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Exploring the Impact of Affective Processing on Visual Perception of Large-Scale Spatial Environments

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EXPLORING THE IMPACT OF AFFECTIVE PROCESSING ON VISUAL PERCEPTION OF LARGE-SCALE SPATIAL ENVIRONMENTS

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by

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I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Auroabah S Almufleh ENTITLED Exploring the impact of affective processing on visual perception of large-scale spatial environments BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science.

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ABSTRACT

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This thesis explores the interaction between emotions and visual perception using large scale spatial environment as the medium of this interaction. Emotion has been documented to have an early effect on scene perception (Olofsson, Nordin, Sequeira, & Polich, 2008). Yet, most popularly-used scene stimuli, such as the IAPS or GAPED stimulus sets often depict salient objects embedded in naturalistic backgrounds, or "events" which contain rich social information, such as human faces or bodies. And thus, while previous studies are instrumental to our understanding of the role that social-emotion plays in visual perception, they do not isolate the effect of emotion from the social effects in order to address the specific role that emotion plays in scene recognition – defined here as the recognition of large-scale spatial environments. To address this question, we examined how early emotional valence and arousal impact scene processing, by conducting an Event-Related Potential (ERP) study using a well-controlled set of scene stimuli that reduced the social factor, by focusing on natural scenes which did not contain human faces or actors. The study comprised of two stages. First, we collected affective ratings of 440 natural scene images selected specifically so they will not contain human faces or bodies. Based on these ratings, we divided our scene stimuli into three distinct categories: pleasant, unpleasant, and neutral. In the second stage, we recorded ERPs from a separate group of participants as they viewed a subset of 270 scenes ranked highest in each of their respective categories. Scenes were presented for 200ms, back-masked using white noise, while participants performed an orthogonal fixation task. We found that emotional valence had significant impact on scene perception in which unpleasant scenes had higher P1, N1 and P2 peaks. However, we studied the relative contribution of emotional effect and low-level visual features using dominance analysis which can compare the relative importance of predictors in multiple regression. We found that the relative contribution of emotional effect and low-level visual features (operationalized by the GIST model, (Oliva & Torralba, 2006)) had complete dominance over emotional effects (both valence and arousal) on most early peaks and areas under the curve (AUC). We also found out that affective ratings were significantly influenced by the GIST intensities of the scenes in which scenes with high GIST intensities were more likely to be rated as unpleasant. We concluded that emotional impact in our stimulus set of natural scenes was mostly due to bottom-up effect on scene perception and that controlling for the low-level visual features (particularly the GIST intensity) would be an important step to confirm the affective impact on scene perception.

Keywords: scene perception, affective processing, valence, arousal, ERP.

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I. GENERAL INTRODUCTION AND PURPOSE

Humans are surrounded by an overwhelming environment, rich in large amounts of incoming sensory inputs that challenges their limited capacity for processing all that information (Marois & Ivanoff, 2005). Traditional bottom-up theories of visual perception describe information processing within a hierarchical system, in which early visual processing feeds into conceptual systems (including both cognitive and emotional), but conceptual systems do not alter early visual encoding (Hubel & Wiesel, 1968; Maunsell & Newsome, 1987). On the other hand, top-down theories view perception as a constructive process which relies on top-down processing which including affective appraisal (Gregory, 1971). Recent neuroimaging findings support the top-down theories in that it had demonstrated that people's emotional reactions (e.g., arousing versus neutral stimuli) are associated with stronger signals across the visual cortex (Lin et al., 2020; Vuilleumier, Richardson, Armony, Driver, & Dolan, 2004). Neural representations in early visual cortex of scene stimuli were modulated by the emotional response to the presented scenes (Minati et al., 2009). These findings revealed *where* emotions influenced visual representations in the cortex. To uncover *when* these effects emerged in time (i.e., early vs. late), electrophysiological studies have demonstrated that emotional arousal and/or valence (pleasantness) impact early ssVEP (steady-state visually evoked potentials) and ERP activity in response to visual scene stimuli (Olofsson et al., 2008; Peyk, Schupp, Keil, Elbert, & Junghöfer, 2009). Nevertheless, the most commonly used scene stimuli often depict salient objects embedded in naturalistic backgrounds, or "events" which contain rich social information, such as human faces or bodies. Thus, there is still a debate around the actual cause of the early effects of emotions on scene perception (Löw, Bradley, & Lang, 2013). Therefore, the objective of the current study is to investigate the putative impact of affective processing on scene recognition, using proper stimuli, and leveraging EEG due to its fine temporal resolution that can identify the specific time of interaction. Thus, we aim to establish whether affective processing impacts visual perception by looking at how people process scenes.

Visual perception

Human visual perception entails a complex interplay between bottom-up (i.e. stimulus-driven) and top-down (observer-based) signals yielding fast and accurate recognition of the visual world (Albright, 2012). This interplay between bottom-up and top-down processing streams have attracted scientific focus since its early inception. To understand this interplay, perceptual regulating systems (attention, motivation, and emotions) contribute to the prioritization and selection of a subset of information to be perceived at the cost of others. Which one or combination of systems is at play depends on the nature of the stimuli (the external input), the explicit goals (including motivation and emotional appraisal), as well as the individual internal state (implicit goals, motivations, and emotions) (Driver & Vuilleumier, 2001; Ungerleider, 2000). It is not a simple task to disentangle the interaction between these intricately complicated processes, which are not yet fully understood. In this thesis, we will focus on the interaction between visual perception and emotions since human emotion is considered a basic evolutionary feature (Turner, 1996). It is essential to understand how much emotion affects perception because it is easy to assume that we see what is out there. For example, most of us assume that as we look at a hill, the incline's steepness in our visual image is an accurate estimation of the real angle—however, perception of the steepness changes depending on one's mood (Riener, Stefanucci, Proffitt, & Clore, 2011). For example, when someone feels sad, he perceives the hill as steeper than when he feels happy. Such findings indicate that the spatial layout's perception is influenced by non-optical factors, such as emotion.

Emotions

Emotions involve three major components, physiological responses, behavioral and cognitive appraisal. Cognitive theories of emotions posit the necessity of complex cognitions or thoughts associated with concept deployment. For sake of simplicity, we will focus on this aspect of emotions (cognitive appraisal)(Lazarus, 1991; Reisenzein, Bördgen, Holtbernd, & Matz, 2006). Accumulating evidence supports cognitive theories of emotions reporting that several neocortical regions are crucial for intact affective functioning (Bush, Luu, & Posner, 2000; Phillips et al., 1998, 1997). Emotion mechanisms can be classified into two major categories; explicit and implicit. Based on cognitive theories of emotions, we assume that unconscious processing of the emotions would reflect the later conscious or explicit emotional response (i.e. ratings).

Negativity bias

In this thesis, we followed the circumplex model of emotion that proposes that all affective states arise from cognitive interpretations of core neural sensations that are the product of two independent dimensions; valence (pleasant to unpleasant) and arousal (activating to calming). Different emotions can impact perception differently. Unpleasant (commonly refer to as negative) events and information evoke stronger physiological and emotional reactions compared to both neutral and pleasant events and information (Cacioppo, Gardner, & Berntson, 1999) (Öhman, 1992). This "negativity bias" is thought to have resulted from evolutionary pressure favoring outcomes in response to threat versus rewards. Thus, preparing the individual to respond quickly and effectively to unpleasant information as an important survival mechanism (Cacioppo et al., 1999).

Emotion (Im)penetrability of Visual Perception

The degree to which visual encoding is influenced by emotional factors, and/or executed through a passive, data-driven system is a central debate in cognitive and affective sciences (Pessoa, 2008). While emotions and perceptual processes certainly combine, at one point in time, to influence how the visual world becomes interpreted, the *extent* to which visual perception and emotion are distinct processes, and precisely *when* and *where* they interact is still in question. The classical framework proposed that visual perception is accomplished additively, in which physical properties of a stimulus are extracted, encoded, and reconstructed hierarchically within an encapsulated modular system (Fodor, 1983). Modular perceptual systems contain innate, neural modules restricted to processing direct inputs and are unable to access information stored elsewhere in the system, such as emotional appraisal or ratings (Pylyshyn, 1999).

When a visual stimulus is presented, light enters the eye striking the retina and transforming into an array of neural signals that travels through the optic nerve. The next stage is what Marr (1982) and Pylyshyn (1999) called “Early vision,” which is the part of visual perception that happens rapidly and completed within 200 ms (Marr, 1976; Pylyshyn, 1999). It includes early perceptual analysis, which according to the modular view must be contained within an unconscious system operating independently of top-down (e.g. emotional) influence because interactions on rapid processing would introduce critical perceptual delays and potential errors. Thus, according to the modular view, early vision is impervious to cognitive or emotional influence. Therefore, emotional factors, such as explicit valence or arousal ratings, interact with visual percepts in later processing stages and do not penetrate early visual perception.

Notably, however, the extent to which the functional architecture of primary visual cortex and the ventral visual pathway support this modularized, hierarchical framework has recently come into question. Recent studies documented early effect of top down factors and particularly emotions on perception which challenge the assumptions of hierarchical framework (Kayser, Körding, & König, 2004; Kravitz, Saleem, Baker, Ungerleider, & Mishkin, 2013). We will elaborate in these studies in the next section.

Neural evidence for top-down influence on visual processing

Recently, increasing evidence reveals that neurons in early visual areas, even in primary visual cortex (V1) do not act as linear feature detectors when faced with natural scenes, highlighting the role of feedback response modulation beyond the classical receptive field (Kayser et al., 2004) . For example, V1 responses to bars within a natural scene are reduced compared to bars on a uniform background (MacEvoy, Hanks, & Paradiso, 2008). Additionally, non-linear receptive field models using natural stimuli predict V1 activity more optimally than a model fit using grating stimuli (David, Vinje, & Gallant, 2004). Thus, early visual neurons transform retinal signals and integrate top-down and lateral inputs, which convey prediction, memory, attention, reward, task, expectation, and emotions (for a review see, Albright, 2012). Such higher processing is fed back (mono-synaptically or otherwise) to V1 from cortical and subcortical sources (Muckli & Petro, 2013). Adding to that, the neuroimaging evidence pinpoints that emotional stimuli not only activate emotional brain circuits (such as Amygdala) but also enhance the activity in the visual cortex (Vuilleumier et al., 2004). Also, decoding algorithms were successful in decoding different emotional experiences from analyzing the pattern of visual cortex activity. Kragel et al, analysis showed that of the seven emotional states were classified, at least five distinct emotion clusters could be reliably differentiated from one another based on occipital lobe activity (Kragel, Reddan, LaBar, & Wager, 2019).

The second step in visual scene processing goes through ventral visual pathway (VVP). This pathway courses through occipitotemporal cortex to the anterior part of the inferior temporal gyrus. It is known as the "what" pathway that mainly represent object quality and identity information (Mishkin, Ungerleider, & Macko, 1983). However, ventral visual pathway representations are not tied to particular physical objects, but they capture a stable configuration of visual information (e.g. texture, scenes). It is traditionally characterized as following the same feedforward process described above (assuming separation between perceptual mechanisms and internally generated signals). However, Recent evidence challenges the traditional framework and proposes that the ventral pathway is best understood as a recurrent network containing neural representations of the world both utilized and controlled by distinct cortical and subcortical systems specialized in behavioral, cognitive, or affective function. Anatomical evidence indicates that the ventral pathway is a complex network of feedforward and feedback projections (Kravitz et al., 2013). These findings, combined with its dense limbic and medial prefrontal cortex connectivity, suggest the VVP may serve to integrate affective and perceptual processing.

The predictive coding theory (Clark, 2013) posits that sensory processes like vision are supported by top-down signals tuned to match incoming information from the outside with internal expectations and predictions that is usually susceptible to fears. For example, it is advantageous to anticipate any potential threat in the scene before the individual gets in there. This added foresight provides beneficial information to the visual system, especially if it can aid in generating richer and more accurate representations. Thus, if the ultimate goal of perception is to build rich representations to understand one's surroundings, it is beneficial for perceptual systems to be permeable to affective factors, especially when prediction can inform the visual system (Egner & Summerfield, 2013). The question remains open as to *precisely* how and when this kind of predictive information interacts with incoming, moment-to-moment operations of the perceptual system. If perceptual mechanisms are part of recurrent networks within an interactive cortical and subcortical systems, the extent to which these processes are temporally separated remains uncertain.

Visual scene perception

One particular domain of visual perception which is best suited to study the extent to which the perceptual system incorporates affective information to better represent one's surroundings, is scene perception. To simulate visual perception in real-life environments while maintaining controlled laboratory settings, we have chosen to focus in this work on the visual processing of real-world scenes. Humans have the ability to quickly and accurately recognize and act within complex real-world scenes in a single, brief glance (M. Potter, 1975; M. C. Potter & Levy, 1969). This ability disguises the immense computational challenges presented to the human brain. Despite variations in how scenes present themselves to the retina (i.e., the unique patterns of photons activated), the brain can extract the relevant physical properties (i.e., geometry, colors, edges), the gist (i.e., overall meaning), and rapidly produce affective reaction if appropriate in just fractions of a second (Antes, Penland, & Metzger, 1981; Schyns & Oliva, 1994).

The new look on perception (Schafer & Murphy, 1943; D. E. P. Smith & Hochberg, 1954) established visual perception as a flexible process that recognizes visual environment depending on external (e.g., environment, context) as well as internal (mainly emotional reactions) factors. That is, applying the same concept to scenes, visual scene perception reflects not only the availability of perceptual information but also the observer's internal emotional biases. But, the question remains, does the emotional reaction to the scenes flexibly adapt to how one *perceives* the scene? In other words, is perceptual processing of the scene adjustable according to the emotional reaction, or is it emotion-independent? To date, an abundance of research on affective scenes had investigated the mechanisms through which affective processes impact the neural basis of scene perception. In the following section, we will expand on empirical evidence that demonstrates how visual perception and emotions are closely linked, challenging the traditional, feedforward view of visual perception (Bekhtereva & Müller, 2014; Minati et al., 2009; Olofsson et al., 2008; Sambuco, Bradley, Herring, Hillbrandt, & Lang, 2020).

The Case for Emotion Penetrability: Neural Evidence

Several lines of evidence suggest an impact of emotional processing on visual scene perception. Neuroimaging studies have provided new insight into affective interaction with sensory processing by showing early visual cortex hemodynamic changes as a response to stimulus affective salience. Minati and colleagues (2009) used Functional near-infrared spectroscopy fNIRS to examine hemodynamic responses evoked by neutral, pleasant, and unpleasant emotional scenes pictures. They reported that emotional content modulated amplitude and latency of oxy-, deoxy- and total hemoglobin response peaks. The processing of pleasant and unpleasant scenes enhanced hemodynamic response amplitude, and this effect was also associated with blood pressure changes. The processing of pleasant scenes resulted in reduced hemodynamic response peak latency (Minati et al., 2009).

Moreover, the functional limbic-visual activity was remarkably reduced in anxiety patients who had high trauma scores when viewing emotional, compared to neutral scenes. This suggests that the stronger interaction between emotion and perception is crucial for healthy emotional as well as perceptual processing (Sambuco et al., 2020). Sambuco and colleagues used fMRI to assess functional activation in the amygdala and visual cortex during emotional scene processing comparing healthy and anxiety and mood disorder patients. They reported a strong covariation between functional activity in the amygdala and ventral visual cortex, with blood-oxygen-level-dependent (BOLD) activity overall significantly enhanced in both regions. When patients reported the highest trauma scores, their brain scan shows the smallest BOLD changes in response to arousing scenes in the amygdala and ventral visual cortex (Sambuco et al., 2020). This could pinpoint the role of the interaction between emotion and perception in healthy emotional processing.

Before taking a definite position regarding these accumulating evidences of the impact of affective processing on visual scene perception, it is essential to define a “scene” precisely since this terminology has been used extensively for various meanings. We define a “scene” as a real-world, large-scale spatial environment comprising background elements and multiple discrete objects . Critically, however, in contrast with this definition most affective scene perception studies have used scenes containing people performing different activities. This creates two potential caveats when one aims to examine the role of emotion on scene perception per se. First, such scenes can trigger extreme affective responses (for example, using erotic pictures to trigger pleasure with high arousal and mutilations to illicit high arousal with unpleasant feelings) or generate responses which are not scene-specific, but rather face-specific. Further complicating the picture, in contrast to prior studies of affective scene perception, most of the scenes used as neutral scenes represent landscapes and inanimate scenes. Unfortunately, such ill-defined scenes or other visual stimuli shaped current understanding of the role that emotion plays in visual perception, particularly in social cognition (since they mainly contained people). However, they cannot be generalized on all circumstances of visual perception, such as the specific role that emotion plays in complex scene perception as defined above.

Therefore, the objective of the current thesis was to examine the time course of emotional valence and arousal on visual scene processing using electroencephalography (EEG) with natural scene images that did not contain human faces or bodies as stimuli. Specifically, we set out to examine if emotional valence and/or arousal ratings flexibly (i.e.

in different contexts) influenced scenes representations in early visual areas reflecting emotional modulation on visual encoding, and if so, assess the relative contribution of explicit affective ratings compared to low-level visual features.

Current Study

Our initial question was whether top-down factors (considering explicit emotion as one of the higher-order cognition processes based on the cognitive theories of emotions) had an early effect on perceptual processing. We conducted a two-step study. First, we collected affective ratings (valence and arousal) of 440 natural scene images selected specifically so they will not contain human faces or bodies. Based on these ratings, we divided our scene stimuli into three distinct categories: neutral (with the lowest arousal), pleasant and unpleasant (with high to medium arousal). Below (Study I Introduction), we will discuss the visual stimuli and explain the criteria and the rationale that led us to select our stimulus set. In the second stage, we recorded ERPs from an independent group of participants as they viewed a subset of the highly ranked scenes in their respective categories and compare the relative contribution of explicit affective ratings versus low-level visual features. Based on previous works on affective scene perception (Olofsson et al., 2008) , we hypothesized that early visual ERPs for scene stimuli would be flexibly modulated by the explicit affective reaction. Based on the negativity bias framework, we predict that explicitly rated unpleasant scenes will be prioritized for processing (i.e., will produce higher amplitude and/or reduced latencies) of early ERP peaks, especially P2, which is one of the most scene-selective components. Moreover, based on the cognitive theories of emotions, we assumed that explicit affective response (ratings) is an informative measure that is sufficient to reflect the impact of implicit affective processing on the early visual ERP.

II. STUDY I: AFFECTIVE RATINGS OF LARGE-SCALE SPATIAL ENVIRONMENTS

Introduction

Many visual scenes stimulus sets are available for use in studies of visual affective processing. The broadest available standardized sample of emotional scene stimuli set is the International Affective Picture System (IAPS;(Bradley & Lang, 2007)). It contains 1182 color pictures of pleasant, neutral, and unpleasant content across the entire affective space, including human faces, landscapes, animals, various objects, erotica, press photographs of war and catastrophes, severe injuries, mutilation, and corpses. Later, the Open Affective Standardized Image Set (OASIS) was presented as an open-access, online alternative to IAPS. OASIS contains 900 color images showing a broad spectrum of themes, as humans, animals, objects, and scenes. Studies that used both sets incorporate scenes that contain people performing different activities to trigger extreme affective responses (for example, using erotic pictures to trigger pleasure with high arousal and mutilations to illicit high arousal with unpleasant feelings). In contrast, most of the landscapes and inanimate scenes in the stimulus set were rated within the neutral category with minimal arousal. In using these scenes, the social content (presence of people) often is confounded with arousal or valence (Colden, Bruder, & Manstead, 2008). Studies using pupillometry and eye-tracking showed that people's presence captures exogenous attention readily compared to affective scenes with decreased social factors (landscapes) (Fitzgerald, 1968). Moreover, affective evaluation of social information engage activity in neural regions that differ from those engaged during nonsocial affective evaluation (Van Den Bos, McClure, Harris, Fiske, & Cohen, 2007).

