS

ROV map: Happy



**ROV map: Sad****ROV map: Fearful**

## **B CLUSTER-SIZE AND -MASS THRESHOLDS**

TABLE 2. Cluster-size (number of voxels) and -mass (sum of Z-scores) thresholds for each combination of personality trait, condition, and significance threshold, and for both the region-of-variance and whole-brain analyses. CLF: Cluster-Forming Threshold. ROV: Regions of Variance

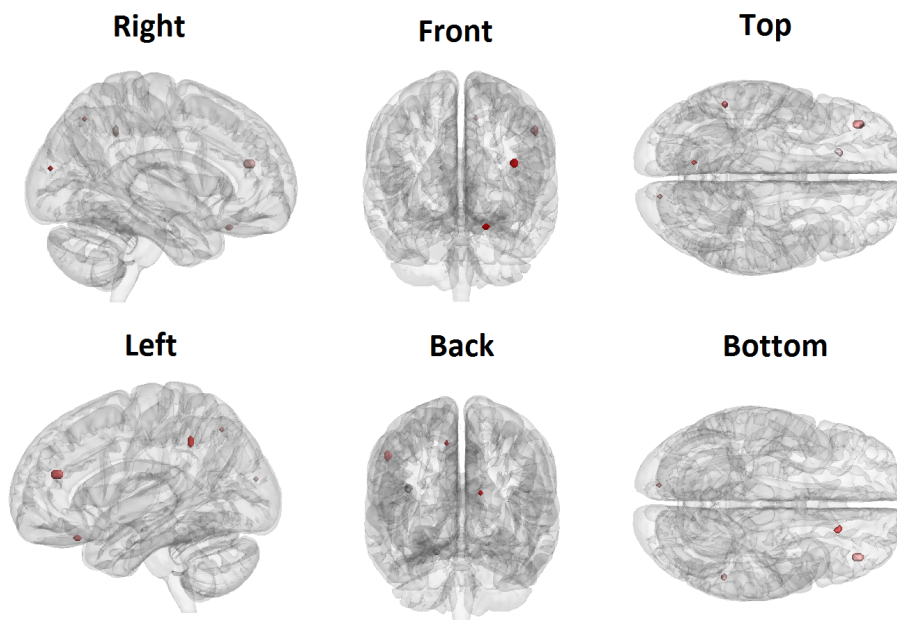
Cluster-forming threshold		<i>ClusterSize</i>		<i>ClusterMass</i>	
		ROV	Whole-brain	ROV	Whole-brain
EXTRAVERSION					
<i>Happy</i>					
	$p < .050$	491	15126	1251.60	37050.27
	$p < .010$	170	1383	512.55	4158.78
	$p < .001$	42	180	152.07	665.44
<i>Sad</i>					
	$p < .050$	801	14746	1992.42	36329.86
	$p < .010$	254	1446	764.35	4388.87
	$p < .001$	50	183	182.97	678.52
<i>Fear</i>					
	$p < .050$	1080	19407	2718.17	47342.37
	$p < .010$	263	1560	782.34	4696.45
	$p < .001$	46	176	167.57	650.13
NEUROTICISM					
<i>Happy</i>					
	$p < .050$	503	14530	1302.21	35471.82
	$p < .010$	189	1433	578.84	4402.41
	$p < .001$	54	209	196.69	777.25
<i>Sad</i>					
	$p < .050$	818	13644	2042.87	33588.34
	$p < .010$	272	1487	837.22	4510.42
	$p < .001$	68	207	248.49	760.68
<i>Fear</i>					
	$p < .050$	987	19203	2472.52	46930.59
	$p < .010$	254	1621	773.39	4913.25
	$p < .001$	59	201	216.90	741.21
OPENNESS					
<i>Happy</i>					
	$p < .050$	507	15137	1295.28	37107.89
	$p < .010$	182	1445	559.85	4392.54
	$p < .001$	49	194	179.83	724.62
<i>Sad</i>					
	$p < .050$	781	14352	1990.24	35319.33
	$p < .010$	253	1484	775.25	4478.00
	$p < .001$	59	193	216.30	709.37
<i>Fear</i>					
	$p < .050$	1018	19825	2528.13	48778.74
	$p < .010$	260	1743	787.52	5222.47
	$p < .001$	54	197	197.57	726.02

