A study of individual differences in the multiscale entropy of EEG recordings during response to emotional stimulation using standardized visual images

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Abstract: The calculation of multiscale entropy (MSE) is a novel method of interpreting complex physiologic behavior and has been used in the analysis of neurophysiologic data derived from psychological research. The current study examined the electroencephalographic (EEG) recordings from healthy volunteers during exposure to standardized photographic images from the International Affective Picture System (IAPS), intended to induce positive, negative, and neutral emotional reactions. EEG readings were analyzed using MSE calculations over 100 time scales, incorporating frequencies from 500 to 5 Hz. A total of 37 participants completed the protocol and a significant difference was noted in MSE measurements when subjects were exposed to pleasant images when compared to unpleasant images ($t(72) = -2.15, p = 0.035$). Subjects were subsequently evaluated using psychometric surveys (Trait Meta Mood Scale, Affect Intensity Measure, and the Big Five Inventory 2nd edition) looking for correlation between measures of affective reactivity and MSE measurements. Inverse relationships between Conscientiousness and MSE values while viewing pleasant images ($r = -0.41$, $p < .01$), and Extraversion with MSE while viewing unpleasant images ($r = -0.33$, $p = .019$) were observed. The results of this study support the potential utility of MSE for affective research and suggest avenues of further study.

"But I don't want to go among mad people," Alice remarked.

"Oh, you can't help that," said the Cat: "we're all mad here. I'm mad. You're mad."

"How do you know I'm mad?" said Alice.

"You must be," said the Cat, "or you wouldn't have come here."

Alice didn't think that proved it at all; however, she went on. "And how do you know that you're mad?"

"To begin with," said the Cat, "a dog's not mad. You grant that?"

"I suppose so," said Alice.

"Well, then," the Cat went on, "you see a dog growls when it's angry, and wags its tail when it's pleased. Now I growl when I'm pleased, and wag my tail when I'm angry. Therefore I'm mad."

"I call it purring, not growling," said Alice.

"Call it what you like," said the Cat.

---from Chapter 6, Pig and Pepper, Alice in Wonderland, Lewis Carroll, 1865.

I. Introduction

The Cheshire Cat, one of the more cryptic characters in Lewis Carroll's *Alice in Wonderland*, able to appear and disappear at random, is a fitting metaphor for emotion. Even Alice declares "I've often seen a cat without a grin…but never a grin without a cat! It's the most curious thing I've ever saw in my life!" The ephemeral and often contradictory behavior of the Cat mirrors the transitory and subtle nature of human emotion.

Even developing a comprehensive definition for emotion can be challenging and depends largely on the perspective chosen---behavioral, evolutionary, or neurobiological, for example. Perhaps the definition provided by the American Psychological Association is the best starting point: emotion is "a complex reaction pattern, involving experiential, behavioral, and physiological elements, by which an individual attempts to deal with a personally significant matter or event…Emotion typically involves feeling but differs from feeling in having an overt or implicit engagement with the world."

Researchers have long attempted to link emotional states to underlying biologic processes in the human brain. Early neuroanatomical studies by Paul MacLean and James Papez explored the role of the limbic system in emotional states, though later research suggests that additional brain structures are equally important (MacLean, 1952; Papez, 1937; Morgane, Galler & Mokler, 2005). Research into the role of neurotransmitters such as serotonin, norepinephrine, and dopamine all confirm the importance of neurochemistry in the processing of emotions (Hensley, 2010; Harley, 1987; Badgaiyan et al., 2009). Invasive neurophysiological investigations using implanted electrodes in the human brain yielded a deeper understanding of the localization of the neural representations of emotions (Guillary & Bujarski, 2014).

Neuroscientists must overcome several major challenges when studying the brain in humans. First, investigators often need to measure brain function indirectly, without maiming or sacrificing experimental subjects. Secondly, numerical results must be generated with sufficient quality and quantity to draw statistically valid conclusions. And finally, objective methods must be developed to deliver standardized emotional stimuli to test subjects and record measurable responses. Given the subjective and complex nature of emotional reactions in humans, overcoming these challenges can be difficult.

Researchers have designed experiments to overcome these limitations and have made significant progress in studying the biologic basis of human emotions. Noninvasive monitoring of brain activity through the electroencephalogram (EEG) and event related potential (ERP) measurements have yielded important data regarding the electrophysiology of emotion. Recent advances in functional magnetic resonance imaging (fMRI) have allowed more precise localization of neuroanatomical structures involved in the regulation of emotional response. Improvements in computer science and signal processing have permitted investigators to obtain more precise and robust interpretation of their data. Finally, methodology has been developed to compensate for the variability and subjectivity in emotion; validated databases of standardized stimuli are available and calibrated to evoke an emotional response in experimental subjects. These sets allow comparison between both experimental subjects and different research studies; researchers can choose among different types of stimuli depending on needs of the study---including words, facial images, photographs, and film clips (Grühn & Sharifian, 2016).

The current research project will utilize some of the principles listed above to investigate the emotional responses elicited in experimental subjects and attempt to relate them to electrical activity in the human brain. This study will use an established data set of images from the International Affective Picture System (IAPS) to stimulate emotional reactions in test subjects. In turn, electroencephalographic measurements will be recorded and a recently developed analytic technique, multiscale entropy (MSE) will be calculated from EEG signals. The findings will be analyzed looking for a significant difference between the valence of the emotional stimuli and associated MSE measurements. The final phase of the study will involve assessment of test subjects using standard psychometric surveys of personality traits such as intensity of affective response and ability to manage emotions. Again, the results will be analyzed looking for trends between MSE measurements in test subjects by valence condition and their scores on the survey instruments.

II. Background Studies

Research on human emotion requires a reliable way to elicit an emotional response from the subject of the experiment. An ideal stimulus set would be reproducible, controllable, quantifiable, and widely available as a standard for the research community. There are several established datasets that have been developed depending on the type of stimulus required for the protocol – words, facial images, pictures, audio, or film clips. Much work in this area has been done by Bradley and Lang, initially with the development of the Self-Assessment Manikin (SAM). The SAM consists of graphical images of a manikin that can be used to describe the dimensions of an emotional content known as valence, arousal, and dominance. Valence is how pleasant or unpleasant one feels while looking at the image, arousal is the intensity of the emotion felt white looking at the image, and dominance is the level of control felt over the emotion elicited by the image (Bradley & Lang, 1994; Mehrabian, 1980).