Due to this unique neural representation, some authors started to debate whether these neural responses are specific to the social component or can be generalized to emotional responses. For instance, Low et al. (2013) used IAPS as stimuli to measure the ERP response to scenes with people and without. He claimed that affective images were associated with facilitated perception only when the images contained people. To examine the effect of emotion on scene perception while avoiding the caveats described above, we developed our own set of 440 complex, naturalistic, inanimate scenes that include representation of real-life environments that are reasonably likely to be encountered in daily life or social media. These images vary along two well-established dimensions of affect: valence (unpleasant to pleasant) and arousal (low to high activation) and cover the canonical affective space, or the combinations of valence and arousal (i.e., affect categories) (Barrett, 2006). Since landscapes and images that do not include social components usually get low arousal ratings, we purposefully looked for images that arose or excite from all the valence spectrum in our a-priori selection process. Our goal in this study is to validate this affective stimulus set which facilitate further understanding of the affective modulation of perceptual processing to be measured in a subsequent ERP experiment (Study II, see details below).

Methods

Participants

Fifty participants participated in the experiment for course credit or monetary compensation, 30 women, age M = 21.1, range = 18–35). Fourteen participants answered the questionnaire online, and the rest performed the study in the lab. All participants were recruited from the Wright state university community, which includes students, faculty, and staff. All of them had normal or corrected-to-normal visual acuity and no history of psychiatric or neurological disorders. All of the participants read and consented an electronic informed consent, approved by the Wright State University Institutional Review Board (IRB).

Stimuli

Stimuli were selected from non-copyrighted images found on the internet. A few of them were selected from other affective images databases including GAPED (2-3 pictures)(Dan-Glauser & Scherer, 2011), OASIS (30 picture)(Kurdi, Lozano, & Banaji, 2017), NAPS (24 picture) (Marchewka, Żurawski, Jednoróg, & Grabowska, 2014), HNVCL scene database (25 picture) (Harel, Groen, Kravitz, Deouell, & Baker, 2016a; Kravitz, Peng, & Baker, 2011) . We selected a variety of real-world full-color naturalistic scene images with multiple focal points, taking in consideration that no human faces, bodies or single objects were included in the scenes. We removed even people or animals in the background, which could be considered indiscernible to effectively control for this confounding factor.

All scenes were outdoor (eye-level); we excluded indoor scenes to control for navigability as a confounding factor. As our goal was to create a set of naturalistic scenes, we excluded pictures that appeared to be posed or digitally enhanced, as well as pictures of famous places or events.

All scenes were in landscape orientation. We re-sized all images to 1024 x 770 pixels by Adobe Photoshop. Also, we used Photoshop to remove written words or logotypes that might capture visual attention and replaced it with the background colors.

We selected scenes of what we considered to be of three categories: pleasant scenes, unpleasant scenes, or neutral. For pleasant scenes, we collected a variety of natural scenes that we expected would elicit feelings of esthetic appreciation. For unpleasant stimuli, we selected a range of disaster area scenes (e.g. destruction after a fire, tsunami, or flood). Neutral stimuli were chosen to be a mixture of natural scenes that we expected would be part of our participants' everyday encounters. To test our assumptions, in the current experiment, we asked our participants to rate these scenes based on their valence, ranging from very unpleasant to highly pleasant (see below). The final set included 143 expected unpleasant, 151 expected neutral, and 146 expected pleasant scenes. Figure (1) shows examples of each category.

Figure 1: Representative examples of scene stimuli used in the rating and the ERP study. Note: the first row contains examples of pleasant scenes, with high or mid arousal levels. The second row contains examples of neutral scenes with mid to low arousal. The third row contains some of unpleasant scenes with high to medium arousal levels

Procedure

For the online subjects (n =14), after we checked their eligibility to participate, we send them the link for the study with instructions to read the informed consent, ask any question, and sign it if they are willing to participate. For the participants who performed the study in the lab (n= 36), we followed the same procedure of checking their eligibility, asking them to read the informed consent form, ask any question and sign it if they are ready to participate.

Following consent, each participant read the explanation of the procedure and completed the computer rating task, a brief demographics questionnaire, inquiring about age, and gender and emotional regulation questionnaire (ERQ) (This was designed as part of a different study and therefore will not be further discussed here). After the completion of the study, participants were granted course credit or monetary compensation.

Each participant was seated on a desktop in the lab or instructed to use their desktop at home. Participants were informed that the purpose of the study was to learn how people respond to scenes that represent different settings and environments, and that they would be viewing and rating these scenes (For an example of a trial, see Figure (2). We employed the SAM (Self-Assessment Manikin) (Bradley & Lang, 1994), a five-pointer scale of a non-verbal pictorial technique which directly measures valence and arousal. The first rating was for how unpleasant or pleasant the scene made them feel (ranging from most unpleasant in the left to mostly pleasant on the right). The second rating was for how arousing or activating they found the scene to be (from low arousal on the left to high arousal on the right). The third question was assessing presence (how much they liked to be in that scene (from –5 to 5)(we did not analyze this question further as it was not pertinent for the purposes of the current thesis work). Participants were informed that the task was not timed, but there was an allotted time of two hours for the whole experiment.

The order of stimuli was randomized for each participant. In each trial, a scene image was presented on the screen with the three questions about it. After the participant answered the three questions, they were allowed to proceed to the next image.

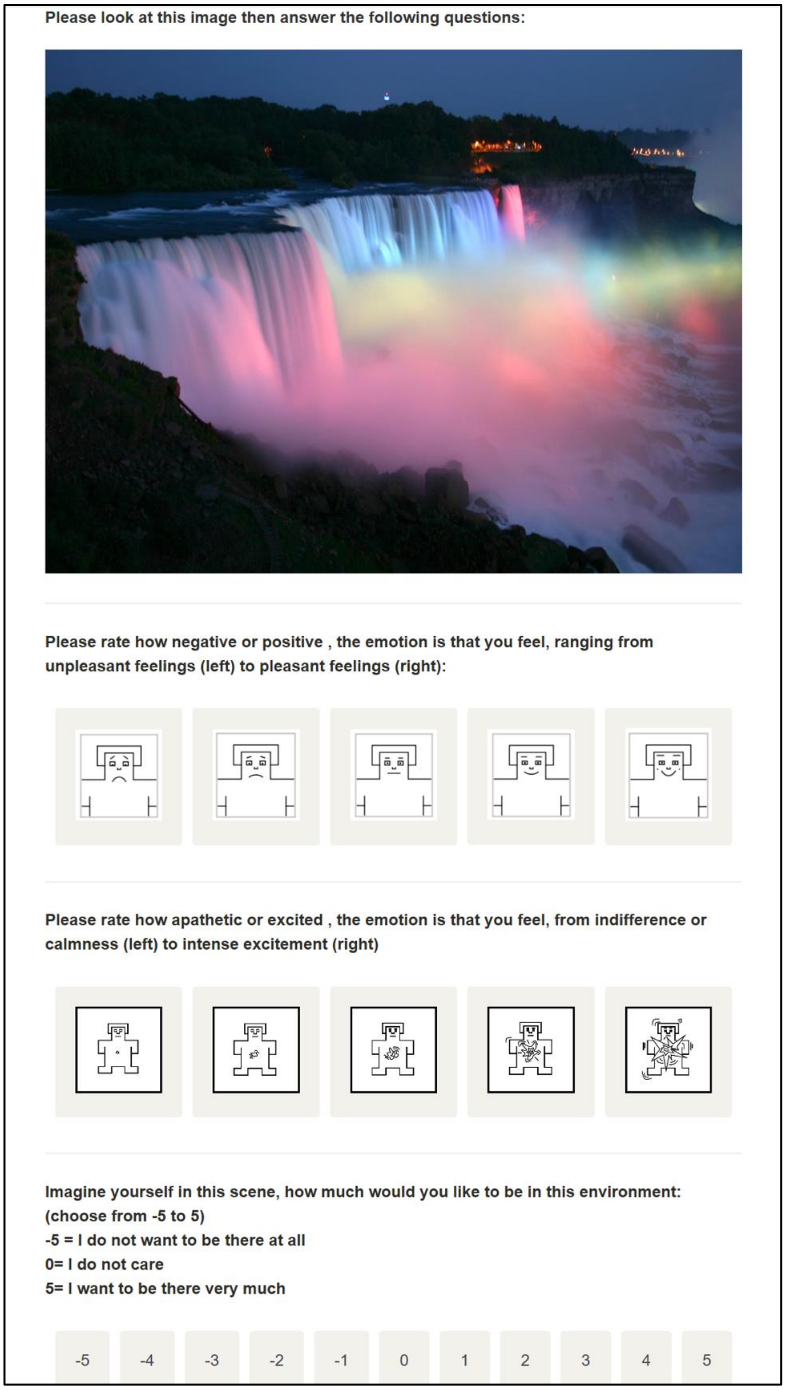

Figure 2: Example trial of the rating study. Note: a trial consists of three questions, rating valence, arousal and presence.

Results

Participants' ratings data were analyzed using Microsoft Excel and SPSS. The variability of valence ratings among the 440 scenes ranges from 0.39 to 1.48. For two examples of the variability of the valence ratings on a given scene, please see Appendix D. Figure 3 presents the average valence and arousal ratings distribution among the 440 scenes after sorting them from highest to lowest valence. The data is slightly skewed to the left (toward pleasant scenes) (skewness = -0.37) and an overlap between the pleasant and the neutral scenes, while unpleasant scenes were also slightly overlapping with the neutral scenes. Figure 4 depicts the full distribution of the individual scenes based on frequency of valence and arousal ratings among the three affective categories.

The average valence rating across all scenes was 3.04 (SD = 1.22). The average arousal ratings across all scenes was 2.6 (SD = 0.48). Consistent with other stimulus sets (e.g., (Barrett, 2006);(Posner, Russell, & Peterson, 2005, COMPASS, 2019), valence and arousal ratings showed a U-shaped relationship, such that scenes at the extremes of the valence dimension were rated as more arousing than scenes in the middle of the dimension (see figure 5).

To examine the extent to which the three scene categories were perceived as separate entities, we performed ANOVA on the three a-priori selected categories (pleasant, unpleasant and neutral) (see Figure *5*) which showed they were significantly distinguished from one another in terms of valence and arousal ratings ($F(2,437)=1801.31$, $p < .0001$),

($F(2,437)= 296.74$, $p < .0001$) respectively. The average valence rating for the a-priori selected unpleasant scenes was 1.44 (SD = 0.24) while the average arousal ratings for these scenes was 2.48 (SD=0.29). For the a-priori selected pleasant scenes, their average valence ratings was 4.2 (SD=0.48) and their average arousal ratings was 3.1 (SD=0.38). Lastly, the average valence ratings of a-priori selected neutral scenes was 3.45 (SD= 0.77) while their average arousal ratings was 2.24 (SD=0.17).

Based on these rankings we selected a subset of scenes from each category to be used in the ERP experiment. To avoid any overlap, we have chosen the 90 highest valence rated scenes as the pleasant ones (M= 4.45, SD=0.14; average arousal ratings was 3.22 (SD=0.35)), the 90 lowest valence rated scenes as the unpleasant scenes (M=1.3, SD=0.08; average arousal was 2.56 (SD=0.28)), and for the neutral scenes, we have chosen the lowest valence among the neutral category (M=3.21, SD=0.31; average arousal rating was 2.1 (SD=0.18)) to avoid the overlap with the pleasant scenes valence. Figure 6 displays the results of ANOVA of the three groups (pleasant, neutral and unpleasant) which showed they were significantly distinguished from one another in terms of valence and arousal ratings ($F(2,267)=5606.41$,$p <.0001$) in mean valence ratings as well as mean arousal ratings ($F(2,267)=361.19$,$p <.0001$).

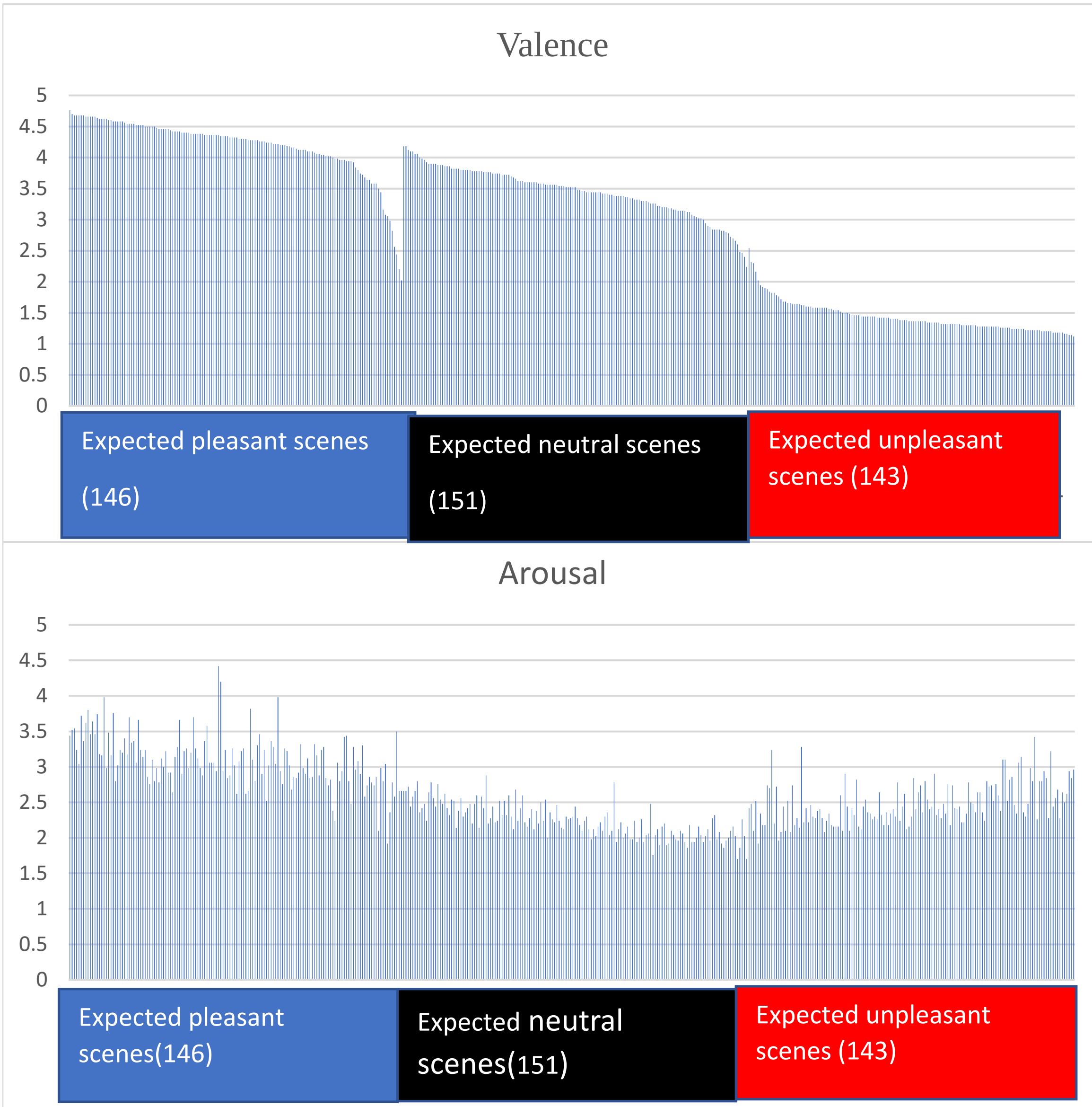

Figure 3: Valence (up) and Arousal (down) ratings distribution across the 440 scenes. Note: the x axis has the 440 scenes starting by the expected pleasant on the right, followed by expected neutral, then expected unpleasant. The Y axis shows the valence (up) and arousal (down) ratings for each scene. They are sorted by the average valence from highest to lowest for each of the proposed categories; the arousal corresponds to that valence above and is not sorted from highest to lowest.

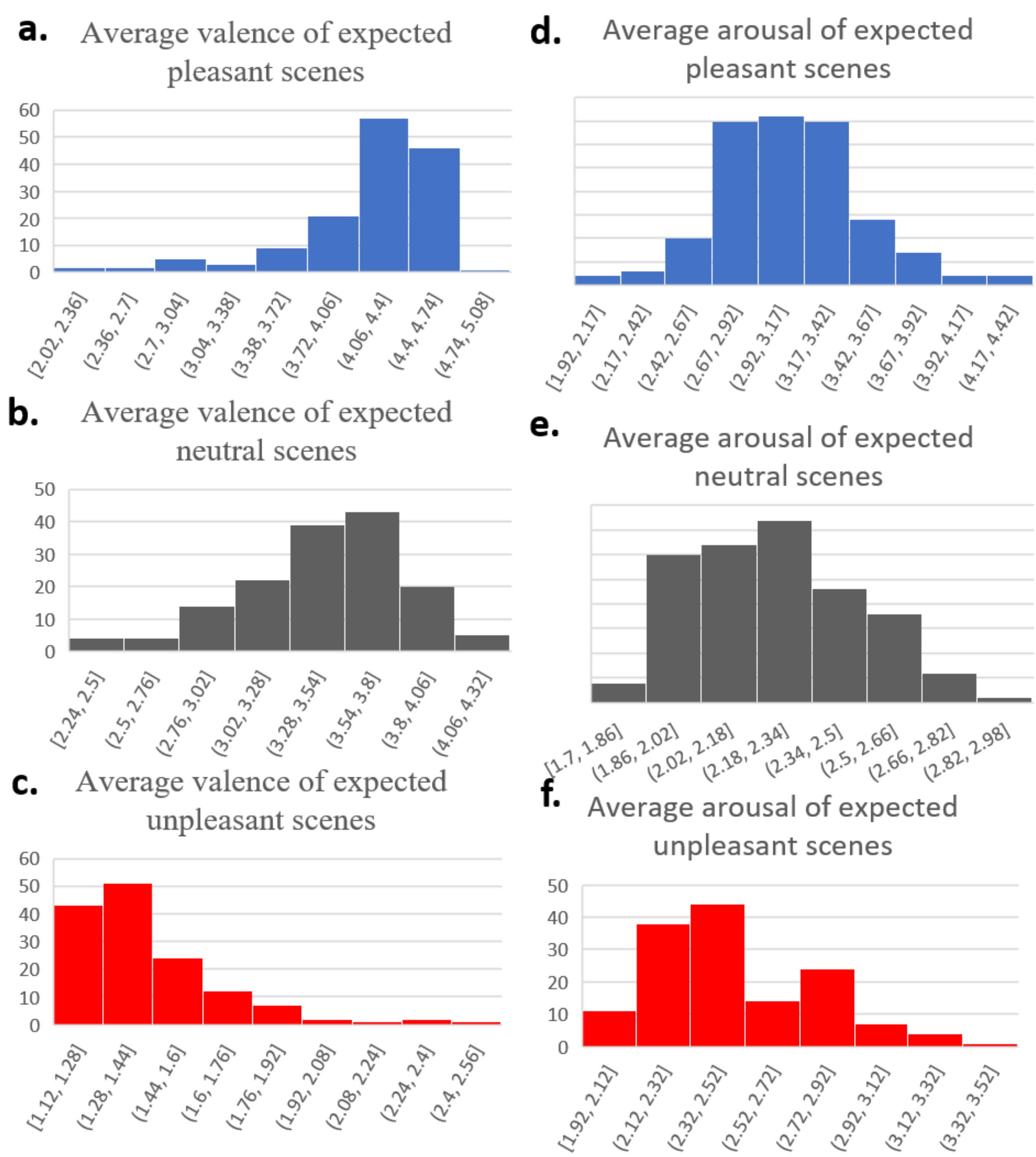

Figure 4: Histogram showing valence (a,b,c) and arousal (d,e,f) distribution among the three affective categories across the 440 scenes.Note: this histogram shows the full distribution of individual scenes among the three expected categories based on frequency of valence (a,b,c) and arousal (d,e,f) ratings across the 440 scenes.