## C RESULTS PRIOR TO CORRECTION FOR MULTIPLE COMPARISONS

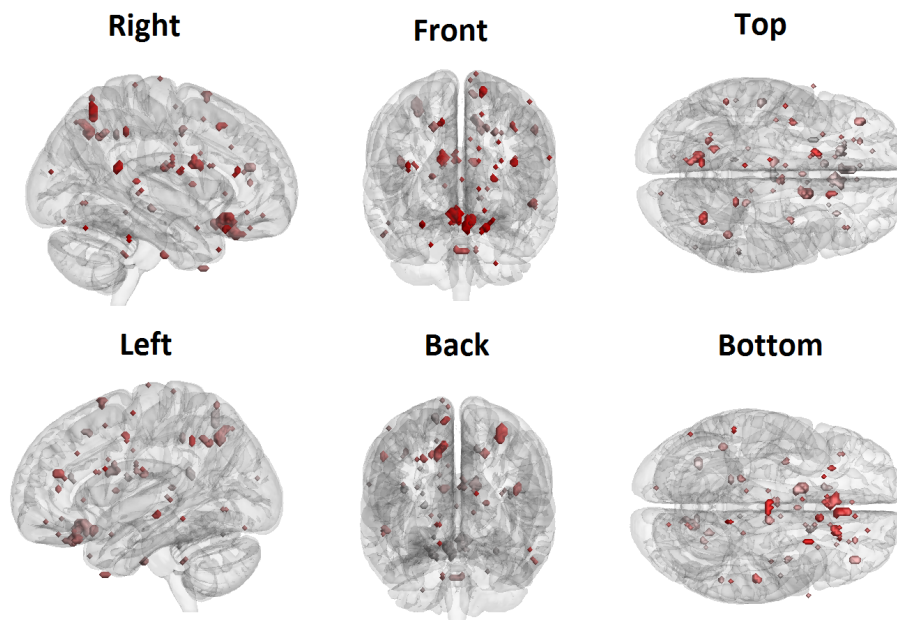
The following figures show the results prior to correction for multiple comparisons, for the two combinations of trait and emotional condition that were expected to show a significant result and did not. These maps were created with a height threshold of  $p < .001$ , uncorrected, with no cluster-size thresholding.



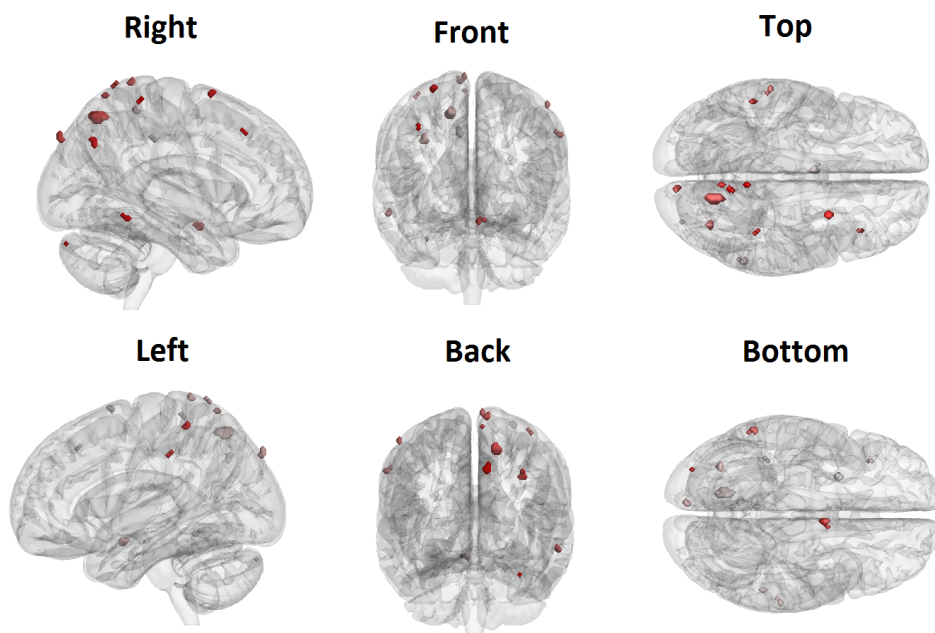
### ROV results before correction: Extraversion & Happy



### Whole-brain results before correction: Extraversion & Happy



### ROV results before correction: Neuroticism & Fearful



### Whole-brain results before correction: Neuroticism & Fearful