The same research group created the International Affective Picture System (IAPS), a widely used standardized image set of color photographs rated on valence, arousal, and dominance using the SAM (Lang, Bradley & Cuthbert, 2008). Exposure to emotionally laden images, especially those with erotic or violent content, generated larger ERP potentials compared with emotionally neutral stimuli (Cuthbert, Schupp, Bradley, Birbaumer, & Lang, 2000). Several studies confirmed that the intensity of emotional content in the IAPS modulates ERPs differentially, suggesting that these images can produce changes in brain activity consistently discernable with EEG (Schupp et al., 2000; Keil et al., 2002; Codispoti, Ferrari & Bradley, 2007). Alternative image datasets have been developed addressing some concerns with IAPS: the Geneva Affective Picture Database (GAPED) which has a larger number of available images and themes, and the Open Affective Standardized Image Set (OASIS) featuring more recent images that are open source and available for online studies (Dan-Glauser & Scherer, 2017; Kurdi, Lozano, Banaji, 2011). Nevertheless, the IAPS remains the gold standard, having been used in hundreds of experimental studies; this stimulus source was therefore chosen for the current study.

A popular tool for studying the electrophysiological response to emotional stimuli is the electroencephalogram (EEG), developed by Hans Berger in 1934. Commonly used in the diagnosis and treatment of epilepsy, the EEG has been widely adopted for research studies in neuroscience and psychology. EEG recordings allow correlation of neural activity with human behavior and provide excellent temporal resolution if suboptimal spatial resolution. When studying emotion, EEG techniques have been used to predict future psychopathology, gain insight into emotional processing capabilities, and even classify emotional states. One wellstudied metric, resting frontal brain asymmetry, is a measure of the differential activity across anterior regions of the brain. EEG asymmetry scores can serve as an index of affective predisposition and can be thought of as an individual trait difference associated with approach and withdrawal behaviors related to psychopathology such as depression (Coan & Allen, 2004; Davidson, 1994). Other researchers have shown asymmetry scores correlate with childhood social competence, predict fear responses to films, and forecast enjoyment of musical stimuli (Fox et al., 1995; Wheeler, Davidson & Tomarken, 1993; Schmidt & Hanslmayr, 2009). Critics of the validity of frontal asymmetry as an individual difference variable have pointed to the suboptimal test-retest reliability, which is .50 to .60 after a two- to six-week period. This finding contrasts to studies showing personality measures that have stability coefficients as high as .87 after 24 years (Hagemannn et al., 2002; Costa & McCrae, 1991). Furthermore, replication studies indicate that depending on which statistical analysis used to measure frontal asymmetry, one could find results matching previous findings, opposed to previous findings, or having no relation at all (Hagemann et al., 1998).

Another research technique derived from the EEG is the measurement of the event related potential (ERP), a stereotyped electrophysiological response measured after exposure to a specific category of stimuli. By using averaging techniques and performing multiple trials, background electrical activity can be minimized, and more relevant sensory and cognitive events can be isolated. Grey Walter identified the first ERP component relating to cognition in 1964, the contingent negative variation (CNV), which was thought related to expectancy or alerting (Walter et al., 1964). ERPs are especially useful when studying the processing of emotional stimuli, as they are time locked to events and follow a comprehensive nomenclature. For example, the P300, a positive inflection occurring in an ERP recording around 300 milliseconds after an event, was originally used to study responses to meaningful information during decision making tasks (Chapman & Bragdon, 1964). More recent applications include using the P300 to differentiate attentional biases to positive information in individuals with major depressive disorder (Deldin, Keller, Gergen & Miller, 2001). The late positive potential (LPP) has been used to study differences in emotional regulation when participants are told that emotional images are real as opposed to when they are told that they are taken from films (Mocaiber et al., 2010). As a general measure, LPP amplitude reflects more arousing and intense emotions, does not habituate to repeated presentation of stimuli, and occurs only during conscious recognition of emotion, lending utility to attention studies (Hajak, MacNamara & Olvet, 2010). ERP studies have also delineated a sequence of automatic attention to emotion: individuals attenuate fastest to negative emotion (105ms after presentation), followed by positive emotion (at 180ms), then neutral (at 240ms) (Carretie et al., 2004).

Although measurement of frontal asymmetry and event-related potentials have offered valuable information about emotional states in prior studies, investigators can always benefit from using novel methods of EEG processing to gain additional knowledge. Multiscale entropy (MSE) is one such technique that has only recently been applied to EEG studies, and research applying MSE analysis to the study of emotional response has become more common. The concept of multiscale entropy was first developed by Costa, Goldberger and Peng at Harvard Medical School in 2002 in response to the observation that many disease states are associated with a decrease in the amount of information provided by physiological processes; conceptually, many biological dysfunctions can be thought of as a loss of complexity and adaptive capability. Statistical entropy, introduced by Shannon (1948) is a measure of predictability in an information system, with higher values indicative of more disorder. The entropy algorithm has since undergone numerous iterations, and here we use an algorithm with improved accuracy called sample entropy (Richman & Moorman, 2000). When applied to biological signals, traditional entropy measurements are an inconsistent general measure of complexity in healthy systems because it is only calculated on the time scale of the original recording. These algorithms neglect the fact that many biological systems include meaningful information on multiple temporal levels. MSE remedies this issue through a process called coarse graining, in which entropy is calculated across increasingly smaller averaged time scales. For example, if entropy were first calculated across 10 one-second EEG segments sampled at 500 Hz (i.e. 5000 data points), two consecutive non-overlapping segments would be averaged and entropy would be calculated across 250 Hz segments (2500 data points), then around 167 Hz and so on. The mathematical result of this abstraction is an MSE curve, with the time scale on the x-axis, and the amount of entropy on the y-axis. Using this technique, meaningful physiological information is captured across multiple time scales that would otherwise be omitted (Costa, Goldberger & Peng, 2002; Shannon, 1948; Costa, Goldberger & Peng, 2005; for an in depth explanation see Grandy, Garrett, Schmiedek, & Werkle-Bergner, 2016).