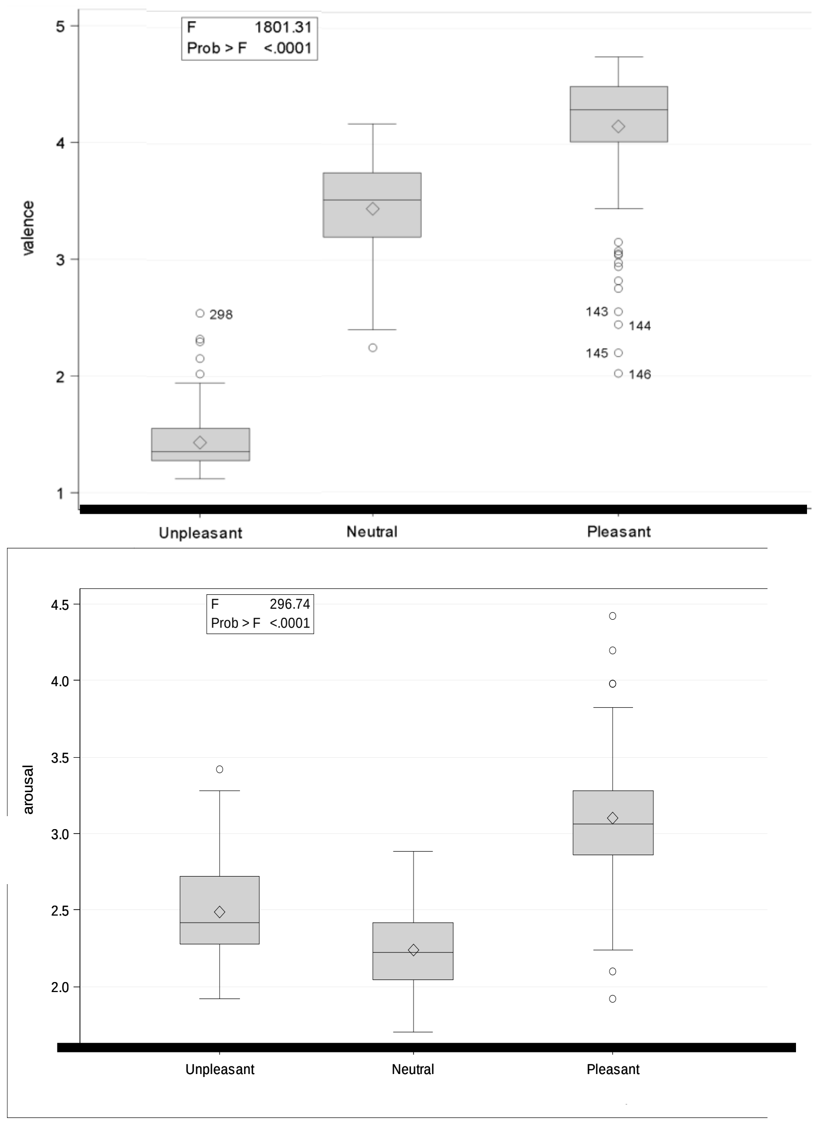

Figure 5: Whisker plot showing Valence and arousal ratings distribution and the central tendency measures (mean, median, sd) across the 440 scenes. Note: this anova analysis showed that the three groups on the x axis (unpleasant, neutral and pleasant) had significantly different valence as well as arousal ratings (p <.0001 when comparing any of the groups to each other).

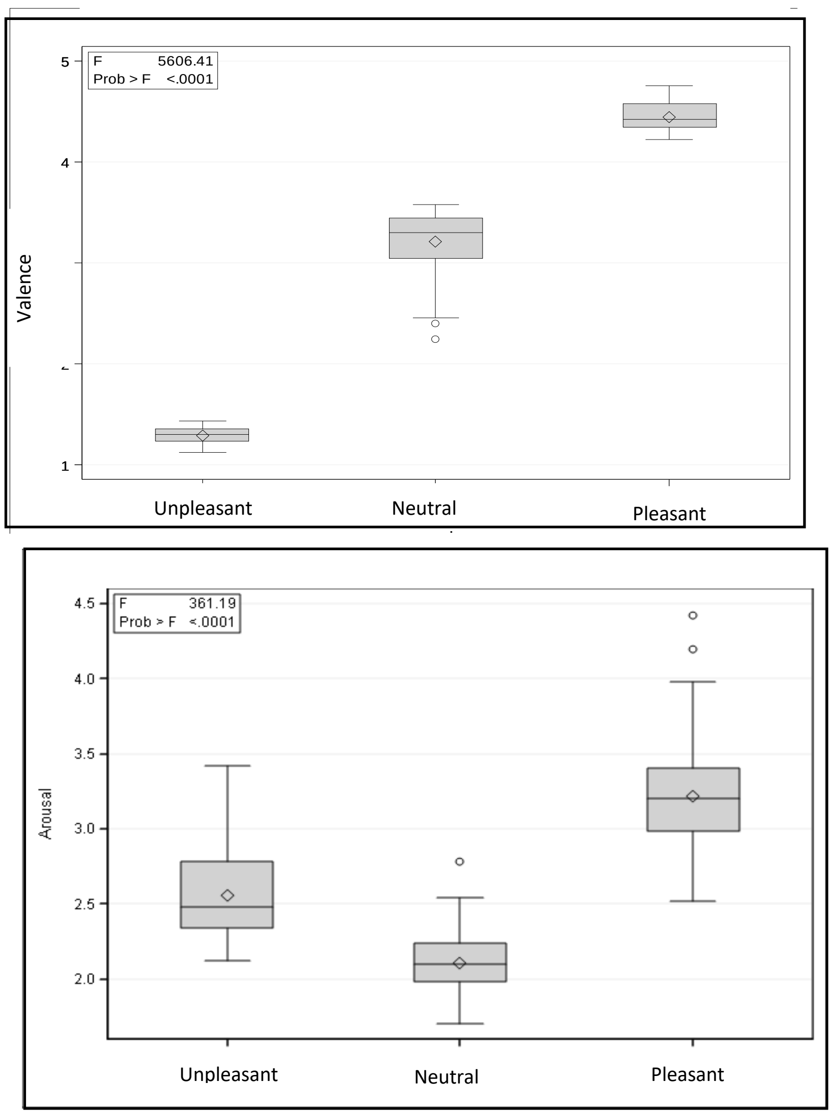

Figure 6: Whisker plot showing Valence and arousal ratings distribution and the central tendency measures (mean, median, SD) across the chosen 270 scenes. Note: this anova analysis showed that the three chosen groups on the x axis (unpleasant, neutral and pleasant) had significantly different valence as well as arousal ratings (p <.0001 when comparing any of the groups to each other), the similarity between whisker plots for the 440 scenes and the chosen scenes shows that they have similar distribution with no overlap on the valence ratings.

The impact of low-level visual properties on affective ratings.

To examine how, the three scenes categories, differ in their physical properties, we assessed their differences in low-level visual features using gist model (spatial envelope). This model categorizes scenes based on computing a statistical abstract of visual features similar to those known to be analyzed in the early stages of the human visual system. This model suggests five perceptual dimensions (naturalness, expansion, ruggedness, openness, roughness) which represent the dominant spatial structure of a scene. The model generates a multidimensional space in which scenes sharing membership in semantic categories (e.g., streets, highways, coasts) are projected closed together (Torallba and Oliva, 2001). The Gist algorithm measures the distribution of oriented bandpass Gabor filter responses in localized portions of images. Our model used default settings of 16 receptive fields (4×4 grid), 8 orientations, and 4 spatial frequencies; (Oliva & Torralba, 2006). This model had a 512-vector output. After applying the algorithm to all our scenes images, we averaged across the 512 vectors of each image to get the average gist. Afterwards, we conducted a univariate ANOVA, with average gist score as the dependent variable, in order to examine the low-level visual properties differences . among the three affective scene categories,

We observed a significant main effect of affective scene category on the average gist ($F(2,1)= 33.2$, $p < .0001$), in which the unpleasant scenes with high to moderate arousal ($M = 0.054$, $SD = .01$) had the significantly highest average gist intensity followed by pleasant scenes (with highest to moderate arousal) ($M = 0.048$, $SD = .012$) and the significantly lowest gist was associated with neutral scenes (with moderate to lowest arousal) (M=0.042, SD=.012).

For the chosen 270 scenes, similarly, we observed a significant main effect of the average gist on affective scene category (F(2,1)=21.16, P<.0001), in which unpleasant scenes (M = 0.055, SD = .009) had higher average gist intensity compared to the pleasant and neutral scenes (M = 0.043, SD = .009 and M=0.046, SD=.009, respectively). In contrast to the whole set of 440 scenes, pleasant and neutral scenes did not show any significant difference in their average gist score (P=0.40).

Discussion

The goal of this study was to prepare a stimulus set that contains naturalistic scene images that vary in their affective content while controlling for the social effect of human presence. Similar to previous affective scene databases, our scenes that scored higher valence rates showed higher arousal rates as well. Thus, consistent with other affective databases, our images fall into three combinations of arousal and valence (higher to moderate arousal pleasant, higher to moderate arousal unpleasant, and moderate to lower arousal neutral) that are represented by the U- shape of the previously mentioned circumplex model of affect(e.g. (Barrett, 2006; Posner, Russell, & Peterson, 2005).

In contrast to previous affective databases (unpleasant scenes usually provoke higher arousal ratings (Bradley & Lang, 2007; Dan-Glauser & Scherer, 2011), a subset of our pleasant scenes evoked higher arousal ratings than unpleasant scenes. We expect that this difference could be due to the relativity of affective scales (i.e., participants are rating the scenes comparing them to each other). This could be explained by the theory of scale relativity that discusses the relative character of all scales in nature (Nottale, 1992). For example, our pleasant scenes were represented as highly ecstatic places that evoke excitement more than the neutral scenes that represented mundane, everyday scenes. At the same time, participants could have considered our unpleasant scenes as repulsive but not as much as other graphic images that appear in social media since it simply contained lands and environments in disrupted situations.

III. STUDY II: NEURAL RESPONSES TO AFFECTIVE LARGE-SCALE SPATIAL ENVIRONMENTS

Introduction

In the first part of this thesis, we chose, designed, and collected emotional ratings for a set of suitable visual stimuli to examine the effect of emotion on scene perception. This stimulus set contains naturalistic scenes representing different environments and controls for the social effects of faces and human presence. In the second part of the thesis, we will discuss the measurement of the neural responses to these scene stimuli in order to facilitate the assessment of the temporal dynamics of the impact of emotion on visual scene perception.

EEG provides an excellent medium to understand the temporal sequence of the neural responses to visual scenes (Luck & Kappenman, 2016). For example, one of EEG techniques, steady-state visual evoked potential (ssVEPs), had shown that emotionally arousing stimuli presented at 10 Hz rate enhanced ssVEP amplitude at parieto-occipital recording sites as compared to neutral stimuli (Keil et al., 2003).

Another common EEG technique is Event-Related Potentials (ERP), which measures voltage changes in cortical neurons that follow the onset of specific visual, auditory, or other sensory stimuli. In our case ERP has the advantage that it can index visual perception as well as affective events (Luck et al, 2014). Thus, ERP can be utilized as proxies to inform us about early visual perceptual processes and whether they are susceptible to emotional factors, the timing of their effect and if certain emotional category impact perception differently (Luck et al, 2014). Moreover, previous studies show that early ERP peaks are influenced by scene perception; for example, a posterior ERP component, the P2 has been shown to index the processing of global scene properties (Harel, Groen, Kravitz, Deouell, & Baker, 2016b). Accordingly, many ERP studies examined the effect of emotion on scene perception (for a review, see (Olofsson et al., 2008)). These studies suggested that some early ERP components are associated with the processing of the affective content of the scenes. The temporal courses of ERP valence and arousal effects differ as valence most commonly appears to influence relatively early (100–250 ms) and arousal influences relatively late (200–1000 ms) components (Olofsson et al., 2008). Such effects can be obtained in passive viewing and active response tasks (Bernat, Bunce, & Shevrin, 2001; Yee & Miller, 1987). These findings support the view that affective processing can be described as an automatic feature of perception (LeDoux, 1989; Öhman & Soares, 1998). Three ERP components in particular seem to be influenced by the emotional content of the scene: P1, N1, and P2 components, prominent exogenous, sensory-driven components which are elicited in the presence of a visual stimulus.

Research examining the **P1**, which occurs approximately 100ms post-stimulus onset and is typically largest over the posterior lateral electrode sites, shows sensitivity to low-level physical properties of the stimulus, such as luminance, shape, and color, as well as selective attention (Hillyard, Vogel, & Luck, 1998). Spatial and selective attention has been shown to modulate the P1 and the N1 (Luck, Heinze, Mangun, & Hillyard, 1990). It also appear to be susceptible to arousal which was induced by encouraging participants by giving feedback and instructing them to respond faster every time (Luck, Woodman, & Vogel, 2000)

The **N1**, a negative voltage change occurring approximately 150-200ms post-stimulus onset, has been widely used to understand the temporal dynamics of object and face processing. When presented with faces, this component is known as the N170, and it is reliably more substantial over lateral occipital electrode sites (especially in the right hemisphere) when participants view faces compared to non-face stimuli (Bentin & Deouell, 2000). The N1 has also been used to examine the influences of emotion on perceptual processing of faces (Blau, Maurer, Tottenham, & McCandliss, 2007). As Blau et al. (2007) showed that the N170 response could be affected by emotional facial expressions such as fearful faces. The topography of this effect supports that fear stimuli exaggerate the N170 response itself.

EPN: Early Posterior Negativity EPN was the most consistent emotional early effects. It is a negative deflection over occipitotemporal sites, peaks around 180 and 250ms. It has been considered a marker of the earliest processing of selective emotional perception. The amplitude of the EPN correlates with emotional arousal regardless of the valence (Schupp, Junghöfer, Weike, & Hamm, 2004) . Peyk and colleagues (2009) had demonstrated that emotionally arousing scenes presented at slow as well as rapid rated (1 to 12 Hz) were associated with greater EPN compared to neutral scenes. Thus, showing that arousal was preferentially processed automatically even under highly demanding conditions (Peyk et al., 2009).

The **P2** component, a positive voltage deflection occurring approximately 200ms post-stimulus onset, is thought to index global properties of scene processing, such as naturalness and openness (Hansen, Noesen, Nador, & Harel, 2018). Additionally, P2 was reported to respond to the emotional reaction to scenes, though it is not conclusive which valence or arousal category result in higher amplitude (Delplanque, Lavoie, Hot, Silvert, & Sequeira, 2004) .

LPP *late positive potential* is a positive voltage that typically consist of an enlarged P3 component in its onset (around 300 ms) and distribution (parietal). It may extend for hundreds of milliseconds and may become more centrally distributed over time. It reflects the intrinsic task relevance of emotion-related stimuli (Cuthbert, Schupp, Bradley, Birbaumer, & Lang, 2000; Hajcak & Olvet, 2008).

As noted above, these studies often use stimuli depicting salient objects embedded in naturalistic backgrounds or “events” which contain rich social information, such as human faces or bodies. Using these sub-optimal scenes, recent affective scene perception neuroimaging studies have demonstrated that emotional content impacts early visual scene processing. However, the question is whether that is a real effect of emotion on scene perception or just the detection of faces and other socially-relevant elements. Sebatiallin and colleagues challenged the idea that the early effects of emotions (especially EPN) are pure effects of emotions by examining the relationship between EPN amplitude and fMRI activation patterns. They demonstrated that the late emotional valence effect (i.e., LPP) was associated with emotional circuits activation in the brain (e.g. amygdala) while the early effects were not. This study raises a concern of the interpretation of the early effects of emotions (Sabatinelli, Keil, Frank, & Lang, 2013). Relatedly, Low and colleagues reported that the presence of people and picture composition (simple figure-ground vs. complex scenes) modulate EPN (and can explain the facilitated perception) more than the emotional arousal categories (Löw et al., 2013)). Miskovic et al. expanded on this caveat by directly examining the relative contribution of luminance and chromatic visual channels to IAPS emotional effect on electrophysiological correlates of visual scene perception. They reported that the early posterior negativity (EPN) was stimulus-specific, present for the low spatial frequencies and greyscale but not for high spatial frequency and green/ red stimuli, while only the later effect, that is, the LPP was not modulated by luminance or colors (Miskovic et al., 2015). Additional examples of low-level features studied in affective pictures are image brightness (Kurt, Eroğlu, Bayram Kuzgun, & Güntekin, 2017), color (Bekhtereva & Müller, 2014) and spatial frequency content (Müller & Gundlach, 2017) .

Therefore, the evidence for the effect of emotion on scene perception is based on comparisons of the responses to scene stimuli that have different low-level visual features (even though some studies match for some of them, see for example, (Sabatinelli et al., 2013)). Hence, it is logically possible that the ascribed ERP emotional effect is not due to emotional content per se, but to some confounding low-level visual feature which is present in affective stimuli but not in neutral ones. Notably, these low-level visual properties may not only be simple image statistics such as contrast or spatial frequency, but also, global properties of scenes that are represented by the gist model or scene spatial envelop. This model, as described earlier, can discriminate between scenes that are open or closed, more natural or more artificial, and so forth (for a full description see (Torallba and Oliva, 2001) Therefore, in the current study we did not only investigate how the emotion impacts early visual processing of scenes, but also whether such attributed effects can also be explained in light of the relative contribution of low-level visual properties represented by the gist model.

By leveraging the advantages of EEG and, specifically, the ERP technique, we examined the temporal dynamics of visual scene processing, with a particular interest in whether emotional scene content modulated early visual responses (i.e., P1, N1, P2). We used the early visual components described above to investigate if and when emotional reaction, as modulated by valence and arousal ratings, influenced incoming visual information to facilitate scene processing. This paradigm allowed us to examine whether early visual ERP responses to scene information are affect-dependent and identify the specific processing stage impacted by it.