MSE derived from EEG recordings has already been used as an innovative way to characterize psychopathologic states. The EEG recordings of individuals with autism spectrum disorder (ASD) have reduced MSE when completing face and chair matching tasks, perhaps mirroring the reduced behavioral adaptability associated with the disorder (Catarino et al., 2011). Schizophrenics with abnormal resting state MSE had these abnormalities reversed after antipsychotic treatment (Takahashi et al., 2011). Studies of emotion that employ EEG multiscale entropy have so far been limited, focusing on the classification and recognition of emotions with machine learning (Lotova, et al., 1998; Tonoyan, Looney, Mandic & Van Hulle, 2016;

Michalopoulos & Bourbakis, 2017; Garcia-Martinez et al., 2016; Kortelainen & Seppänen, 2013). While some of these ambitious studies have successfully classified affective states elicited from videos and images, the classifications are limited to emotional valence, are only predictive for emotional responses to the eliciting stimuli, and are only accurate for smaller datasets (Sohaib, Qureshi, Hagelbäck, Hilborn & Jerčić, 2013). One classification study noted a general relationship between EEG MSE and emotional valence, suggesting that signals are less complex than baseline during negative emotions (Hosseini & Naghibi-Sistani, 2011). Apart from classification studies, few have focused on multi-scale entropy as an individual difference variable of emotional response or have searched for any broader relationship between affect, personality, and multiscale entropy measurements. The aim of the present study will be to consider associations between individual difference factors and emotionally evoked brain signal entropy.

Humans vary widely in their experience of emotion, and variation in an individual's levels of emotional reactivity and intensity can be measured. Affective scientists have developed many psychometric tests to identify these trait differences. Established surveys to quantify emotionality and personality traits include the Affect Intensity Measure (AIM), the Trait Meta-Mood Scale (TMMS), and the short form of the Big Five Inventory (BFI-2-S). The AIM survey measures the intensity of positive affect, negative affect, serenity and guilt (Larsen, 1984; Larsen & Diener, 1987). Multidimensional subsets of the AIM have been proposed to better reflect the construct of affective intensity than the total score, with positive affectivity, negative reactivity and negative intensity providing the best goodness-of-fit and discriminant validity compared to other measures (Bryant, Yarnold & Grimm, 1996). The Trait Meta-Mood Scale (TMMS) measures an individual's ability to reflect upon and manage their emotions, also known as

Perceived Emotional Intelligence (PEI). The subscales of the survey measure the attention an individual pays to their feelings, the clarity with one which one experiences their feelings, and their beliefs about terminating negative mood states (Salovey, Mayer, Goldman, Turvey & Palfai, 1995). The Big Five Inventory-2 is a survey based on personality traits measured in five dimensions: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism; the short form can be completed in three to five minutes which minimizes testing fatigue (Soto & John, 2017a; Soto & John, 2017b). Several personality traits correlate with trait affect: neuroticism is positively correlated with negative affect, extraversion with positive affect, and more specifically, conscientiousness is related to positive attentiveness while low agreeableness is related to trait hostility (Watson & Clark, 1992). Identification of relationships between emotional multiscale entropy measurements, affective reactivity and personality traits would require a much larger sample size than planned in this study to draw any statistically valid conclusions. Nevertheless, any trends identified could point to areas of future investigation.

III. Study Design

This study will examine the differences in the multiscale entropy of EEG recordings measured during positive, negative, and neutral emotional stimulation elicited by viewing images from the IAPS database. The study will have two parts. The primary phase of this study will be to determine whether the multiscale entropy of EEG signals is different during the experience of positive emotion, negative emotion, or no emotion (neutral). This section will be confirmatory and will test for significant differences across the three conditions. The null hypothesis is that there is no significant difference in multiscale entropy while viewing standardized images intended to elicit positive, negative, or neutral emotional responses in test subjects.

The secondary phase of the study will be purely exploratory and seeks to generate hypotheses about possible relationships between an individual's MSE response during emotion and broader measures of affect and personality traits as measured by psychometric testing. If MSE does indeed reflect the complexity inherent in adaptive biological systems, it is possible that relationships exist between an individual's entropy scores and specific affective and personality traits. Individual differences in neutral, pleasant, and unpleasant emotional MSE will be calculated and compared to individual scores on three measures: the Affect Intensity Measure (AIM), the Trait Meta-Mood Scale (TMMS), and the short form of the Big Five Inventory 2 (BFI-2-S). Any correlations identified will serve as a basis for future studies.

IV. Methods

IV.1. Participants

Participants were chosen from a research pool consisting of undergraduate students at the University of Virginia recruited in the fall of 2019. As an incentive to participate, research subjects were awarded two credits in the participant pool, which is a third of their total requirement. A G*Power analysis was performed in advance, and it was calculated that a minimum of 63 participants would be required to test for significant differences in MSE with a repeated measures ANOVA at 80% power, assuming a moderate effect size of .3.

IV.2. Experimental Protocol

The protocol was approved by the Institutional Review Board at the University of Virginia. Upon arrival to the laboratory, participants signed informed consent forms. Participants were informed that mirrored screen in the testing room was turned off during survey collection to preserve privacy and anonymity. After being fitted for EEG, they were brought to a small, well-lit room and seated approximately one meter in front of the stimulus computer. Participants were given standardized instructions that they would be presented with pleasant, unpleasant, and neutral photographs on the screen, were requested not to blink while viewing the images, and were given opportunities to rest their eyes between trial blocks. Images were presented for 1000 ms on a black background with inter-stimulus interval that lasted between 500 ms and 1000 ms chosen randomly to reduce predictability. After viewing the entire sequence of images, lasting approximately seven minutes, the EEG recording was terminated. Participants then completed three brief psychometric surveys: the AIM, TMMS, and BFI-2-S.

IV.3 EEG recording and preprocessing

A 32-electrode BioSemi electrode headcap with electrodes affixed according to the standard 10-20 system, two eye electrodes, and two mastoid electrodes were placed on subjects and attached to a BioSemi ActiveTwo™ AD box to record EEG data. Event markers began at image onset and lasted the duration of the image (1000 ms) while recording continuously for the full length of the experiment at a resolution of 2048 Hz. EEG signals were digitized on a Windows computer using the BioSemi ActiView™ software. Using the EEGLab and ERPLab toolboxes in MATLAB® software, EEG data was resampled to 500 Hz and the Cz electrode was used as the reference (Delorme & Makeig, 2004; Lopez-Calderon & Luck, 2014). An IIR Butterworth filter was applied with a high-pass filter of .1 - .20 Hz and a low-pass filter of 50.0 - 32.8 Hz. The average reference was computed and then valence condition bins were extracted with a whole baseline correction. Artifact rejection in the epoched data was completed with a moving window peak-to-peak voltage threshold of 100 uV, a moving window of 200 ms, and a window step of 100 ms. An independent component analysis was performed on remaining trials if there were at least 10 repetitions per condition remaining after artifact rejection to separate sources of variance mixed across different electrodes.

IV.4. Stimulus Materials

Participants were shown 150 images from the International Affective Picture System, including 50 pleasant (e.g. beautiful landscapes, adventurous activities), 50 neutral (e.g. chairs, buildings), and 50 unpleasant (e.g. mutilation, crashes) images. Participants were presented with 10 blocks of 5 images of the same valence, for a total of 30 blocks. Mean valence and arousal of conditions were matched to similar ERP studies using IAPS (see Fig. 1). There were no significant differences in luminance, contrast, or spatial frequency between image groups. The order of images within each valence group was randomized, and the order of valence group presentation was initially randomized but then followed the same pattern. For example, one participant might be assigned “UNP” meaning that they first see a block of 5 unpleasant images, then neutral, then pleasant. The remaining 27 blocks would continue in this order. After every block there was a prompt for the participant to rest their eyes and press a button to continue to the next block.

Condition	Valence	Arousal
Pleasant	7.46	6.00
Neutral	4.97	2.63
Unpleasant	2.28	6.37

Fig. 1: Mean valence and arousal

IV.5 Calculation of Multiscale Entropy

Multiscale entropy was calculated across discontinuous segments using the method described in Grandy, Garrett, Schmiedek, & Werkle-Bergner's 2016 article for the estimation of signal entropy from sparse neuroimaging data, using MATLAB code adapted from Kovacevic's work with brain variability in development (Grandy, Garrett, Schmiedek & Werkle-Bergner, 2016; McIntosh, Kovacevic, & Itier, 2008). MSE reflects the predictability of a signal at differing time scales and must be derived from estimating the sample entropy (SampEn) at each time scale. In order to calculate the SampEn within a specific time scale, one must count how often patterns of *m* successive data points reoccur in time period (U^m) and then compare to how often patterns of *m+1* data points reoccur in time period (U^{m+1}). Since neuroimaging data such as EEG signals are often mathematically too precise for data points to recur exactly, it becomes necessary to define a range of values that would qualify as a "recurrence." A similarity criterion (*r*) is created and set for each scale so that all points meeting the similarity criterion are considered equal, a value defined as typically between 10% to 50% of the standard deviation of all points in the time series. For this study, the similarity criterion was set to half of the standard deviation of the original time series ($r = .5$), and the pattern length was set to 2 (two consecutive points in a pattern). The sample entropy value is then calculated by taking the negative natural logarithm of the second count divided by the first count (see Fig. 2). First, the within-person average event-related potential was subtracted from each segment. Then, segments were coarse-grained as described above and calculated to the 100th time scale, across approximately 50 data points for the last scale.

$$S_E = -ln \frac{U^{m+1}(r)}{U^m(r)}$$

Fig. 2: Calculation of sample entropy for a single time scale (adapted from Costa, Goldberger & Peng, 2005)

V. Results and Data Analysis

V.1 Participant Group

Seventy participants (55 female, 15 male, approximate age range 18-22 years) completed the experimental protocol. Upon further analysis, data from fifteen subjects were unusable due to hardware issues with the EEG. Another eighteen subjects were determined to lack sufficient repetitions after artifact filtering parameters and were excluded from further analysis. A total of 37 participants (27 female, 10 male) remained and were included in the final results. All subjects in the final sample group completed all portions of the experimental protocol.

V.2 Multiscale Entropy Measurements

EEG measurements from 36 leads were recorded during baseline and during emotional stimulation for all subjects per protocol. Multiscale entropy measurements were calculated during stimulation with pleasant, neutral and unpleasant conditions and plotted (excluding eye electrodes, see Fig. 3).