Methods

Participants

Twenty-three participants (13 females, mean age 18.8; range: 22-18) participated in the experiment for course credits. Three participants were removed for extensive EEG artifacts (e.g., excessive blinking, motion). All participants were recruited from the Wright state university community, had normal or corrected-to-normal visual acuity, and no history of psychiatric or neurological disorders. Participants provided their written informed consent, which was approved by the Wright State University Institutional Review Board (IRB).

Stimuli

Two hundred seventy scenes were selected from the first study as top-rated based on the criteria described above. In order to examine how our scenes stimuli, differ in their image ("low-level") visual properties and how that might impact the observed neural responses, we applied the Gist model algorithm (Torallba and Oliva, 2001) using Matlab 2016 on the chosen 270 scenes. This algorithm (as described earlier) extracts the spatial envelope, or gist descriptors, of the scene, which can then be used to categorize a scene based on its global image features.

Experimental Design and Procedures

Participants were given a brief description of the experiment, followed by obtaining their informed consent orally and in writing, then EEG electrodes attached to the subjects.

Presentation Software (Neurobehavioral system, Inc., Albany, CA) was used to present and control the presentation and timing of the stimuli. Photographs were displayed in colors with (770 x 1024) resolution. Afterward, participants sat in an isolated room at approximately 50 inches from a computer monitor piloted from a PC computer in an adjacent room. They viewed the 270 images repeated five times, which made a total of 1350 trials distributed in thirty blocks. Each block consists of 45 images. The order of individual stimulus presentation was pseudo-randomized across participants. Each individual image was only repeated after all the 270 images was presented once at least. Scene stimuli were presented for 200 milliseconds, followed by white noise back-mask to prevent any emotional carry over from the previous image. The back-mask was followed by a jittered inter-trial interval (ITI) ranging from 1000-2000ms. We presented ten randomized white masks to prevent the habituation to their effects.

Participants performed a fixation cross task, in which they were required to report whether the horizontal or vertical bar of the central fixation cross lengthened in width or height, respectively. Changes in the fixation cross were randomized across trials, and hence were independent from the actual content of the underlying image, essentially requiring the participants to pay very little, if any, attention to the background images while completing this task (see figure 7). Furthermore, to ensure participants' engagement in the task, they were given feedback on their performance at the end of each block. Participants were instructed to keep their eyes open during the trial duration. If/when they had to blink, they were reminded to blink during the ITIs to prevent artifacts in the ERP analysis. The experimental session lasted approximately two hours. At the completion of the study, participants were debriefed and granted credits.

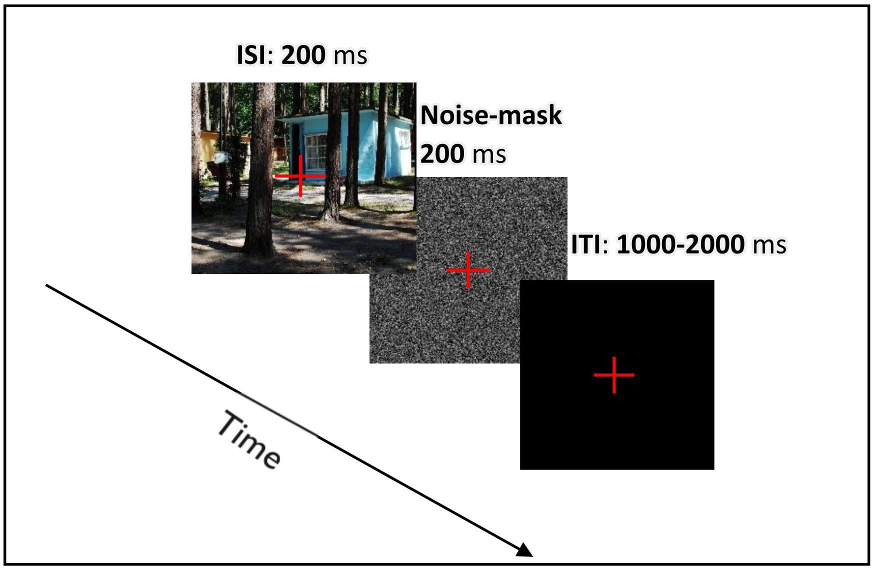

Figure 7: Example trial from the ERP experiment. Note: Each trial starts with Scene stimuli (ISI) presented for 200 milliseconds, followed by white noise back-mask to prevent any emotional carry over from the previous image, then followed by a jittered inter-stimulus interval (ITI) ranging from 1000-2000ms.

EEG Recording

EEG was recorded continuously by a set of electrodes by 64 Ag-AgCl pin-type active electrodes (ActiveTwo, Biosemi) mounted on an elastic cap (ECL) according to the extended 10-20 system, and from six additional electrodes, two placed at the right and left mastoid, and an electrode on the tip of the nose. Two pairs of EOG electrodes used to monitor the eye movements, as well as the blinks, one pair attached to the external canthi, and the other pair to the infraorbital and supraorbital regions of the right eye. Both EEG and EOG were sampled at 512 Hz with a resolution of 24 bits and an active input range of

-262 to +262 mV/bit, with on-line low-pass filtering of 51 Hz to prevent aliasing. The digital EEG was saved and processed off-line.

Data processing

We processed the data using Brain Vision Analyzer 2 (Brain Products GmbH, Munich, Germany), which included applying a 0.3 Hz high-pass filter and referencing to the tip of the nose. We used ocular correction infomax ICA procedures to correct for eye movements and blinks. We rejected any remaining artifacts that exceeded ± 100 mV in amplitude or contained an absolute change of over 100 mV in a period of 100ms. Next, we segmented the preprocessed data into epochs ranging from − 200ms before to 800ms after stimulus onset for all conditions. We rejected trials containing EEG artifacts, and no more than 30% of trials were rejected within any of the valence categories for any individual participant (thus left us with a large number of trials, not less than 317 trials out 450).

ERP analysis

Since we are interested in determining whether emotion modulates perceptual encoding during early visual stages of visual scene processing, we focused on the early visual evoked potentials: P1, N1, and P2 (Luck et al , 2005). Specifically, these ERP components have been shown to be involved in several aspects of visual scene perception (Hansen et al., 2018; Harel et al., 2016b). We extracted peak information for the P1, N1, and P2 across each experimental condition for every participant. The P1 was defined as the most positive peak between 100 and 140ms, the N1 was defined as the most negative peak between 150 and 190ms, and P2 was defined as the most positive peak between 200-240ms. We restricted our analysis to the posterior lateral electrode sites (averaged across P7, P5, P9, PO7 for the left hemisphere and across P8, P6, P10, PO8 for the right hemisphere) because these regions maximally capture early visual activity.

Area under the curve (AUC)

We measured the impact of emotional valence and arousal on scene processing over an extended epoch of time rather than on isolated peaks. We computed the rectified AUC for each condition, and each individual image for two distinct time epochs: 50 – 200ms, and 200 – 350ms, to index early and late visual processing, respectively.

Statistical tests

We conducted multiple regression analysis after averaging right and left posterior lateral leads of each peak and latency (P1, N1, and P2) and the early and late AUC to study the effect of valence (as a continuous measure using the individual image valence ratings), arousal (as a continuous measure using individual image arousal ratings) and the average gist (for each image) Also, we averaged across repetition of each individual scene (5 trials x 20 participants) to get the individual scenes ERP data. Thus; examining the impact of each variable on early visual ERPs. Then, we run a dominance analysis to determine which factor had the maximum effect. We adopted the 0.05 significance level to ascertain statistical significance.

Results

To test whether the emotional valence and arousal of the scenes influenced early perceptual scenes processing, we examined their effect on early visual ERP components. Figure 8) depicts the grand averaged ERP waveforms for each emotional valence category. As can be seen, the unpleasant scenes evoked a higher amplitude across all early visually evoked potentials (P1, N1, and P2) relative to neutral scenes. Pleasant scenes evoked a similar response to the neutral scenes. The effect of unpleasant scenes started around 130ms post-stimulus onset, was most pronounced at 230 ms (around the P2 peak) and persisted until around 350ms, at which point the backward mask operated and prevented further processing (notice the converging waveforms after that point). To formally quantify these apparent trends, we performed a univariate ANOVA, multiple linear regression and dominance analysis, further explained below.

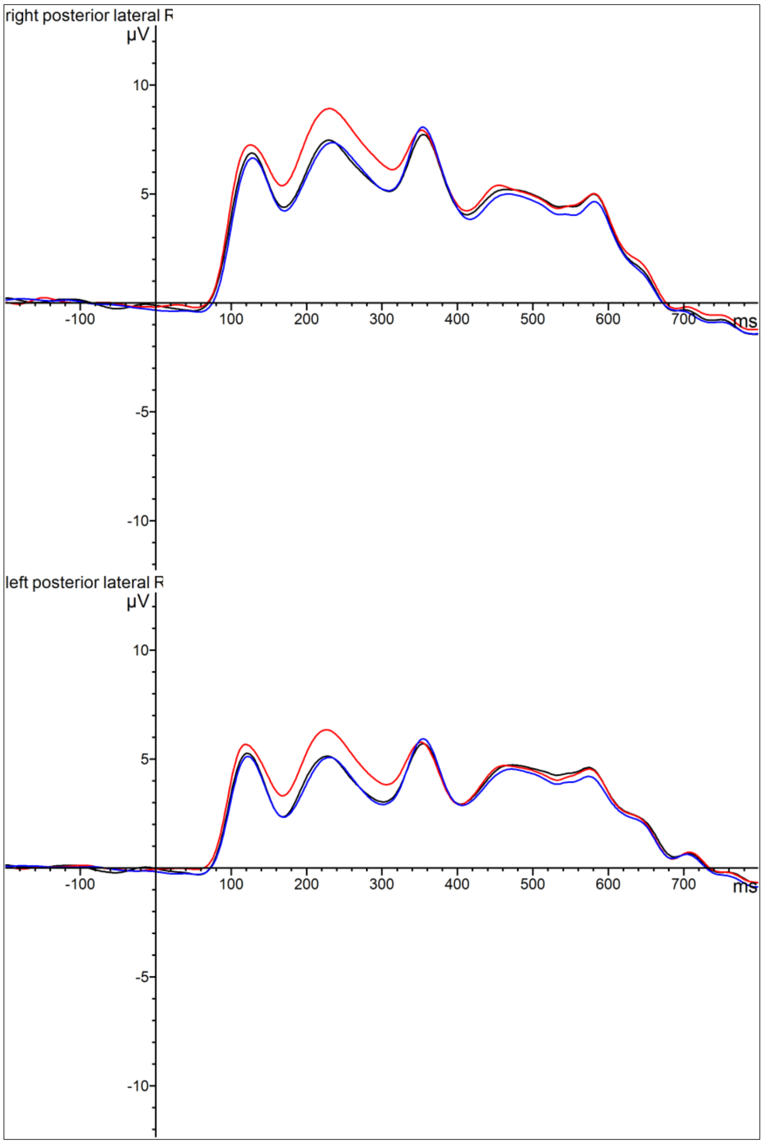

Figure 8: Grand averaged ERP waveforms for the three emotional category (unpleasant with high to mid arousal (red), neutral with mid to low arousal (black) and pleasant with high to mid arousal ratings (blue). Note: the red line shows grand average ERP response for unpleasant group including the 90 unpleasant scenes and their five repetition making up to 450 trial, black line for neutral and blue line for pleasant group, right posterior lateral above and left posterior lateral below. n=20

To examine the extent to which the observed ERP trends are also due to emotional valence, arousal or merely low-level visual properties of the scenes, we conducted two analyses. First, we examined how the individual scenes ratings correlate with the peak amplitude of the early visually-evoked ERP components (P1, N1, P2) to individual scenes. Second, we examined how the individual scenes ratings correlate with the early (50ms-200ms) or late (200ms-350ms) occipitotemporal activity, operationalized by the measure of area under the curve. In both analyses, we conducted a multiple regression analysis to estimate the relative contribution of valence, arousal and the average gist, and their potential interactions to the modulation of the ERP activity. The peak analysis results are reported next, followed by the AUC analysis. For a complete report of the peak voltage and latency analyses for each ERP component, please see the multiple regression tables in Appendix A.

Multiple linear regression

In all of the ERP components (P1, N1 and P2) and AUC (early and late) analysis down, we did not observe any interaction between the three variables (valence, arousal, and the average gist) (for the full statistics, see Appendix A and B). Thus, we are reporting the main effect of each one of the variables on the ERP components.

We will report the amplitude and latency results of each ERP component. The amplitude changes reflect stronger or weaker effect while latency changes reflect faster and slower responses.

P1 component

P1 amplitude is typically sensitive to low-level stimulus properties, as well as selective attention (Hillyard et al., 1998). It also appear to be susceptible to arousal (Luck et al., 2000). Looking to explain variance in P1 amplitude, we found that the significantly explained variance (R-squared) for the model containing average gist, arousal, and valence as independent predictors was 0.22 ($F(3,266) = 25.52$, $p < 0.0001$). We observed a significant main effect of arousal on the amplitude of the P1 component ($t(1) = -2.52$, $p = .01$). Secondly, the average gist showed significant main effect on P1 peak amplitude $t(1) = 7.92$, $p < .001$). With controlling for arousal and the average gist, valence had no significant effect on P1 peak amplitude ($p=0.33$). Figure 9 displays the average gist and arousal effect on P1 mean posterior lateral peak amplitude.

As for latency, we found that the significantly explained variance (R-squared) for the model containing average gist, arousal, and valence as independent predictors was 0.016 ($F(3,266) = 1.41$, $p= 0.242$). The only significant predictor of variance in P1 latency was the average gist ($t(1) = -1.99$, $p= 0.047$). Figure 10 displays the average gist effect on latency of P1 mean posterior lateral latency.

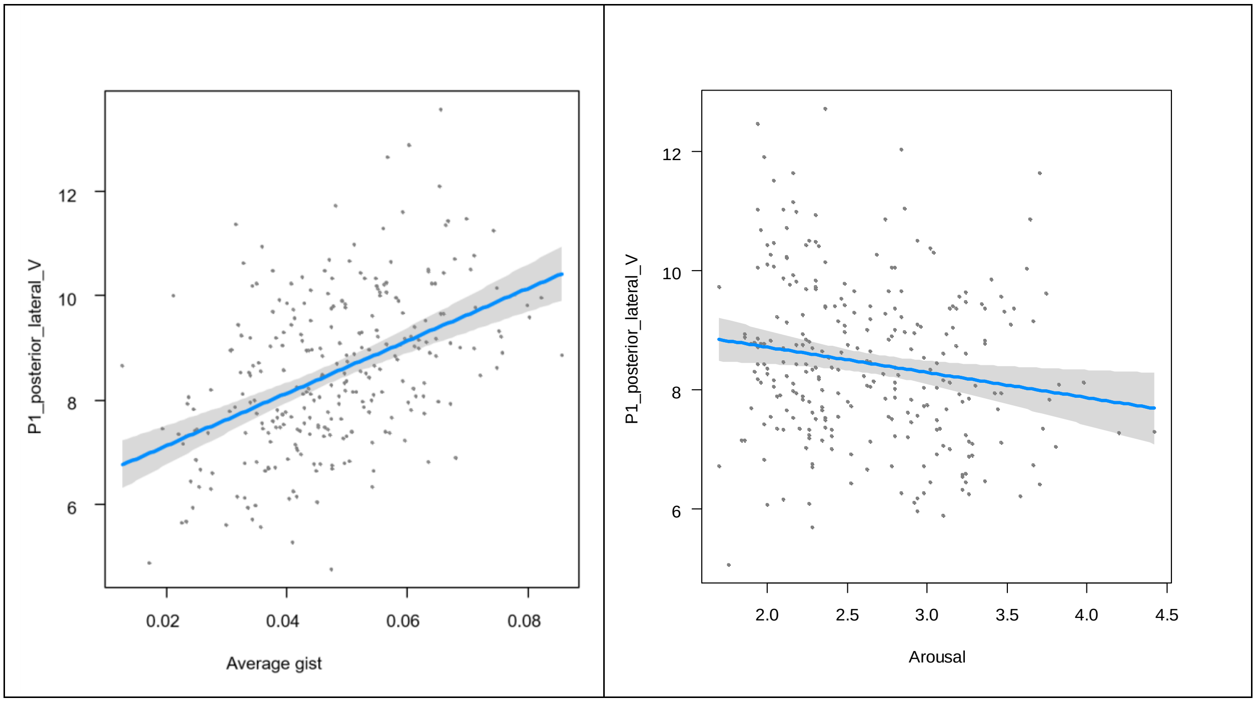

Figure 9: The impact of the significant factors (average gist and arousal) on mean peak amplitude of P1 posterior lateral leads. Note: the average gist (right) is positively related to P1 peak amplitude while arousal (left) is negatively related to P1 peak amplitude in the posterior lateral leads

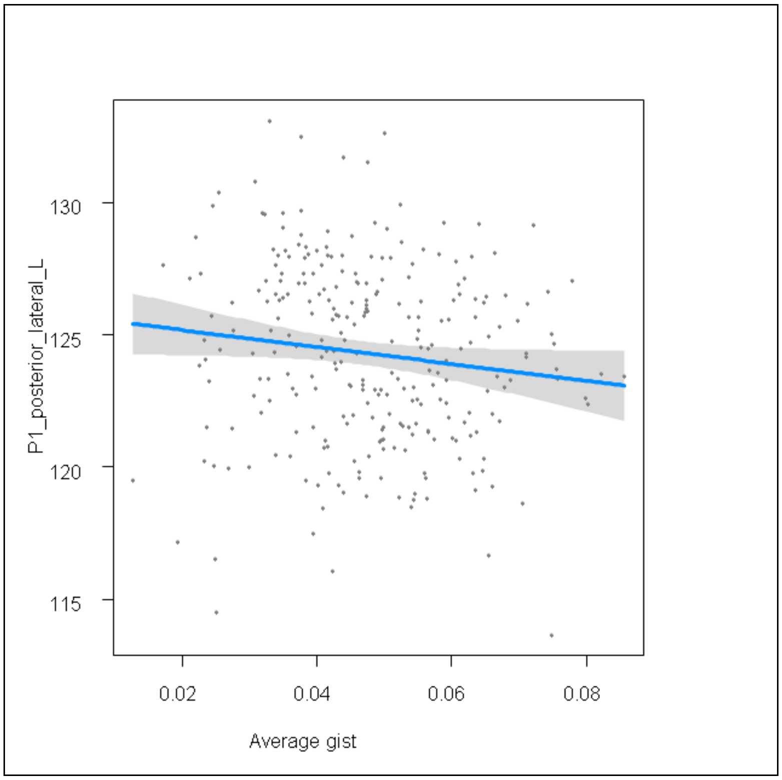

Figure 10: The impact of the only significant factor (average gist) on mean latency of P1 posterior lateral leads. Note: : the average gist is inversely related to mean latency of P1 in the posterior lateral leads

N1 component.

N1 has been used to examine the influences of emotion on perceptual processing of faces (Blau et al., 2007). In our study, while looking to explain variance in N1 amplitude, we found that the significantly explained variance (R-squared) for the model containing average gist, arousal, and valence as independent predictors was 0.21 (F (3,266) = 23.77, p < 0.0001). We observed a significant main effect of valence on the amplitude of the N1 component (t (1) = -4.85, p < .001). Secondly, the average gist showed significant main effect on N1 peak amplitude t (1) = 4.97, p < .001). With controlling for valence and the average gist, the arousal had no significant effect on N1 peak amplitude (p=0.06). Figure

11 displays the average gist and valence effect on N1 mean posterior lateral peak amplitude.