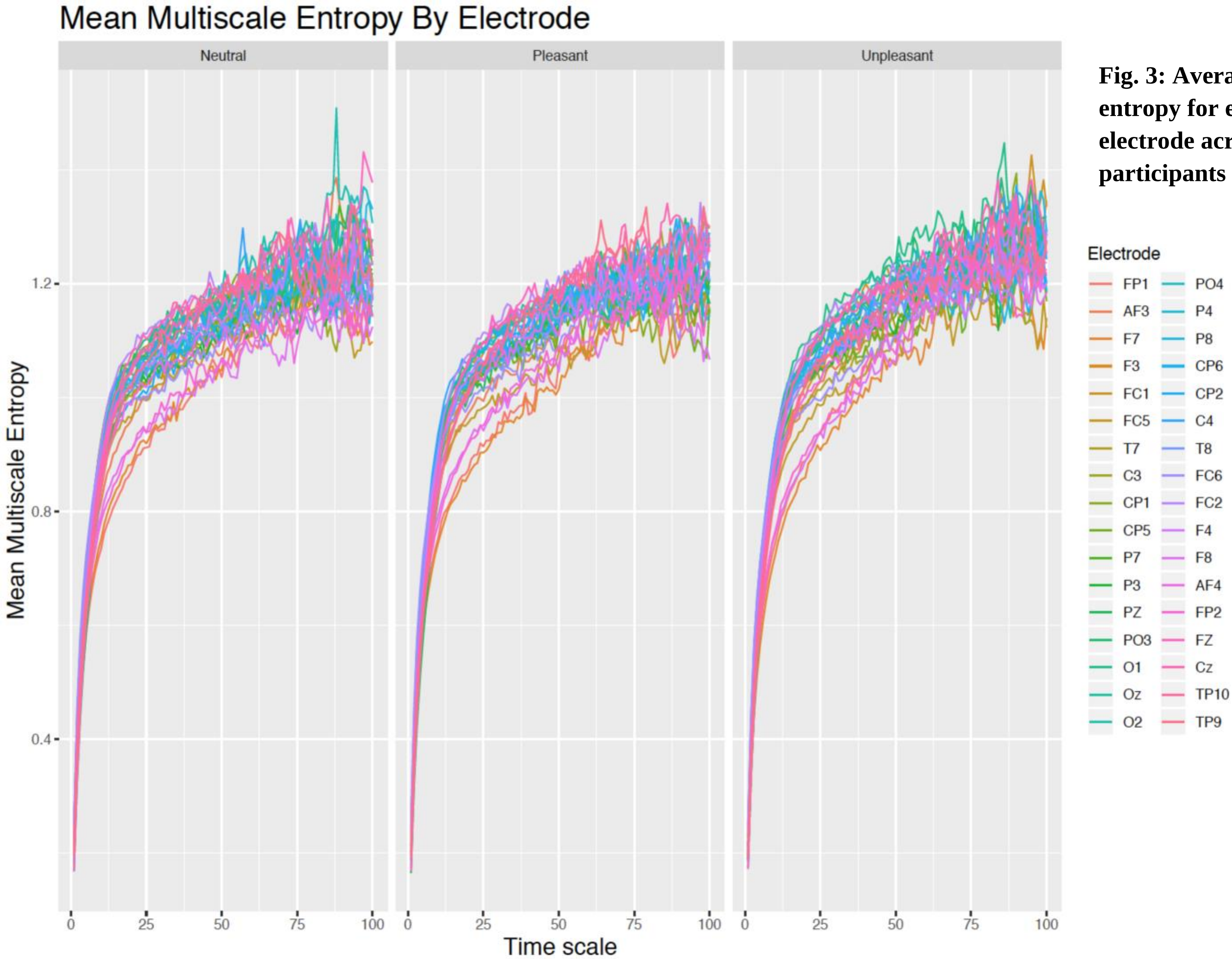

Fig. 3: Average entropy for each electrode across all participants

V.3 Hypothesis Testing

To test for significant differences in MSE between the pleasant, unpleasant and neutral valence conditions, the mean MSE across all electrodes on each time scale was calculated within subjects for each condition. The area under the resulting three MSE curves was calculated in R from time scales 1 to 100 (500 to 5 Hz), creating a single score per participant per condition. A repeated measures ANOVA was conducted on these scores to compare the effects of valence condition on MSE: There was a significant effect of valence condition on MSE ($F(2,36) = 5.82, p < .01$). Post-hoc t-tests revealed significantly more MSE while viewing unpleasant images (*M* = *109.5*) than while viewing pleasant images (*M* = *107.4*; $t(72) = -2.15, p = 0.035$), but there were no significant differences between other conditions (see Fig. 4).

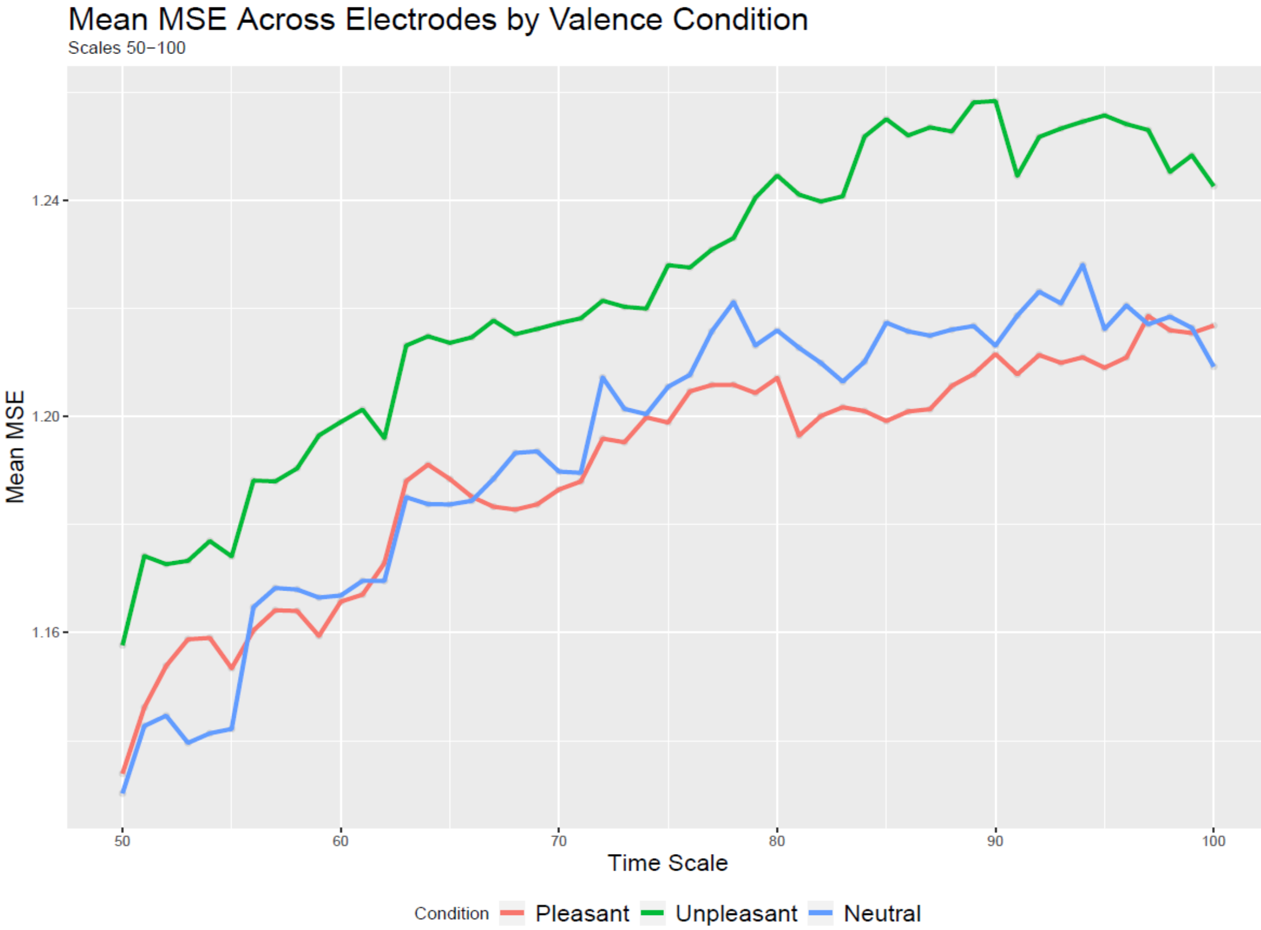

Fig. 4: Average entropy across all electrodes for each valence condition. Time scales 50-100 are shown here to better illustrate differences.

V.3 Behavioral Surveys and Linear Models

To generate hypotheses about emotional MSE as an individual difference variable, linear models were constructed to predict behavioral measures from an individual's area under the MSE curve score. Scores from the BFI-2-S demonstrated the only significant relationships; Trait Conscientiousness had an inverse relationship with MSE while viewing pleasant images (r = *-0.41*, $p < .01$) and Extraversion had an inverse relationship with MSE while viewing unpleasant images (r = *-0.33*, p = *.019*; See Fig. 5). An individual's openness scores could be used to approximate neutral MSE scores in a nonlinear model, although not all predictors were significant. None of the facets of the Affect Intensity Measure or the Trait Meta-Mood Scale had significant correlations with MSE as measured by mean area under the curve. Overall, the responses on the surveys showed good variation relative to the mean, suggesting heterogeneity in personality and emotional traits (see Fig. 6).