As for latency, we found that the significantly explained variance (R-squared) for the model containing average gist, arousal, and valence as independent predictors was 0.93 ($F(3,266) = 1077$, $p < 0.0001$). In contrast to P1 latency, valence ($t(1) = 44.43$, $p < .001$) and arousal ($t(1) = 8.32$, $p < .001$) had highly significant effect on N1 latency while the average gist did not show any significant effect ($p = 0.07$). This is the only component that had such strong association with valence and arousal and insignificant effect of GIST. Figure 12 displays the valence and arousal effect on N1 mean posterior lateral latency.

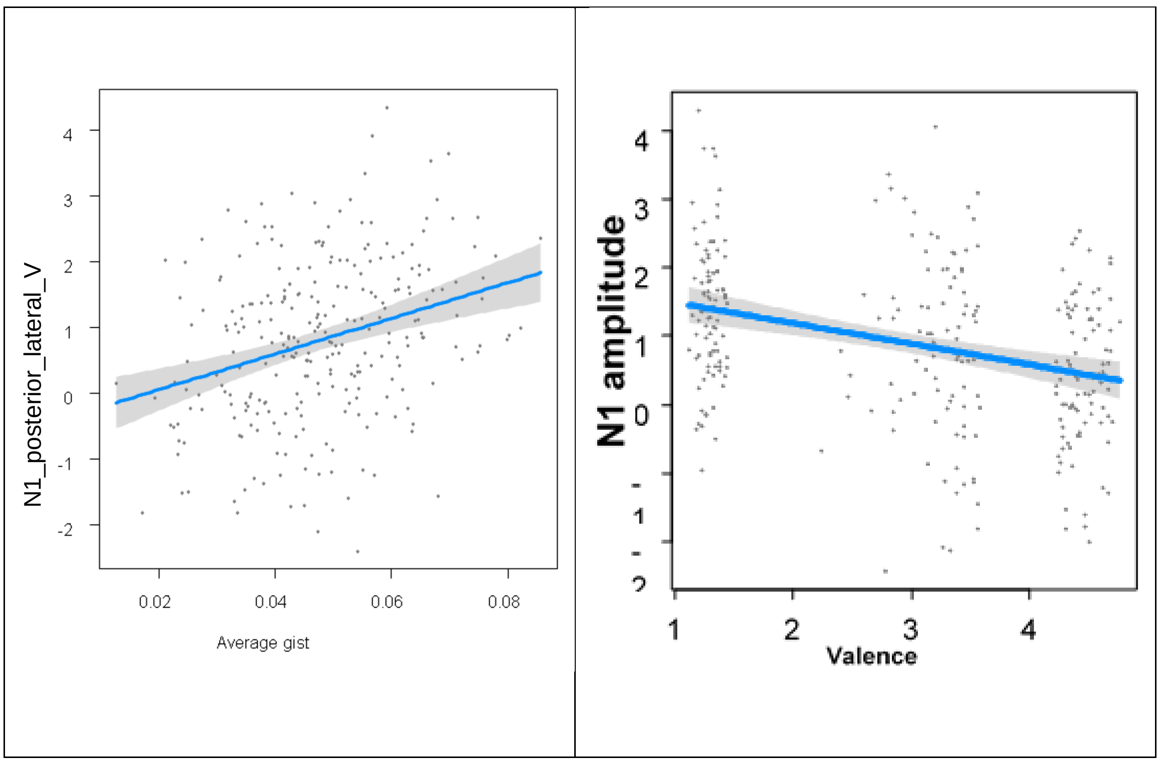

Figure 11: The impact of the significant factors (average gist and valence) on mean peak amplitude of N1 posterior lateral leads. Note: the average gist (right) is positively related to N1 peak amplitude while valence (left) is inversely related to N1 peak amplitude in the posterior lateral leads

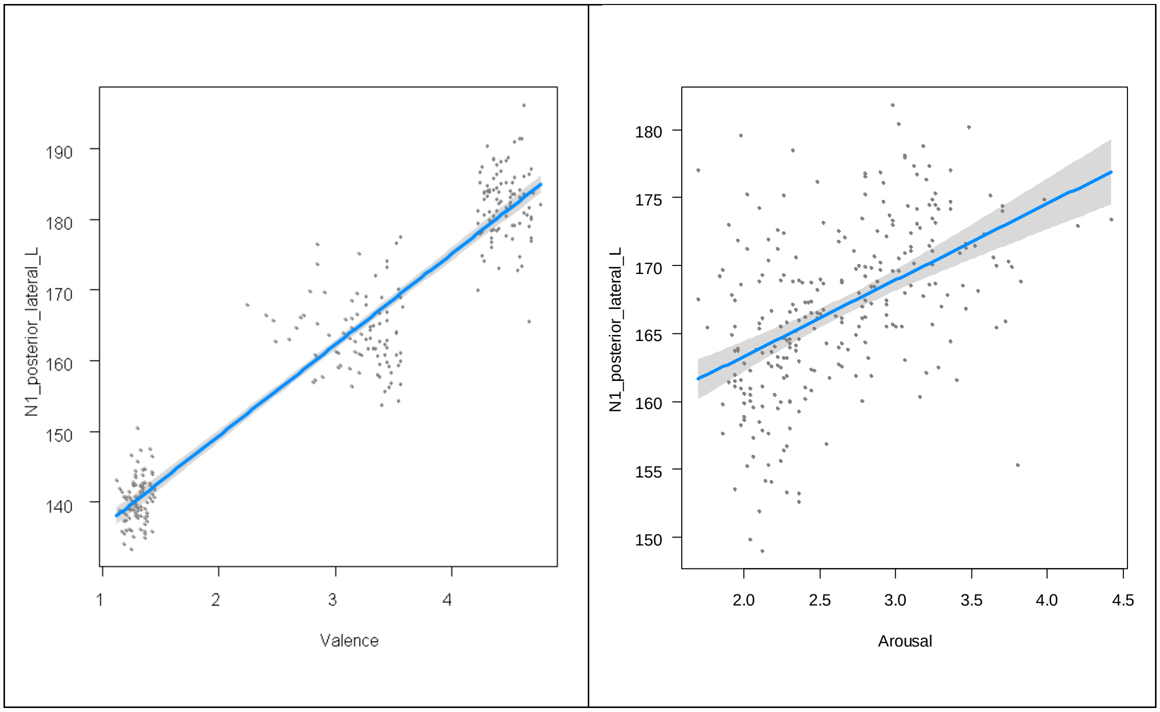

Figure 12: The impact of the significant factors (valence and arousal) on mean latency of N1 posterior lateral leads. Note: : valence (right) and arousal (left) are both positively related to mean latency of N1 in the posterior lateral leads

P2 component

P2 is thought to index global properties of scene processing, such as naturalness and openness (Hansen et al., 2018). Here, while looking to explain variance in P2 amplitude, we found that the significantly explained variance (R-squared) for the model containing average gist, arousal, and valence as independent predictors was 0.24 ($F(3,266) = 28.81$, $p < 0.0001$). Exceptionally, P2 was modulated by all three variables. We observed a significant main effect of arousal on the amplitude of the P2 component ($t(1) = 2.86$, $p = .01$). Secondly, the average gist showed significant main effect on P2 peak amplitude (t

(1) = 6.51, p < .001). Furthermore, valence ratings showed a significant main effect on P2 peak amplitude t (1) = -4.25, p < .001. Figure 13 displays the average gist, valence and arousal effect on P2 mean posterior lateral peak amplitude.

As for latency, we found that the significantly explained variance (R-squared) for the model containing average gist, arousal, and valence as independent predictors was 0.025 (F (3,266) = 2.23, p= 0.085). Similar to P1 latency, the only significant predictor of variance in P2 latency was the average gist (t (1) = 2.06, p= 0.040). Figure 14 displays the average gist effect on P2 mean posterior lateral latency.

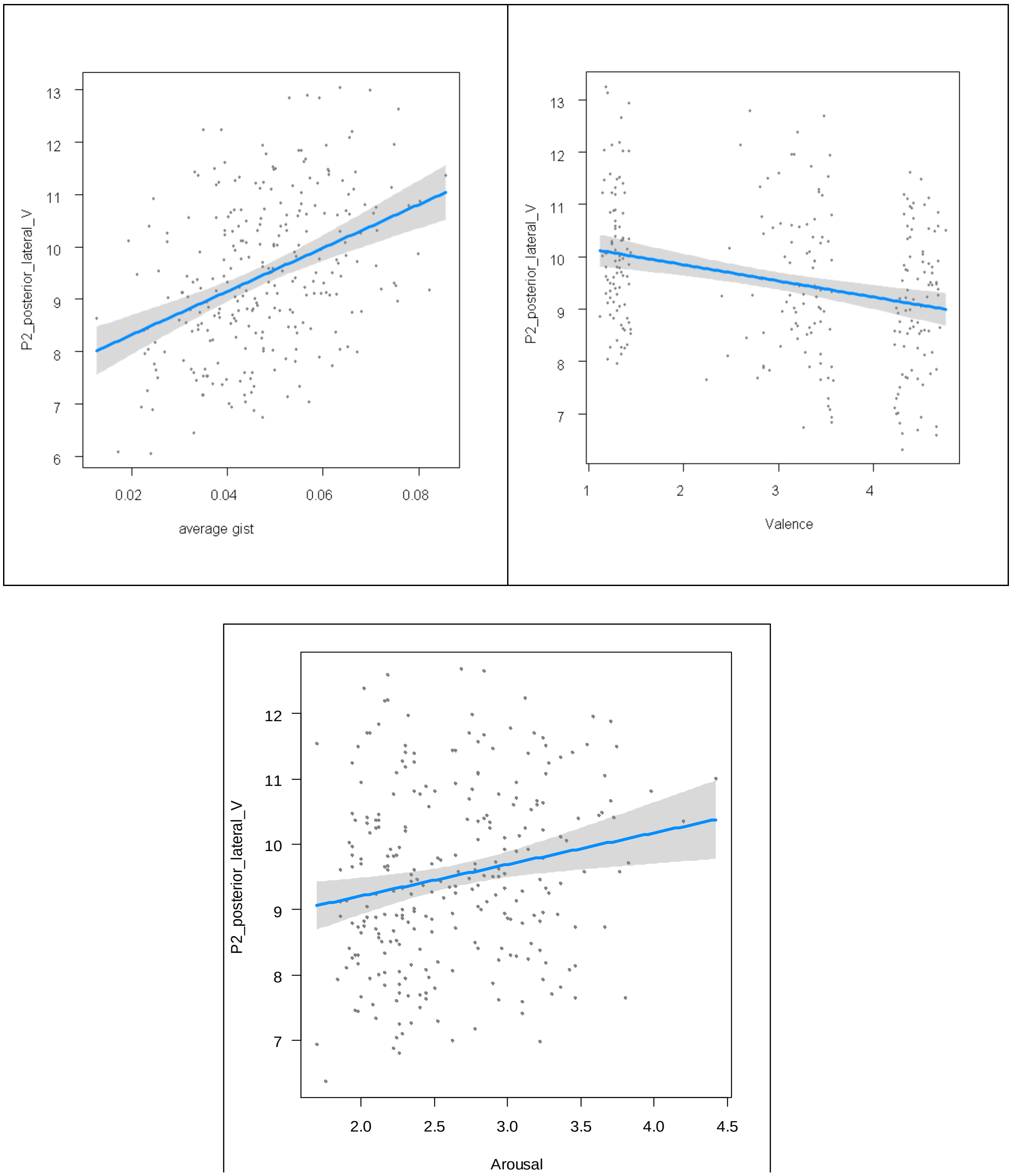

Figure 13: The impact of the three significant factors (average gist (top right), valence (top left) and arousal (down)) on mean peak amplitude of the P2 posterior lateral leads. Note: the average gist (top right) and arousal (down) are both positively related to P2 peak amplitude while valence (top left) is inversely related to P2 peak amplitude in the posterior lateral leads

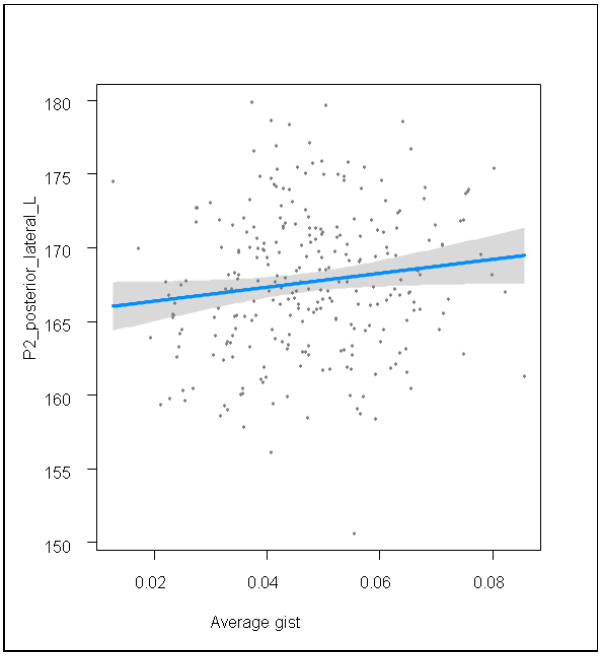

Figure 14: The impact of the only significant factor (average gist) on mean latency of P2 posterior lateral leads. Note: the average gist is inversely related to mean latency of P2 in the posterior lateral leads

Early Activity (Area under the curve: 50ms-200ms)

Above, we have described the effect on the traditionally reported ERP peaks, to facilitate comparison with previous studies. Peak amplitudes are the easiest to measure but they are not particularly meaningful theoretically. Since, the time at which the voltage reaches a maximum amplitude has no special interpretation, measuring this time only may provide an overly simplistic and incomplete picture of the effect (Luck et al , 2005). In fact, our results can be explained more reliably and is affected less by the signal noise, by looking into the continuous, whole ERP activity that were not constricted in specific peaks (measured by AUCs) both during the early and late time periods.

Seeking to explain variance in the early activity, we found that the significantly explained variance (R-squared) for the model containing average gist, arousal, and valence as independent predictors was 0.24 ($F(3,266) = 28.36$, $p < 0.0001$). We observed a significant main effect of arousal on the early area, $t(1) = -2.24$, $p = 0.03$. Secondly, the average gist showed a significant main effect on the early area = 7.25, $p < .0001$. With controlling for arousal and the average gist, the valence had no significant effect on the early area ($p=0.15$). Figure 15 displays the average gist and arousal effect on mean early area.

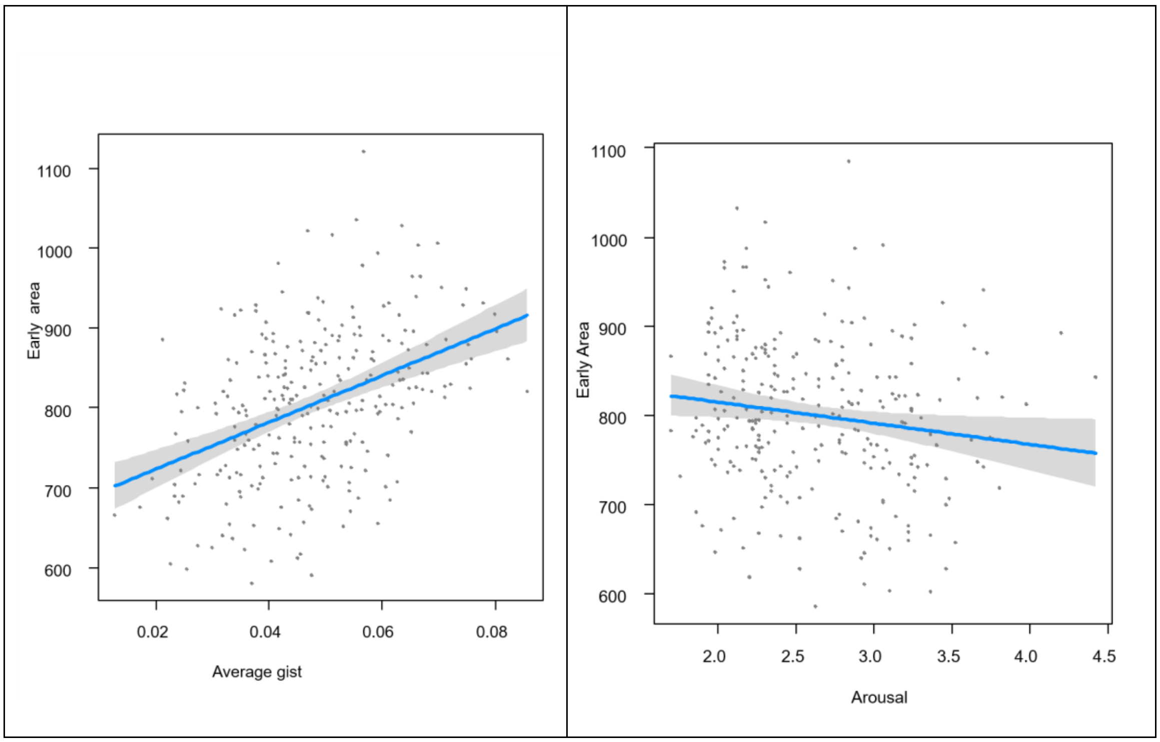

Figure 15: The impact of the significant factors (average gist and arousal) on mean early area (50-200ms) in the posterior lateral leads. Note: the average gist (right) is positively related to mean early area while arousal (left) is inversely related to it in the posterior lateral leads.

Late activity (Area under the curve (200ms-350))

Looking to explain variance in the late activity, we found that the significantly explained variance (R-squared) for the model containing average gist, arousal, and valence as independent predictors was 0.18 (F (3,266) = 19.95, p < 0.0001). We observed a significant main effect of valence on the late area, t (1) = -2.88, p =0.004. Secondly, the average gist showed a significant main effect on the late area = 5.89, p < .0001. With controlling for valence and the average gist, the arousal had no significant effect on the late area (p=0.12). Figure 16 displays the average gist and valence effect on mean late area.