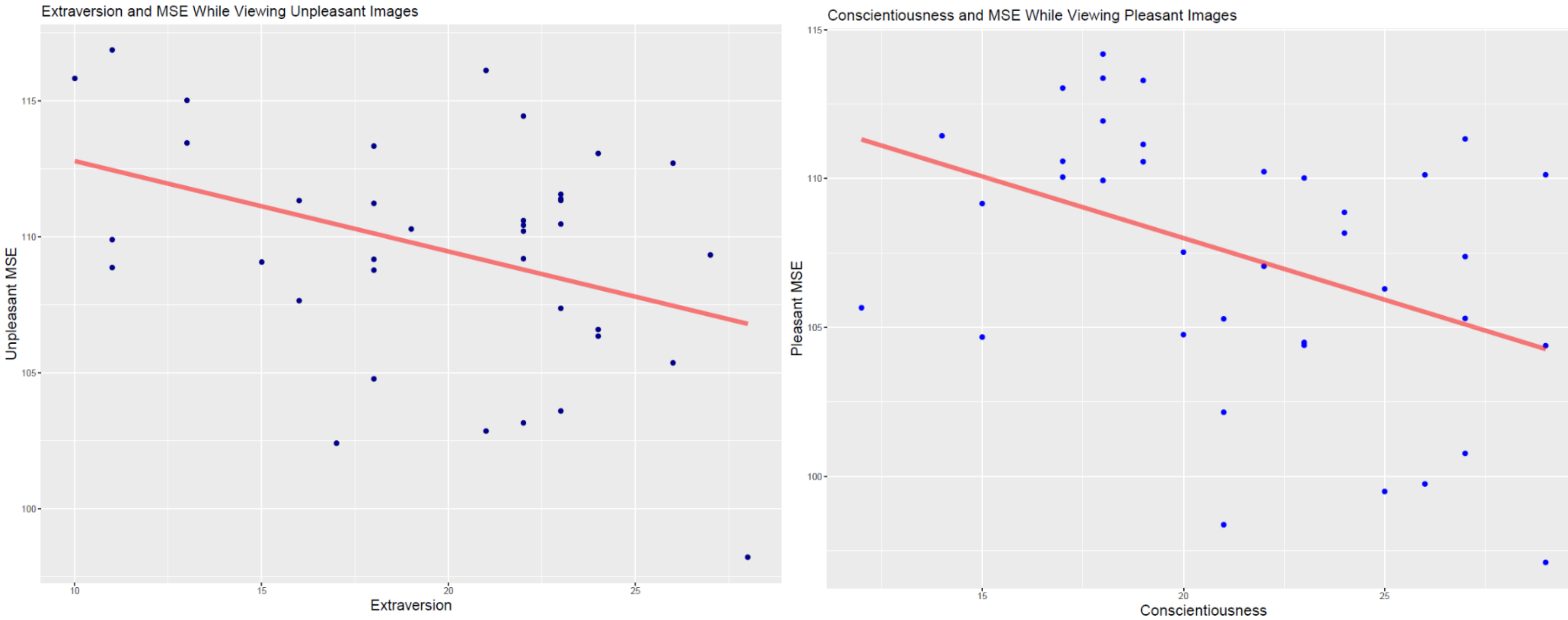

Fig. 5: Inverse linear relationships between Extraversion scores and unpleasant MSE (left) and Conscientiousness and pleasant MSE (right)

V.4.1 Exploratory Analyses: Path Modeling

Fig. 6: Mean and SD of behavioral meaures

	Mean	SD
AttentionTMMS	50.97	7.51
RepairTMMS	21.08	4.81
ClarityTMMS	36.68	7.52
AIM total	148.00	19.52
Positive Affectivity	67.24	13.25
Negative Reactivity	28.81	4.85
Negative Intensity	31.22	5.08
Positive Intensity	20.73	4.62
Extraversion	19.81	4.83
Agreeableness	22.68	4.42
Conscientiousness	21.54	4.53
Neuroticism	18.16	5.18
Openness	23.03	3.74

As there is considerable variation in multiscale entropy between electrodes (see Fig. 3 above), analyses that would incorporate multiple electrodes as predictors of behavioral measures were attempted. Two path models were completed in warpPLS (Kock, 2010). WarpPLS uses structural equation modeling (SEM), a group of statistical methods used to represent hypotheses about an underlying structural relationship between empirical measurements (Kaplan, 2008). Measurements that are meant to reflect the same construct are grouped into latent variables, a structural model is hypothesized, and statistical summaries about the relationships are calculated by warpPLS.

The first model was based on a previous study of EEG and emotion that suggested differential neural activity depending on the type of emotion being experienced: greater right frontal activity during all emotion, left temporal activity during negative emotion, and right temporal activity during positive emotion (Müller, Keil, Gruber & Elbert, 1999). The electrodes were set to predict personality traits and the meaningful facets of the AIM separated by affect (Positive Affectivity, Positive Intensity, Negative Reactivity and Negative Intensity). Grouping the model in this localized way resulted in small but significant relationships between each of these groups and the behavioral measures (see Fig. 7a).

The second path model was designed with the MSE values from every electrode combined into separate latent variables depending on the valence condition (Fig.7b). Using all the electrodes explained more variance in the model and correlated with the AIM measures that did not correlate with the area under the curve values. Unfortunately, this second model was rank deficient (96 columns predicting 37 rows) and not statistically accurate. Although one cannot draw strong conclusions about the relationship between specific behavioral measures and MSE due to the number of analyses used, these models could provide a starting point for future studies.

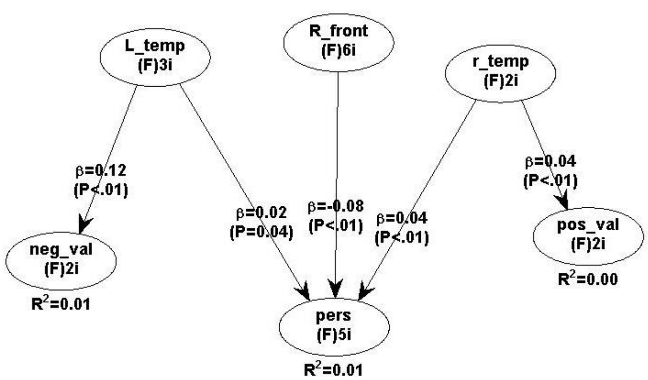

Fig. 7a: A path model based on localization of activity during emotional experience. Clockwise from bottom left: Negative valence surveys, left temporal activation (T7, F7, P7, unpleasant condition), right frontal activation (F4, F8, all conditions), right temporal activation (T8, P8, pleasant condition), positive valence surveys, personality surveys.