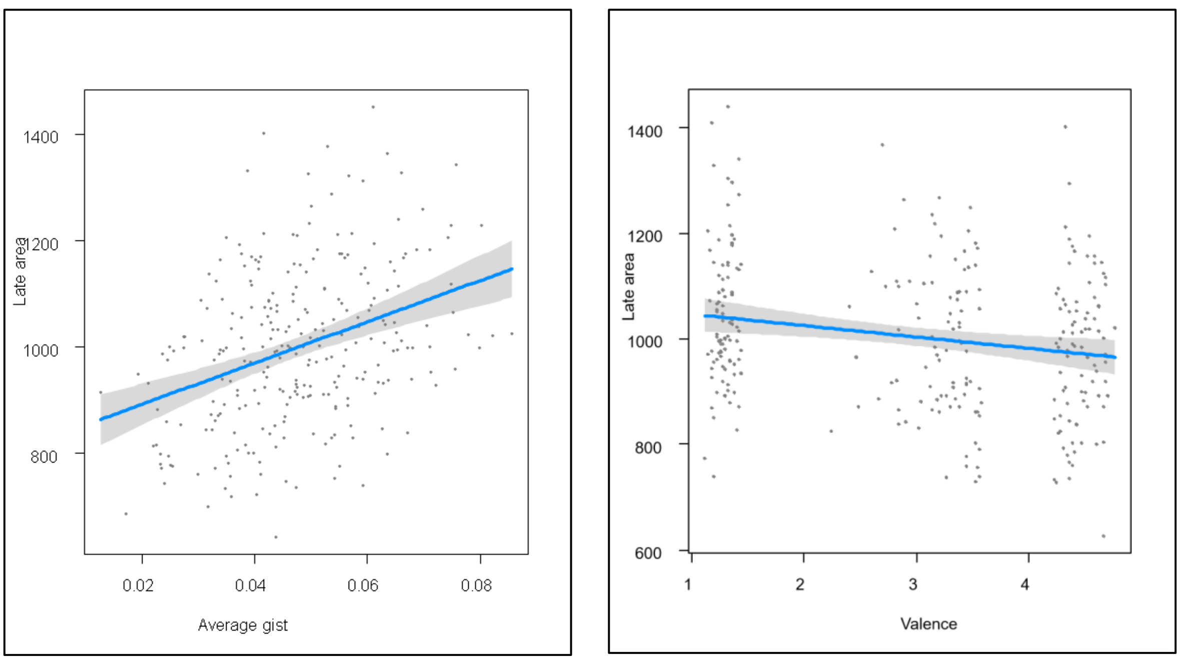

Figure 16: The impact of the significant factors (average gist and valence) on mean late area (200-350ms) in the posterior lateral leads. Note: the average gist (right) is positively related to mean late area while valence (left) is inversely related to it in the posterior lateral leads

Dominance analysis (DA)

Dominance analysis is a statistical method used to compare the relative importance of predictors in multiple regression. It determines the dominance of one predictor over another by comparing their additional coefficient of determination, R2, contributions across all subset models. For example, for P1 posterior lateral peak amplitude, the added contribution of the gist is 0.205, which is greater than the added contribution of valence (0.024), when either one is the first term in the model. The model where arousal is included first, adding the gist results in 0.188 contribution, while adding valence results in 0.007 contribution. Since 0.188 is greater than 0.007, gist dominates valence here as well. Lastly, in the model that already contains valence and arousal, the added contribution of gist is 0.183. In contrast, in the model with Gist and Arousal already included the added contribution of valence is 0.003. Since 0.183 is greater than 0.003, gist dominates valence here as well. Since gist dominates valence for every model, it has complete dominance over valence. If overall averaged additional R2 contribution of one predictor (e.g gist) is greater than another then that predictor is said to generally dominate the other.

Using the dominance analysis matrix tables in appendix (C), we carried out a similar process with gist compared to arousal and arousal compared to valence to see how gist dominates arousal as well arousal has complete dominance over valence. So, for P1 posterior lateral peak amplitude, in terms of contribution to R-squared, the average gist has the largest effect, arousal has the second largest effect, and valence has the weakest effect.

We summarized the results tables of dominance analysis matrix in table 1. For P1 posterior lateral latency, carrying on the same process will demonstrate that the average gist has complete dominance over both arousal and valence. Valence has general dominance over arousal. So, for P1 posterior lateral latency, in terms of contribution to R-squared, the average gist has the largest effect, valence has the second largest effect, and arousal has the weakest effect.

Similarly, for N1 posterior lateral peak amplitude, the average gist has complete dominance over both arousal and valence. Valence has complete dominance over arousal. So, for N1 posterior lateral peak amplitude, in terms of contribution to R-squared, the average gist has the largest effect, valence has the second largest effect, and arousal has the weakest effect.

In contrast, for N1 posterior lateral latency valence has complete dominance over both arousal and average gist. Arousal has complete dominance over average gist. So, for N1 posterior lateral latency, in terms of contribution to R-squared, the valence, arousal has the second largest effect, and average gist has the weakest effect.

Similar to N1 amplitude, for P2 posterior lateral peak amplitude and its latency, the average gist has complete dominance over both arousal and valence. Valence has complete dominance over arousal. So, for P2 posterior lateral peak amplitude and latency, in terms of contribution to R-squared, the average gist has the largest effect, valence has the second largest effect, and arousal has the weakest effect.

For the early and late area, the average gist has complete dominance over both arousal and valence. Valence has general dominance over arousal for the early area and complete dominance over arousal for the late area. So, for the early area, in terms of contribution to R-squared, the average gist per scene has the largest effect, valence has the second largest effect, and arousal has the weakest effect.

Table 1: Dominance analysis results for all ERP peaks, latency and areas:

I. P1 posterior lateral peak amplitude dominance analysis results		
Variable	Type of Dominance	Over
Average Gist	Complete	Arousal and Valence
Arousal	Complete	Valence
Valence	None	
II. P1 posterior lateral latency dominance analysis results		
Variable	Type of Dominance	Over
Average Gist	Complete	Arousal and Valence
Valence	General	Arousal
Arousal	None	
III. N1 posterior lateral peak amplitude dominance analysis results		
Variable	Type of Dominance	Over
Average Gist	Complete	Arousal and Valence
Valence	Complete	Arousal
Arousal	None	
IV. N1 posterior lateral latency dominance analysis results		
Variable	Type of Dominance	Over
Valence	Complete	Arousal and Average Gist
Arousal	Complete	Average Gist
Average Gist	None	
V. P2 posterior lateral peak amplitude dominance analysis results		
Variable	Type of Dominance	Over
Average Gist	Complete	Arousal and Valence
Valence	Complete	Arousal
Arousal	None	

VI. P2 posterior lateral latency dominance analysis results		
Variable	Type of Dominance	Over
Average Gist	Complete	Arousal and Valence
Valence	Complete	Arousal
Arousal	None	

VII. The early Area dominance analysis results		
Variable	Type of Dominance	Over
Average Gist	Complete	Arousal and Valence
Valence	General	Arousal
Arousal	None	

VIII. The late Area dominance analysis results		
Average Gist	Complete	Arousal and Valence
Valence	Complete	Arousal
Arousal	None	

Discussion

We examined the effect of emotional valence and arousal on perception using ERP measurements while participants view naturalistic scenes differing in their affective content as well as low-level visual properties measured by Gist descriptors. The goal of this study was to examine the effect of the emotional content of the scenes in their perception. Secondly, we aimed to distinguish the low-level image features' effect on perception from the emotional effect and compare them when they occur concurrently. At first glance on ERP grand average results, unpleasant scenes with moderate to high arousal showed the highest amplitude in P1, N1, and P2. This widespread effect was inconsistent with prior affective scene research. As mentioned in the introduction, previous studies have reported specific and isolated differences such as valence effects (while controlling for arousal) were reported as P1 or P2 amplitude change while arousal (while controlling for valence) influences P1, N1 or later components (Olofsson et al., 2008). We clarified this inconsistency between our finding and previous studies using the univariate analysis that we performed to show the average gist of the unpleasant scenes was higher than pleasant and neutral scenes which had an insignificant difference between their means. This finding, by itself, could explain the ERP grand average waveform difference between unpleasant scenes on the one hand and pleasant/neutral scenes on the other.

As a further step, to investigate the relative contribution of the low-level image features and emotional effect on scene perception, we run multiple linear regression and dominance analysis that include the individual scenes' emotional ratings (valence and arousal) as well as the average gist to represent low-level image properties. Table (2) below summarizes the multiple regression and dominance analysis results.

Table 2: summary of the multiple regression and dominance analysis results. *Note: the + symbol describe the positive relationship while the – symbol describes the negative relationship. The larger symbol in the same column shows who completely dominates over the other variables, which have smaller symbols. C indicates complete dominance over the blank cell in the same column. When the cell is blank, that means non-significance in the multiple regression analysis. G indicates general dominance over the blank or smaller symbol containing cell in the same column.*

	P1 amplitude	P1 latency	N1 amplitude	N1 latency	Early AUC	P2 amplitude	P2 latency	Late AUC
Average Gist	+	-	+		+	+	+	+
Valence		G	-	+	G	-	C	-
Arousal	-			+	-	+		

The multiple regression and dominance analysis showed that both average gist and emotional ratings impact early ERP components. The average gist exhibited complete dominance and showed a consistent, mostly positive effect on all peaks and latencies. The only exception was N1 latency, which is exactly the component that was affected strongly by valence while having no significant interaction with gist. Our study demonstrated that, during the early perception period (P1, N1, and P2), the gist had a widespread effect, which is not the usual pattern for most measures of low-level visual properties. P1 and N1 are sensitive to very low levels of stimulus properties, such as the local texture of scenes (for example, roughness, smoothness), while P2 is mostly sensitive to the global layout (Greene

& Hansen, 2018; Harel et al., 2020). A previous study that balanced the scenes' complexity as the only low-level visual feature showed the only difference of higher EPN amplitude for less complex scenes regardless of its emotional ratings (Löw et al., 2013). We could explain our widespread ERP effect by our choice of the gist model. This simple model spans over all levels of visual information ranging from very low-level features (e.g., color, contour) to intermediate (e.g., texture, shapes) and high level (semantic knowledge activation) (Oliva & Torralba, 2006). Further discussion of this observation will be in the general discussion section).

Negativity bias

Since our study's emotional effect was inferior to the effect of the gist descriptors, we cannot decisively answer our question of the effect of emotion (with decreased social factor) on scene perception. Nevertheless, we cannot neglect the reported effects of valence as the second effector (after gist) on the ERP pattern and mostly dominate over arousal. Two critical findings supported the Negativity bias framework that highlights unpleasant (or aversive) information can produce a more robust brain response than pleasant or neutral due to the rapid activation of the amygdala processing (Phelps & LeDoux, 2005). First, valence ratings were very strongly (R=.93) correlated directly proportional to N1 latency, while the gist did not affect it. Shorter N1 latencies were associated with lower valence ratings, which could reflect faster perceptual processing providing an evolutionary advantage for unpleasant scenes (Hillyard et al., 1998). However, this particular correlation with N1 latency was not reported in previous studies. Thus, we recommend verifying this correlation which could serve as an index for the unpleasant inanimate scenes effect on perceptual processing. Second, valence ratings were inversely proportional to N1 and P2 amplitude in which the lower valence ratings were associated with higher amplitude. This resonates with empirical evidence of the Negativity bias framework showed that unpleasant scenes had inconsistently higher P1, N1, or P2 peaks differing with different methodologies and stimuli types (Olofsson et al., 2008).

IV. GENERAL DISCUSSION

We examined the effect of affective valence and arousal on perception using ERP measurements while participants view naturalistic scenes (that reduced the social factor by eliminating the presence of people). We found that unpleasant scenes (with high to moderate arousal) had higher grand average ERP peaks (P1, N1, and P2) than pleasant (with highest and moderate arousal) and neutral scenes (with moderate to low arousal). Upon further analysis of the image summary statistics, explicitly rated unpleasant scenes showed higher gist scores than neutral or pleasant scenes, suggesting the ERP results might be driven by image properties rather than affective ratings. To compare the relative contribution of all these factors (low-level visual properties, valence and arousal ratings), we ran multiple linear regression and dominance analysis studying the impact of individual scenes gist scores and explicit affective ratings on the ERP amplitude and latency. We found that the average gist had the most dominant effect over affective ratings for all early peaks, latencies, and areas except N1 latency. For this particular latency, valence had complete dominance over the other factors, while arousal had complete dominance over the gist. Secondly, valence had the second-largest dominance effect, and it showed complete dominance over arousal on all peaks, latencies, and areas except P1 peak amplitude where arousal ratings had complete dominance over valence.

Is scene perception (im)penetrable to emotion?

Our study suggests that scenes, even general scenes with reduced social factors, can evoke an emotional reaction, confirmed by ratings and the differences in ERP response. However, since this ERP response is also associated with differences in GIST, we cannot confirm our hypothesis regarding the impact of emotion on scene perception. In the current stimulus set, the majority of the early electrophysiological responses (P1, N1, and P2) seem to reflect the processing of image properties, followed by ratings of valance, then arousal, which had the least effects as expected. We had expected a small effect -if any- of arousal since it was relatively minor in the current scene stimulus set compared to other stimulating images (e.g. erotica or graphic content). For the valence, the literature is inconsistent, depending on stimulus selection, tasks, and methodology. We expected the unpleasant scenes to have higher P1 peaks as reported **by** (Carretié, Hinojosa, Martín-Loeches, Mercado, & Tapia, 2004; Delplanque et al., 2004; A. P. R. Smith, Dolan, & Rugg, 2004)**.** Also, we expected P2 to be higher with unpleasant scenes as it was reported in several affective studies and it is scene specific component that can be modulated by different characteristics of scenes (Hansen et al., 2018; Olofsson et al., 2008).

Given the above studies, how can the weak effect of valence in the current study be explained? The weak effect of valence can be understood in five ways: The first one is that based on our results, we can deduce that our hypothesis was proven false. That is, implicit affective processing had a weak effect on ERP of early visual perceptual processes.

This weak effect is not consistent with previous research. It could be due to our stimuli's nature, as suggested in previous studies that inanimate and landscape scenes result in less affective neural activity (that could be small to be detected by external electrodes) than affective scenes with people (Löw et al., 2013). We can reject the hypothesis, that valence can affect neural response to scene perception, if we got complete negative results, i.e no change in ERP response between the three conditions (neutral and affective scenes). Even then, the design of the experiment made it impossible to conclude that affect (particularly valence) is not salient feature of scene perception. The most obvious reason is that we did not control for important confounding factors (low-level visual properties, arousal while measuring valence and vice versa).

In our case, we had differences between those conditions. Although low level visual properties ,in form of gist, explained those differences more than affective factors, we still cannot disregard the minor effect of valence on the neural response.

Secondly, limitations in the trial size, and/or experimental design preclude any conclusion. The trial size of individual scenes in the regression analysis was relatively small (maximum of five repetitions; some were lost due to artifact rejection) compared to the number of trials used in standard ERP experiments which typically include more than 14 trials for adequate test–retest reliability (Larson, Baldwin, Good, & Fair, 2010). The low number of trial in our study had reduced the statistical power to detect the effect (Luck et al, 2014). When determining the appropriate number of experimental trials necessary to test a hypothesis, Boudewyn and colleagues (2018) recommend considering additional factors, such as the size of the sample and noise/signal ratio. Future work may potentially compensate for the relatively low trial count by increasing the sample size and minimizing the noise level in the EEG recording. The other possible reason for this weak impact of implicit affective processing is that it was reduced due to top-down attentional task demands (the orthogonal task might have won the competition). Support for this conjecture comes from a study by Schupp and colleagues (2014), which showed that explicit simple categorization task requiring little attentional resources suppressed the implicit emotional processing (Schupp, Schmälzle, & Flaisch, 2014). We used the orthogonal task to control for endogenous attention; future studies can compare it with an explicit affective categorization task.

Thirdly, we might need to re-evaluate our assumption that detailed explicit affective ratings can reflect implicit affective processing. The weak correlation could be due to this assumption instead of the genuinely weak impact of implicit processing on ERP. The assumption was based on previous affective perception studies that did not acquire explicit ratings during the neural recording, simply using IAPS or other dataset affective ratings to examine the implicit affective processing influence on perceptual and cognitive processes (Feng et al., 2012; Olofsson & Polich, 2007). This assumption led us to design our study so that we do not enable further conscious emotional processing of the scenes by distracting the participants (instead of using a task that engages the explicit emotional system) and using brief stimulus presentation time and backward masking. This allowed us to present a large number of trials for each scene category while getting higher signal-to-noise ratios and avoiding fatigue effects. However, it prevented us from looking at the neural correlates of the conscious emotional response. This assumption may not necessarily be accurate since emotional processing could be viewed along a continuum, ranging from an implicit level to an explicit level (Lane, 2008; Lane et al., 1998), which might influence various cognitive processes differentially (e.g. executive function and cognitive control) (Cohen, Moyal, Lichtenstein-Vidne, & Henik, 2016). Each process has different characteristics and neural mechanisms. Implicit processing of emotions is known to be automatic, procedural, non-conceptual process that does not necessitate conscious processing (bottom-up) and has been linked to the amygdala and anterior cingulate cortex (H. D. Critchley, 2005). In contrast, explicit processing entails declarative evaluation and involves top-down higher cognitive resources to define conscious emotional states and involve the temporoparietal junction and medial prefrontal cortex (H. D. Critchley, 2005; H. Critchley et al., 2000). With this distinction in mind, it is plausible that implicit processing does not impact the ERP response because cortical neurons (that our electrodes were measuring) are not sensitive to the early emotional activity in the subcortex, except when it is strong enough to propagate to the cortical areas. This is supported by the evidence that masked emotional stimuli are processed in the subcortex (Tamietto & De Gelder, 2010).

Fourthly, we did not control for arousal when we are measuring the effect of valence and vice versa. This could have caused confounding results since arousal and valence had opposite effects at some components. Yet, we have measured the relative contribution of each affective dimension. Furthermore, we did not attempt to control for low-level visual properties. But we were able to account for that and examine their relative contribution to the resulting neural response. Additionally, we used that drawback to expand the study scope and to understand the fundamental relationship between emotion and the early perceptual processing.

The fifth alternative explanation for the current results, relates to the question of the generalizability of the first group's affective ratings to those of the second group. Although the two groups had only minor differences in demographics, the convenience sampling nature includes potentially unmeasurable selection bias that does not allow generalizability of the results due to the possible under-representation of subgroups in the sample compared to the population of interest (Bornstein, Jager, & Putnick, 2013). Besides that, even if the sample was representative, the experimental conditions were different (the task, timing, and use of EEG electrodes) which would result in different emotional and cognitive states of the participants.

At the current moment, we cannot prove or disprove our hypothesis of the expected impact of implicit affective processing on ERP of early visual processing because gist turns out to be varying in our scenes and likely causing the majority of EEG differences; and other possible explanations mentioned above. This study merely presents a first step in exploring this interaction of emotion and large-scale spatial environment scene perception. See below for further discussion of the future potential directions this study presents.

Arousal

In our stimulus set, we noticed three findings about arousal. Foremost, it had the weakest effects on scene perception (in all peaks and latencies except for P1 peak amplitude). For P1, arousal ratings were inversely proportional to P1 amplitude. This is inconsistent with previous research, that report positive effect of arousal on P1 amplitude (Luck et al , 2014). Moreover, we did not even observe EPN which is most consistent finding in arousing stimuli. We expected that arousal in our set would be much less than other studies which use scenes of people (e.g. erotic) that could trigger sexual or autonomic arousal through mirror neuron activation (Mouras et al., 2008). A mirror neuron fires when an individual acts and when the individual observes the same action performed by another and its activation is thought to be a mechanism of social connections (Rizzolatti & Craighero, 2004). Future studies should look for ways that activate arousal mechanisms without involving social brain systems (Tso, Rutherford, Fang, Angstadt, & Taylor, 2018). Moreover, arousal self-reports are not accurate and misattributed in many situations as documented previously (Dutton & Aron, 1974)

Does GIST intensity influence affective ratings?

Our analysis of the gist descriptor of various affective rating categories also points to the more fundamental fact that affective ratings were associated with different gist values (i.e. intensities), in which unpleasant scenes have higher gist intensity. In other words, participants in Study 1 rated the scenes for their affective dimensions, and they were describing scenes with high gist scores as more unpleasant with moderate to high arousal.