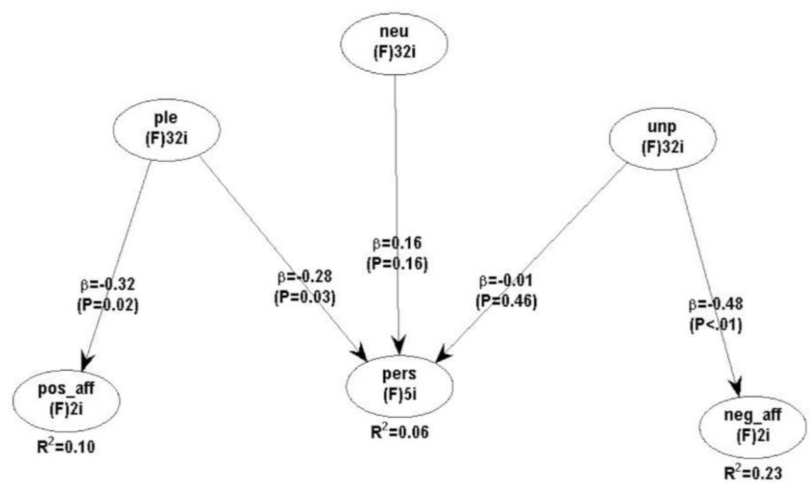

Fig. 7b: A larger path model including all electrodes, separated by the condition during recording (pleasant, neutral, unpleasant), attempting to predict the same behavioral surveys.

V.4.2 Exploratory Analyses: Late Positive Potential

Grand average event-related potentials were calculated across all participants in ERPLab and plotted by condition to check if the late positive potential (LPP), an emotionally modulated component, was present. While there is considerable variety in how LPPs are presented in the literature, a standard definition is a positive inflection with a slow voltage change beginning around 300 ms that is more positive for affective stimuli (Hajak & Olvet, 2008; Cuthbert, Schupp & Bradley, 2000; Brown et al., 2012). LPPs are usually calculated on parietal and central electrodes, and the Pz electrode is shown here as a reference (Gable & Harmon-Jones, 2010, see Fig. 8). The later part of the positive component (>400 ms) had greater amplitudes for the unpleasant emotional condition. While no statistical analyses were run in this section, some modulation of ERP amplitude based on valence condition is present.

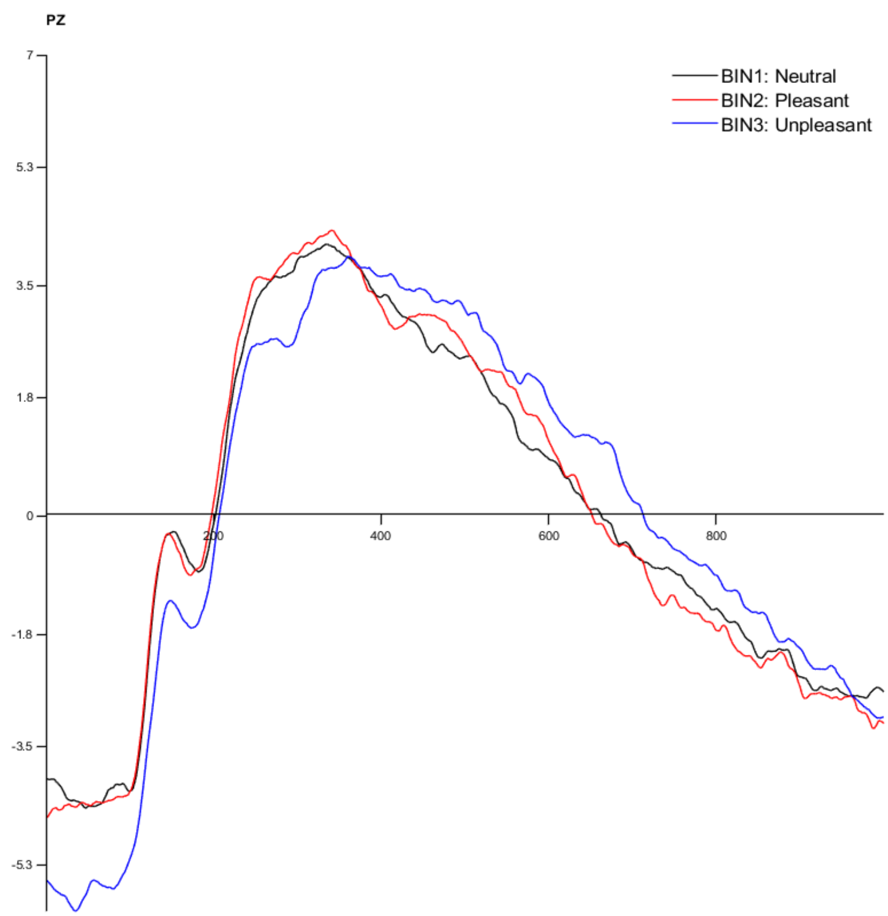

Fig. 8: The grand average ERP of the Pz (parietal) electrode plotted by condition. After 400 milliseconds, the amplitude is greatest for unpleasant stimuli (x axis: milliseconds, y axis: microvolts)

VI. Discussion

VI.1 Interpretation of results

The results of this study suggest that multiscale entropy levels of EEG activity in the brain changes with the emotional content of visual stimuli in test subjects. Significant differences in MSE measurements between pleasant and unpleasant conditions were observed using time scales 1-100, and also between unpleasant and neutral conditions using time scales 50-100 – even with the low statistical power of the present study. The specific aspect of emotional processing that is reflected by these MSE differences is far less clear, however. While MSE did correlate moderately with trait conscientiousness and extraversion, lending some credibility to the idea of MSE as an individual difference variable, there is insufficient evidence to conclude that MSE is reflective of one's affective predisposition. The survey measures that are specifically designed to measure emotional traits did not show relationships with MSE when measured by mean area under the curve. One can only speculate about the basis of a relationship between MSE and personality traits. Extraversion, as noted by Watson and Clark, is related to trait positive affect (Watson & Clark, 1992). A more robust study, utilizing a larger sample size with greater statistical power, might show that a more extraverted individual has less complex EEG signals while looking at unpleasant images. It is possible that on a neurophysiological level, a happier individual processes negative affective information in a less complex fashion. Similarly, more conscientious individuals might display less complex processing of positive emotional stimuli.