Redies and colleagues (2020) analyzed the predictability power of 13 global image properties (including color, symmetry, complexity, and self-similarity) to affective ratings of five affective pictures datasets including IAPS and OASIS. They pointed out that these datasets differ widely in their low-level perceptual qualities, which covary with different affective ratings (both valence and arousal). They recommended controlling for these global properties *before* rating acquisition. Alternatively, they offered an open-source that generates picture sets (e.g., pleasant versus unpleasant) that are matched for the image properties with a prominent effect on the ratings and allows scientists to use the established values of individual pictures covariates for statistical analyses (Redies, Grebenkina, Mohseni, Kaduhm, & Dobel, 2020). Rhodes et al. (2019) reported similar findings in machine vision that low-level features such as un-localized, two-dimensional (2-D) Fourier spectra can be diagnostic of affective scene content. However, because exchanging amplitude spectra between picture categories did not affect the affective ratings, the authors concluded that it is not used by the human visual system (Rhodes et al., 2019). Since stimulus properties are different among different affective categories, the question, of which one – if any – is used by the human visual system, remains open.

From our analysis, gist was correlated with affective ratings (valence and arousal) but we did not investigate the correlation between gist and valence or gist and arousal in particular. Apparently, the correlation cannot be absolute since gist had effects on the ERP that neither valence nor arousal had. In the future, we would like to advance our analysis to explore the relationship between gist and valence in scenes that have same arousal values. Also exploring the relationship between gist and arousal in scenes that have same valence ratings. This would enable further understanding of this interesting effect of physical stimulus properties on different dimensions of the affective spectrum.

As a future direction, it will be interesting to use “scrambled” images (abstract without semantic meaning) that has different gist intensities and ask participants to affectively rate them. We would predict the highest gist intensities (regardless of image content) to be associated with unpleasant valence and moderate to high arousal ratings. Another experiment to expand on this finding is by asking participants to rate the same scenes before and after controlling for physical properties and to examine the ERP response of these scenes.

Emotions as bottom-up effectors on perception

These findings raise a question if we can ever separate the physical properties of the stimulus from its affective processing (both implicit and explicit). Our results pinpoint to the primarily bottom-up (stimulus-driven) characteristics of emotional triggers. It also highlights the notion of common emotional triggers imbedded in the stimulus properties regardless of the semantic meaning. This view supports Malcom et al (2016) who argue that for a complete understanding of scene perception, it is essential to account for both differing observer goals and the contribution of diverse scene properties (Malcolm, Groen, & Baker, 2016).

Does GIST influence affective processing and their impact on ERP?

If the GIST descriptors have a direct effect on affective ratings, we would also expect an effect on ERP response to affective stimuli. The gist dominance pattern over affective processing resonates with other studies. Affect ERP studies that have evaluated variables such as stimulus complexity, color, spatial frequency, etc., find some influences of physical variables on affective waveforms (Löw et al., 2013; Miskovic et al., 2015). Although most affective scenes studies had controlled for one or two physical variables such as luminance, color, contrast, spatial frequencies or complexity Feng et al., 2012; Löw et al., 2013; Sabatinelli, Keil, Frank, & Lang, 2013), limited affective scene studies had controlled for the gist or looked into its combined effect with emotional ratings. Our study stands out in that we accounted for the relative contribution of gist on the relationship between emotion and scene perception. Because low level visual properties have various levels and factors, it was essential to use the gist, which covers local and global scene properties. Please refer to the implications section for discussion of applications to this finding.

Potential of the study

Our study is a *first step* in exploring the effect of emotional processing on the perception of real-life environments. The detected minor effect should be further explored while controlling for low-level image properties before affective rating acquisition. To assess the influence of emotion on perception, we need to be clear about which emotional processes we would like to examine. I would like to further explore that by asking how early perception is influenced when individuals are not aware of certain emotional triggers (implicit) versus conscious emotional involvement (explicit). To answer this question, we need to examine the differences between implicit affective processing (while passive viewing versus a task that requires minimum attentional interaction with the stimuli) versus explicit processing (while describing how they feel) and their impact on the neural processing of scene perception. This future experiment will guide us in exploring a potential dissociation between implicit and explicit emotional processes, which should be taken into consideration in any affective study. This gap had been the basis of psychoanalytic psychotherapy, which aims at moving implicit emotions to be explicitly expressed to treat or prevent various mental and psychosomatic disorders (Lane, 2008). To explore this gap, we will evaluate individuals' introspection and emotional awareness and assess implicit and explicit affective processes by various autonomic measures and ERP. These measures would show the factors that could shorten the gap between explicit and implicit emotional processing (Katkin, Wiens, & Öhman, 2001). A further step is to mask the stimulus and measure the gap between conscious/ unconscious versus explicit/ implicit emotional processing to ascertain the neural mechanisms behind different emotional processes. This potential dissociation is an important area that must be explored to understand the mind-body integration and introduce various preventive measures of mental health disorders.

Moreover, one application of the relationship between low-level visual features and affective processing supports *artificial intelligence* research aiming to teach machines to understand and share emotions to communicate better with humans. Unlike facial emotional expressions, it is more difficult for machines to interpret natural scenes' emotional content. Using gist descriptors and EEG reading of a human operator, robots can learn emotional reactions in response to natural scenes (Zhang & Lee, 2009). Zhang and Lee, 2009 invented an emotion understanding system based on electrical brain activity and GIST that foster the brain-computer interface to aid robots/ computers in recognizing and categorizing emotional scenes. They used GIST as input signals, and the computer can analyze the combined brain activity and the GIST and share the emotional category as an output. We recommend further exploration of similar applications, which could enhance our understanding of human emotionality as well.

Conclusion

In summary, the interaction between emotion and scene perception involves many facets including low-level visual properties interaction with affective appraisal and explicit-implicit emotion interactions. Our study is a first step in exploring this interaction using large scale spatial environment with reduced social component. In our stimulus set, the 'assumed' explicit affective ratings had minor impact on neural response to scene perception compared to low-level visual properties (particularly GIST). We did not measure the implicit affective processing so that we cannot comment on its correlation with neural response to scene perception. Instead, we documented the influence of low-level visual properties on explicit affective ratings. That could mean, emotional triggers do not only depend on the overall appraisal of the scene, but they are fundamentally embedded in the basic elements of the scene (physical properties). Our data thus demonstrates . the role of physical stimulus properties (bottom-up) in affective processing rather than the top-down (cognitive) side of it. As an implication, when humans are out in nature, certain triggers embedded in the low-level visual properties of the large spatial scale environment can generate affective reaction. This affective reaction could be playing role in how we filter the world around us. This is also related to previous research that point to the cognitive benefit of interacting with nature while our study showed the other side of being out in nature, i.e the unpleasant effect (Berman, Jonides, & Kaplan, 2008).

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Appendix A:

Table 3: multiple linear regression tables for all early components (P1, N1 and P2) and AUCs (early and late). Note: For each component, the first and second tables show the overall variance of the model including the R-square and the F value. The third Table contains Type I sums of squares when each variable is the first term entered into the model, while fourth table contains type III sums of squares when each variable is entered last in the model. Statisticians generally prefer type III because they show the additional contribution of that variable after controlling for the effects of all the other variables. The fifth table contain the t and p values for each variable which we have reported in the text.

I. P1 Posterior Lateral peak amplitude Main Effects Model, multiple linear regression

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	137.6438481	45.8812827	25.57	<.0001
Error	266	477.2445602	1.7941525		
Corrected Total	269	614.8884083			

R-Square	Coeff Var	Root MSE	P1_posterior_lateral_V Mean
0.223852	15.83844	1.33946	8.457017

Source	DF	Type I SS	Mean Square	F Value	Pr > F
average gist	1	126.2045002	126.2045002	70.34	<.0001
valence	1	0.0071066	0.0071066	0	0.9499
Arousal	1	11.4322413	11.4322413	6.37	0.0122

Source	DF	Type III SS	Mean Square	F Value	Pr > F
average gist	1	112.5374236	112.5374236	62.72	<.0001
valence	1	1.6937773	1.6937773	0.94	0.3321
Arousal	1	11.4322413	11.4322413	6.37	0.0122

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	6.97498399	0.54529573	12.79	<.0001
average gist	50.11095463	6.32723358	7.92	<.0001
valence	0.07017042	0.07221969	0.97	0.3321
Arousal	-0.42405571	0.16799134	-2.52	0.0122

II. P1 Posterior Lateral latency Main Effects Model, multiple linear regression

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	48.663999	16.221333	1.41	0.2416
Error	266	3070.733671	11.544112		
Corrected Total	269	3119.39767			

R-Square	Coeff Var	Root MSE	P1_posterior_lateral_L Mean
0.0156	2.733425	3.397663	124.3005

Source	DF	Type I SS	Mean Square	F Value	Pr > F
average gist	1	47.68957536	47.68957536	4.13	0.0431
valence	1	0.6701999	0.6701999	0.06	0.8098
arousal	1	0.30422379	0.30422379	0.03	0.8712

Source	DF	Type III SS	Mean Square	F Value	Pr > F
average gist	1	45.79833376	45.79833376	3.97	0.0474
valence	1	0.27318917	0.27318917	0.02	0.8779
arousal	1	0.30422379	0.30422379	0.03	0.8712

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	126.0890967	1.38319266	91.16	<.0001
average gist	-31.9675263	16.04960873	-1.99	0.0474
valence	-0.0281811	0.18319186	-0.15	0.8779
arousal	-0.0691757	0.42612546	-0.16	0.8712

III. P2 Posterior Lateral peak amplitude Main Effects Model, multiple linear regression

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	156.7397801	52.2465934	28.81	<.0001
Error	266	482.4406604	1.8136867		
Corrected Total	269	639.1804405			

R-Square	Coeff Var	Root MSE	P2_posterior_lateral_V Mean
0.24522	13.98642	1.346732	9.628852

Source	DF	Type I SS	Mean Square	F Value	Pr > F
average gist	1	141.2237839	141.2237839	6.04	0.0146
valence	1	13.3516724	13.3516724	0.57	0.4505
arousal	1	1.6688567	1.6688567	0.07	0.7896

Source	DF	Type III SS	Mean Square	F Value	Pr > F
average gist	1	99.62974962	99.62974962	4.26	0.04

valence	1	7.89551728	7.89551728	0.34	0.5617
arousal	1	1.66885669	1.66885669	0.07	0.7896

Parameter	*Estimate*	*Standard Error*	*t Value*	*Pr > |t|*
Intercept	166.3497514	1.96854686	84.5	<.0001
average gist	47.1496759	22.8416531	2.06	0.04
valence	-0.1515013	0.26071695	-0.58	0.5617
arousal	-0.1620193	0.60645777	-0.27	0.7896

IV. P2 Posterior Lateral latency Main Effects Model, multiple linear regression

Source	*DF*	*Sum of Squares*	*Mean Square*	*F Value*	*Pr > F*
Model	3	156.244313	52.081438	2.23	0.0853
Error	266	6219.68393	23.38227		
Corrected Total	269	6375.928243			

R-Square	*Coeff Var*	*Root MSE*	*P2_posterior_lateral_L Mean*
0.024505	2.88313	4.835522	167.7178

Source	*DF*	*Type I SS*	*Mean Square*	*F Value*	*Pr > F*
average gist	1	141.2237839	141.2237839	6.04	0.0146
valence	1	13.3516724	13.3516724	0.57	0.4505
Arousal	1	1.6688567	1.6688567	0.07	0.7896

Source	*DF*	*Type III SS*	*Mean Square*	*F Value*	*Pr > F*
average gist	1	99.62974962	99.62974962	4.26	0.04
valence	1	7.89551728	7.89551728	0.34	0.5617
Arousal	1	1.66885669	1.66885669	0.07	0.7896

Parameter	*Estimate*	*Standard Error*	*t Value*	*Pr > |t|*
Intercept	166.3497514	1.96854686	84.5	<.0001
average gist	47.1496759	22.8416531	2.06	0.04
valence	-0.1515013	0.26071695	-0.58	0.5617
Arousal	-0.1620193	0.60645777	-0.27	0.7896

V. N1 Posterior Lateral peak amplitude Main Effects Model, multiple linear regression

Source	*DF*	*Sum of Squares*	*Mean Square*	*F Value*	*Pr > F*

Model	3	94.7043579	31.5681193	23.77	<.0001
Error	266	353.2050642	1.3278386		
Corrected Total	269	447.909422			

R-Square	*Coeff Var*	*Root MSE*	*N1_posterior_lateral_V Mean*
0.211436	122.8364	1.152319	0.938093

Source	*DF*	*Type I SS*	*Mean Square*	*F Value*	*Pr > F*
average gist	1	63.45626159	63.45626159	47.79	<.0001
valence	1	26.5539427	26.5539427	20	<.0001
arousal	1	4.69415357	4.69415357	3.54	0.0612

Source	*DF*	*Type III SS*	*Mean Square*	*F Value*	*Pr > F*
average gist	1	32.79820506	32.79820506	24.7	<.0001
valence	1	31.23311048	31.23311048	23.52	<.0001
arousal	1	4.69415357	4.69415357	3.54	0.0612

Parameter	*Estimate*	*Standard Error*	*t Value*	*Pr > |t|*
Intercept	-0.1653163	0.4691104	-0.35	0.7248
average gist	27.05261367	5.44323187	4.97	<.0001
valence	-0.30132388	0.0621296	-4.85	<.0001
arousal	0.27172893	0.14452064	1.88	0.0612

VI. N1 Posterior Lateral latency Main Effects Model, multiple linear regression

Source	*DF*	*Sum of Squares*	*Mean Square*	*F Value*	*Pr > F*
Model	3	93288.7896	31096.2632	1077.12	<.0001
Error	266	7679.3467	28.8697		
Corrected Total	269	100968.1363			

R-Square	*Coeff Var*	*Root MSE*	*N1_posterior_lateral_L Mean*
0.923943	3.301225	5.373055	162.7594

Source	*DF*	*Type I SS*	*Mean Square*	*F Value*	*Pr > F*
average gist	1	12113.80607	12113.80607	419.6	<.0001
valence	1	79176.4669	79176.4669	2742.54	<.0001

arousal	1	1998.51664	1998.51664	69.23	<.0001

Source	*DF*	*Type III SS*	*Mean Square*	*F Value*	*Pr > F*
average gist	1	94.24107	94.24107	3.26	0.0719
valence	1	56983.79976	56983.79976	1973.83	<.0001
arousal	1	1998.51664	1998.51664	69.23	<.0001

Parameter	*Estimate*	*Standard Error*	*t Value*	*Pr > |t|*
Intercept	111.80417	2.18737749	51.11	<.0001
average gist	-45.8568592	25.38081201	-1.81	0.0719
valence	12.870684	0.28969917	44.43	<.0001
arousal	5.606749	0.67387377	8.32	<.0001

VII. Early area, posterior lateral, Main Effects Model, multiple linear regression

Source	*DF*	*Sum of Squares*	*Mean Square*	*F Value*	*Pr > F*
Model	3	620359.983	206786.661	28.36	<.0001
Error	266	1939451.478	7291.171		
Corrected Total	269	2559811.461			

R-Square	*Coeff Var*	*Root MSE*	*Early_Area Mean*
0.242346	10.62199	85.38835	803.883

Source	*DF*	*Type I SS*	*Mean Square*	*F Value*	*Pr > F*
average gist	1	535808.3298	535808.3298	73.49	<.0001
valence	1	48003.8551	48003.8551	6.58	0.0108
arousal	1	36547.7984	36547.7984	5.01	0.026

Source	*DF*	*Type III SS*	*Mean Square*	*F Value*	*Pr > F*
average gist	1	382921.9646	382921.9646	52.52	<.0001
valence	1	14914.689	14914.689	2.05	0.1538
arousal	1	36547.7984	36547.7984	5.01	0.026

Parameter	*Estimate*	*Standard Error*	*t Value*	*Pr > |t|*
Intercept	747.301131	34.7617042	21.5	<.0001
average gist	2923.070778	403.3507169	7.25	<.0001
valence	-6.584655	4.6038861	-1.43	0.1538
arousal	-23.976613	10.7091714	-2.24	0.026

VIII. Late area, posterior lateral, Main Effects Model, multiple linear regression

Source	*DF*	*Sum of Squares*	*Mean Square*	*F Value*	*Pr > F*
Model	3	1157856.365	385952.122	19.95	<.0001
Error	266	5146249.116	19346.801		
Corrected Total	269	6304105.482			

R-Square	*Coeff Var*	*Root MSE*	*Late_area Mean*
0.183667	13.77764	139.0928	1009.555

Source	*DF*	*Type I SS*	*Mean Square*	*F Value*	*Pr > F*
average gist	1	993286.7323	993286.7323	51.34	<.0001
valence	1	116772.7418	116772.7418	6.04	0.0147
arousal	1	47796.8914	47796.8914	2.47	0.1172

Source	*DF*	*Type III SS*	*Mean Square*	*F Value*	*Pr > F*
average gist	1	671458.8402	671458.8402	34.71	<.0001
valence	1	160931.1698	160931.1698	8.32	0.0042
arousal	1	47796.8914	47796.8914	2.47	0.1172

Parameter	*Estimate*	*Standard Error*	*t Value*	*Pr > |t|*
Intercept	817.678642	56.6248419	14.44	<.0001
average gist	3870.739017	657.0354111	5.89	<.0001
valence	-21.629477	7.4994689	-2.88	0.0042
arousal	27.419344	17.444632	1.57	0.1172

Appendix B: Multiple linear regression Figures for the non-significant factors effect on ERP components (P1, N1, P2) and AUC (early and late):

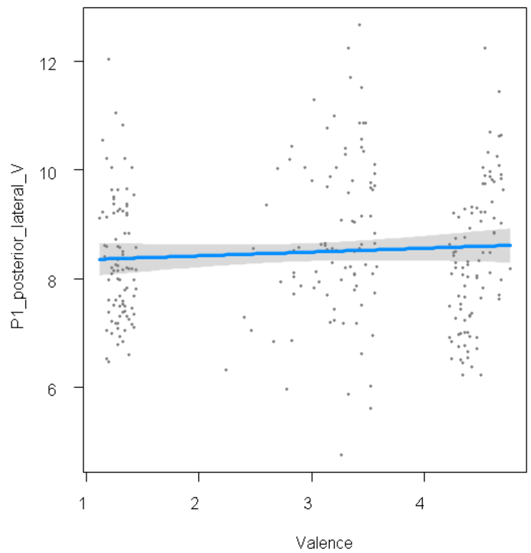

Figure 17: The relationship between non significant factor (valence) and peak amplitude of P1 posterior lateral leads. Note: the relationship between valence and P1 peak amplitude is almost flat line

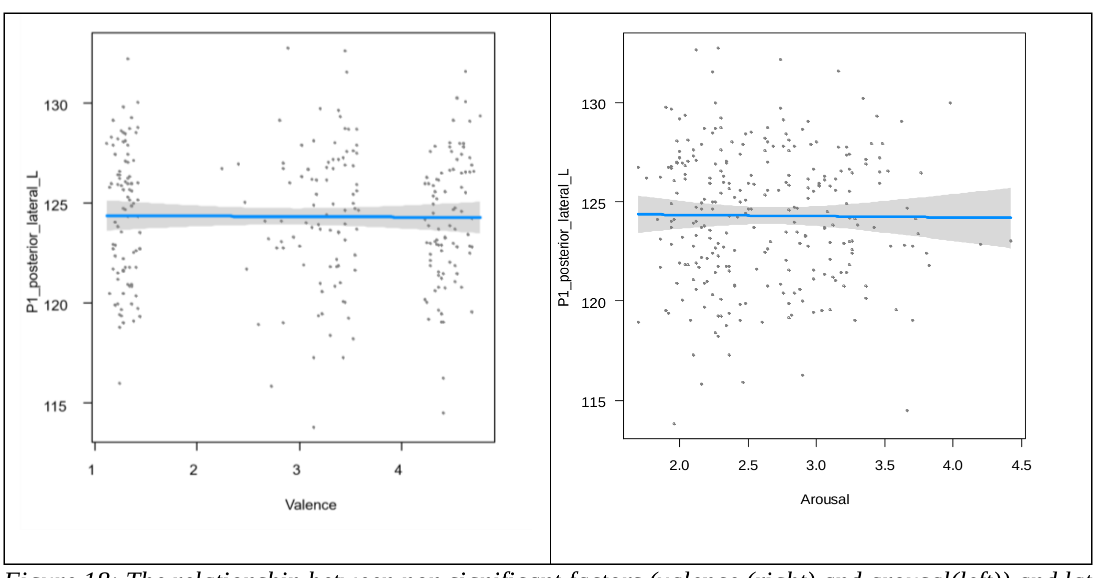

Figure 18: The relationship between non significant factors (valence (right) and arousal(left)) and latency of P1 posterior lateral leads. Note: the relationship between valence or arousal and P1 latency is almost flat line

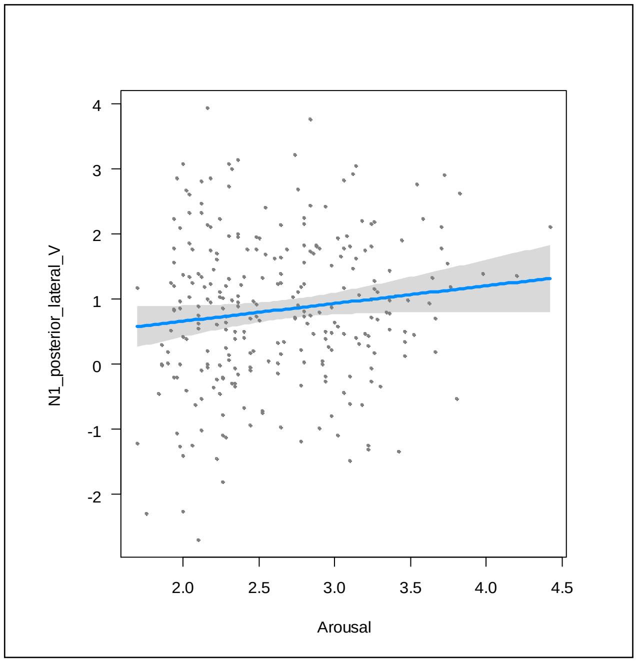

Figure 19: The relationship between non-significant factor (arousal) and peak amplitude of N1 posterior lateral leads. Note: the relationship between arousal and N1 peak amplitude is almost flat line

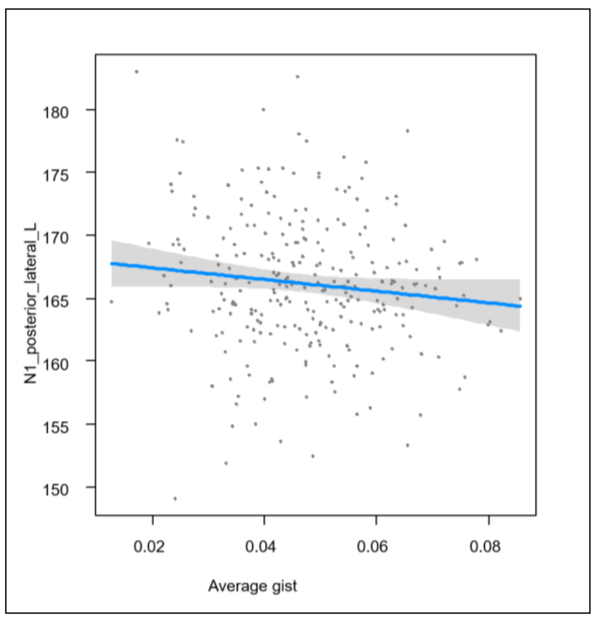

Figure 20: The relationship between non-significant factor (average gist) and latency of N1 posterior lateral leads. Note: the relationship between average gist and N1 latency is almost flat line

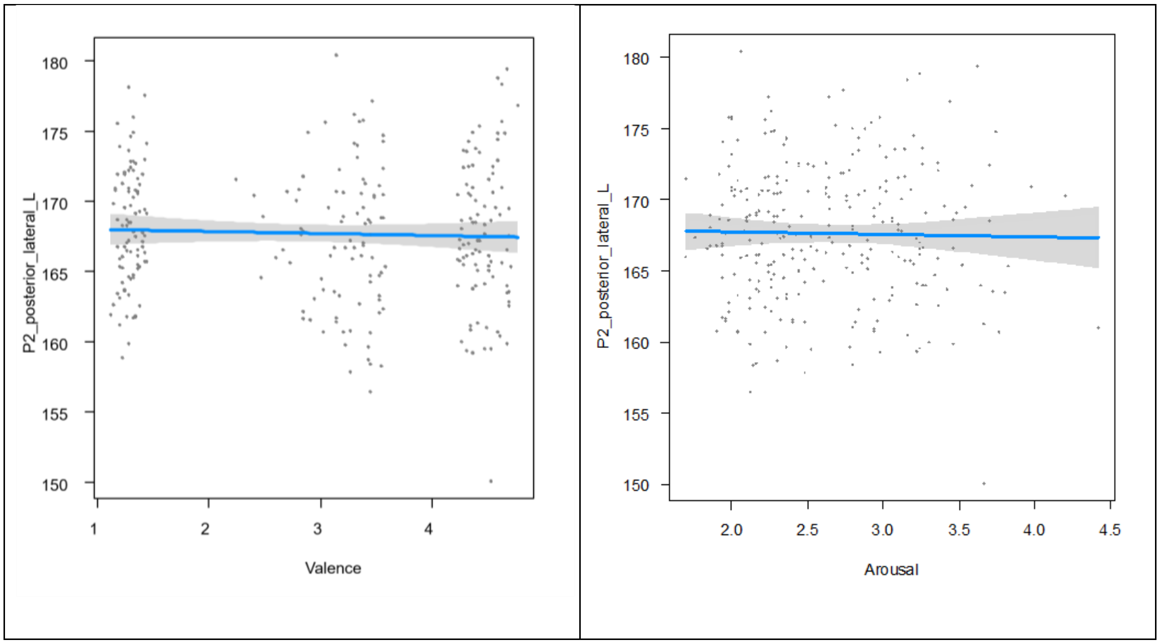

Figure 21: The relationship between non-significant factors (valence and arousal) and latency of P2 posterior lateral leads. Note: the relationship between valence or arousal and P2 latency is almost flat line

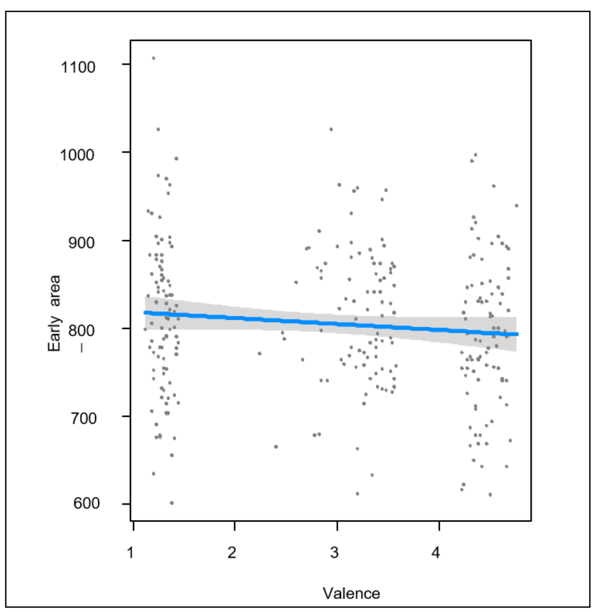

Figure 22: The relationship between non-significant factor (valence) and mean early area (50- 200ms) in posterior lateral leads. Note: the relationship between valence and mean early area is almost flat line

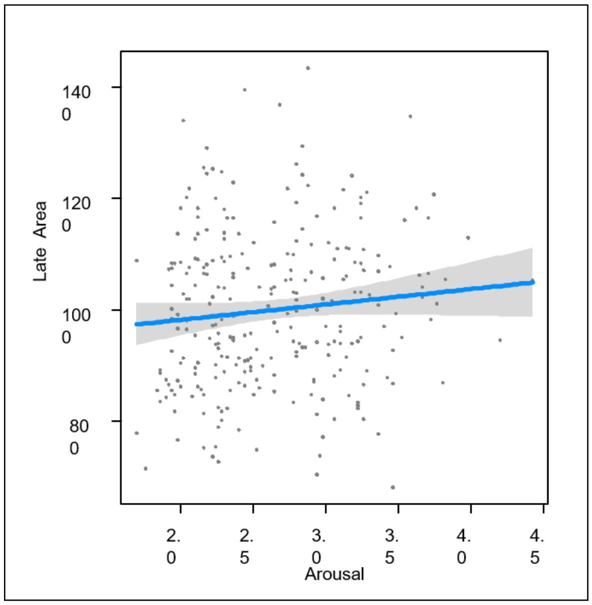

Figure 23: The relationship between non-significant factor (arousal) and mean late area (200ms-350ms) in posterior lateral leads. Note: the relationship between arousal and mean late area is almost flat line

Appendix C:

Table 4: Dominance analysis matrix for all components (P1, N1, P2) and AUCs (early and late). *Note: The first row is the intercept only model, (The "fit" equal to zero since it does not include any of the three variables) and the added contribution of each variable when they are added by themselves (e.g for P1 amplitude: 0.205 for gist, .024 for valence, and .033 for arousal). The next three rows are when the variable in the first column is in the model, and the values in the final three columns are the added contribution when each variable is added to that model. The fifth row is the average contribution of each variable when one other variable is included. The sixth through eighth rows are the added contribution of each variable when the two variables listed in the first column are already in the model, and the ninth row is the R-squared of the full model with all three variables.*

I. P1 posterior lateral peak latency dominance analysis matrix					
Model	# of variables	fit	Gist	Valence	Arousal
Intercept Only	0	0.000	0.205	0.024	0.033
Gist	1	0.205		0.000	0.016
Valence	1	0.024	0.181		0.017
Arousal	1	0.033	0.188	0.007	
Average 1 Variable	1		0.184	0.004	0.016
Gist + Valence	2	0.205			0.019
Gist + Arousal	2	0.221		0.003	
Valence + Arousal	2	0.041	0.183		
Average 2 Variables	2		0.183	0.003	0.019
Gist + Valence + Arousal	3	0.224			

II. P1 posterior lateral peak latency dominance analysis matrix:					
Model	# of variables	fit	Gist	Valence	Arousal
Intercept Only	0	0.000	0.015	0.001	0.000
Gist	1	0.015		0.000	0.000
Valence	1	0.001	0.015		0.000
Arousal	1	0.000	0.016	0.001	
Average 1 Variable	1		0.015	0.001	0.000
Gist + Valence	2	0.016			0.000
Gist + Arousal	2	0.016		0.000	
Valence + Arousal	2	0.001	0.015		
Average 2 Variables	2		0.015	0.000	0.000
Gist + Valence + Arousal	3	0.016			

III. N1 posterior lateral peak amplitude dominance analysis matrix:

Model	# of variables	fit	Gist	Valence	Arousal
Intercept Only	0	0.000	0.142	0.127	0.003
Gist	1	0.142		0.059	0.000
Valence	1	0.127	0.074		0.011
Arousal	1	0.003	0.139	0.135	
Average 1 Variable	1		0.107	0.097	0.006
Gist + Valence	2	0.201			0.010
Gist + Arousal	2	0.142		0.070	
Valence + Arousal	2	0.138	0.073		
Average 2 Variables	2		0.073	0.070	0.010
Gist + Valence + Arousal	3	0. 211			

IV. N1 posterior lateral peak latency dominance analysis matrix

Model	# of variables	fit	Gist	Valence	Arousal
Intercept Only	0	0.000	0.120	0.903	0.281
Gist	1	0.120		0.784	0.240
Valence	1	0.903	0.001		0.020
Arousal	1	0.281	0.079	0.642	
Average 1 Variable	1		0.040	0.713	0.130
Gist + Valence	2	0.904			0.020
Gist + Arousal	2	0.360		0.564	
Valence + Arousal	2	0.923	0.001		
Average 2 Variables	2		0.001	0.564	0.020
Gist + Valence + Arousal	3	0.924			

V. P2 posterior lateral peak amplitude dominance analysis matrix:

Model	# of variables	fit	Gist	Valence	Arousal
Intercept Only	0	0.000	0.190	0.100	0.000
Gist	1	0.190		0.032	0.004
Valence	1	0.100	0.122		0.025
Arousal	1	0.000	0.194	0.125	
Average 1 Variable	1		0.158	0.079	0.015
Gist + Valence	2	0.222			0.023

Gist + Arousal	2	0.194		0.051	
Valence + Arousal	2	0.125	0.120		
Average 2 Variables	2		0.120	0.051	0.023
Gist + Valence + Arousal	3	0.245			
VI. P2 posterior lateral peak latency dominance analysis matrix					
Model	# of variables	fit	Gist	Valence	Arousal
Intercept Only	0	0.000	0.022	0.009	0.003
Gist	1	0.022		0.002	0.001
Valence	1	0.009	0.016		0.000
Arousal	1	0.003	0.021	0.006	
Average 1 Variable	1		0.018	0.004	0.001
Gist + Valence	2	0.024			0.000
Gist + Arousal	2	0.023		0.001	
Valence + Arousal	2	0.009	0.016		
Average 2 Variables	2		0.016	0.001	0.000
Gist + Valence + Arousal	3	0.025			
VII. The early Area posterior lateral dominance analysis matrix:					
Model	# of variables	fit	Gist	Valence	Arousal
Intercept Only	0	0.000	0.209	0.080	0.049
Gist	1	0.209		0.019	0.027
Valence	1	0.080	0.148		0.013
Arousal	1	0.049	0.187	0.044	
Average 1 Variable	1		0.168	0.031	0.020
Gist + Valence	2	0.228			0.014
Gist + Arousal	2	0.237		0.006	
Valence + Arousal	2	0.093	0.150		
Average 2 Variables	2		0.150	0.006	0.014
Gist + Valence + Arousal	3	0.242			
VIII. The late Area posterior lateral dominance analysis matrix:					
Model	# of variables	fit	Gist	Valence	Arousal
Intercept Only	0	0.000	0.158	0.069	0.001
Gist	1	0.158		0.019	0.001
Valence	1	0.069	0.108		0.009
Arousal	1	0.001	0.157	0.076	
Average 1 Variable	1		0.132	0.047	0.005

Gist + Valence	2	0.176			0.008
Gist + Arousal	2	0.158		0.026	
Valence + Arousal	2	0.077	0.107		
Average 2 Variables	2		0.107	0.026	0.008
Gist + Valence + Arousal	3	0.184			

Appendix D: Two Examples of the variability of human judgements of valence ratings among 50 participants (study I)

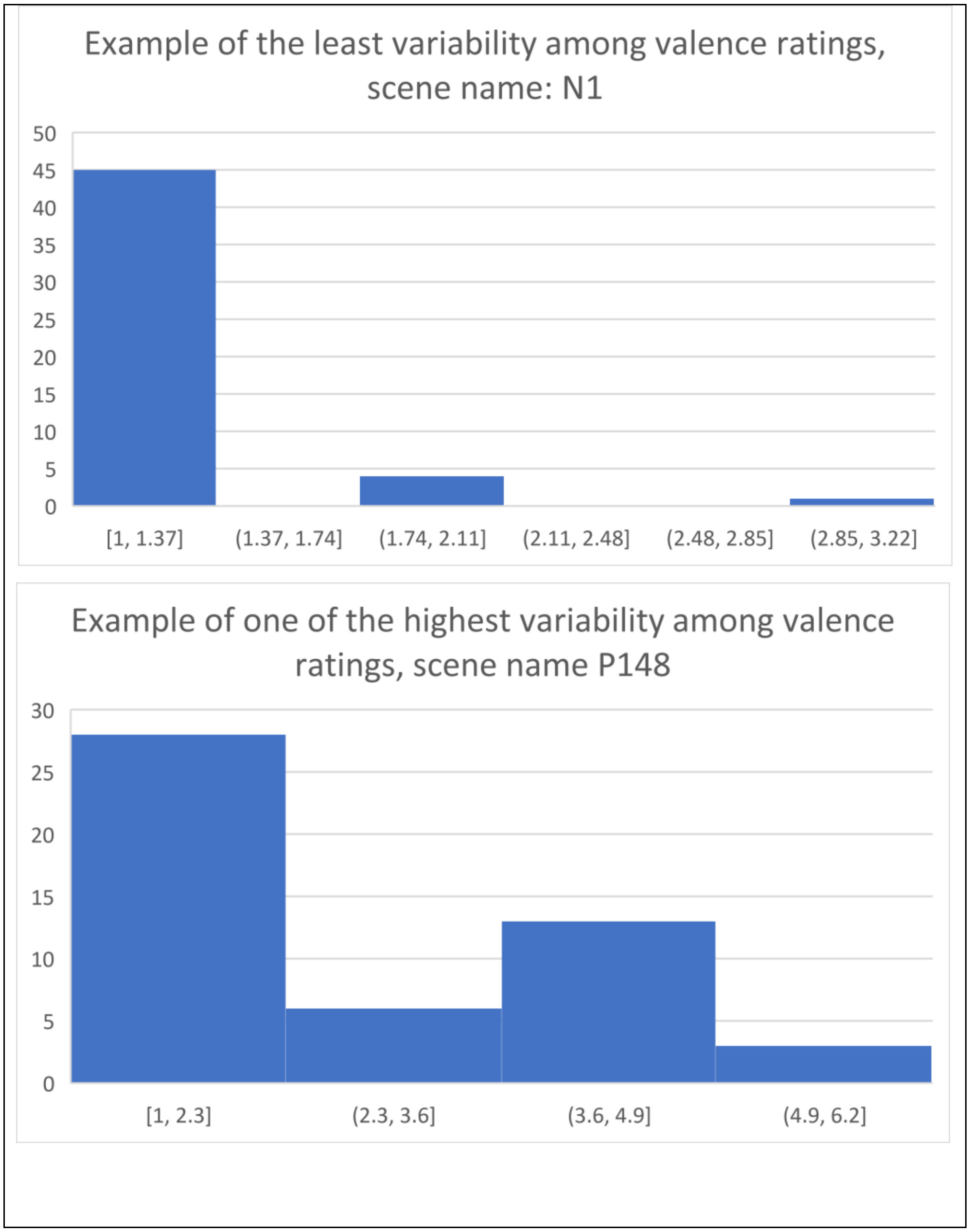

Figure 24: Examples of the variability among valence ratings