Of the studies that examined the relationship between emotional stimulation with IAPS images and MSE, only one noted a relationship between MSE and emotional valence. Hosseini & Naghibi-Sistani observed that EEG signals were *less* entropic during the experience of negative emotion when compared to neutral visual experiences (Hosseini & Naghibi-Sistani, 2011). These previous results are contradicted by the results of the current study, with negative emotion being significantly *more* entropic. The reason for the opposite entropy readings with negative images in these methodologically similar protocols is not clear but may result from differences in experimental technique and calculation of entropy values.

VI.2 Limitations

A significant limitation of this study is the sample size. While there was a sufficient sample size to detect a significant difference between conditions to test the study hypothesis, there were not enough participants to be able to adequately analyze the relationship between behavioral measures and MSE. For example, when attempting to path model the relationship between MSE and behavioral measures using many electrodes, the data is substantially rank deficient – with 96 predictor columns for 37 trials. With many more trials, the efficacy of MSE as a potential emotional correlate could be more readily determined. Another limiting factor with psychological research using undergraduate college students as a study population is that the results may not be generalizable to the broader population. However, with a study measuring a neurophysiological value like multiscale entropy, using a population with a narrowly restricted age range is an advantage. Having a sample with a broader age range might confound results since brain signal complexity has been shown to change across the lifespan (Sleimen-Malkoun, 2015; McIntosh, 2018).

The most extreme images from the IAPS were not used in the stimulus presentation. The images rated the most positive and arousing in the dataset were erotic, which if used could have created further confounds relating to gender and sexual orientation. The most negative and arousing emotional images were avoided to prevent participant dropout. A study that included these images might find more substantial differences between valence conditions.

Finally, individuals react differently to emotional stimuli due to experience and memory influences, which are difficult to control. One subject might be disgusted at the images of a graphic surgical procedure, while another might find it to be fascinating. The standardization of the IAPS takes these differences into account with valence and arousal ratings from many individuals, and in theory should balance out with a large enough sample size. While there was no evidence to suggest the subjects in this sample were reacting differently to the images than the general population, consideration should be given to the subject matter of emotional stimuli in future studies investigating individual differences in emotional reactivity.

VI.3 Future Directions

Future studies should further explore the potential of multiscale entropy as a measure of affective individual differences. This can be accomplished through more extensive behavioral measures and the inclusion of biological measures. Behavioral coding, experience sampling, or tests such as the Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT) could be used to determine if MSE is more reflective of other aspects of emotional behavior (Mayer & Salovey, 2007). Further hormonal (e.g. cortisol) and physiological measures (electrodermal activity, heart rate) could also be included. Other forms of emotional stimuli could be employed (e.g. films, audio) and utilized with different populations of interest. In turn, this would provide a basis for understanding the meaning of signal complexity as it relates to emotion. Based on the limited relationships between MSE and emotional disposition identified here, further study of MSE as a method for understanding emotional behavior is warranted.

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References

Aftanas, L. I., Lotova, N. V., Koshkarov, V. I., Makhnev, V. P., Mordvintsev, Y. N., & Popov, S. A. (1998). Non-linear dynamic complexity of the human EEG during evoked emotions. *International Journal of Psychophysiology*, *28*(1), 63-76.

Badgaiyan, R. D., Fischman, A. J., & Alpert, N. M. (2009). Dopamine release during human emotional processing. *NeuroImage*, *47*(4), 2041–2045. doi: 10.1016/j.neuroimage.2009.06.008.

Bradley M. M. & Lang, P. J. (1994). Measuring emotion: The Self-Assessment Manikin and the semantic differential. *Journal of Behavioral Therapy and Experimental Psychiatry*, 25, 49-59.

Brown, S. B., van Steenbergen, H., Band, G. P., de Rover, M., & Nieuwenhuis, S. (2012). Functional significance of the emotion-related late positive potential. *Frontiers in human neuroscience*, *6*, 33.

Bryant, F. B., Yarnold, P. R., & Grimm, L. G. (1996). Toward a measurement model of the affect intensity measure: A three-factor structure. *Journal of Research in Personality*, *30*(2), 223-247.

Carretie, L., Hinojosa, J. A., Martin-Loeches, M., Mercado, F., & Tapia, M. (2004). Automatic attention to emotional stimuli: Neural correlates. Human Brain Mapping, 22, 290–299

Catarino, A., Churches, O., Baron-Cohen, S., Andrade, A., & Ring, H. (2011). Atypical EEG complexity in autism spectrum conditions: a multiscale entropy analysis. *Clinical neurophysiology*, *122*(12), 2375-2383.

Chapman, R.M. & Bragdon, H.R. (1964). "Evoked responses to numerical and non-numerical visual stimuli while problem solving". *Nature*. **203** (4950): 1155–1157. doi:10.1038/2031155a0.

Coan, J.A. & Allen, J.B. Frontal EEG asymmetry as a moderator and mediator of emotion, Biological Psychology, Volume 67, Issues 1–2, 2004, Pages 7-50, ISSN 0301-0511, https://doi.org/10.1016/j.biopsycho.2004.03.002

Codispoti, M., Ferrari, V., & Bradley, M. M. (2007). Repetition and event-related potentials: distinguishing early and late processes in affective picture perception. *Journal of Cognitive Neuroscience*, *19*(4), 577-586.

Costa, M., Goldberger, A. L., & Peng, C. K. (2002). Multiscale entropy analysis of complex physiologic time series. *Phys Rev Lett.*, *89*(6), 068102.

Costa, M., Goldberger, A. L., & Peng, C. K. (2005). Multiscale entropy analysis of biological signals. *PhysRevE.*, *71*(2), 021906.

Costa, M., & Healey, J. A. (2003). Multiscale entropy analysis of complex heart rate dynamics: discrimination of age and heart failure effects. In *Computers in Cardiology, 2003* (pp. 705-708). IEEE.

Costa Jr, P. T., & McCrae, R. (1991). Trait psychology comes of age. *Faculty Publications, Department of Psychology*, 363.

Cuthbert, B. N., Schupp, H. T., Bradley, M. M., Birbaumer, N., & Lang, P. J. (2000). Brain potentials in affective picture processing: covariation with autonomic arousal and affective report. *Biological psychology*, *52*(2), 95-111.

Dan-Glauser E. S. & Scherer K. R. (2011) The Geneva affective picture database (GAPED): a new 730-picture database focusing in valence and normative significance. *Behav Res Methods*, 43(2):468-77. doi: 10.3758/s13428-011-0064-1

Davidson, R. J., (1994). Asymmetric brain function, affective style, and psychopathology: The role of early experience and plasticity. Development and Psychopathology, 6(4), 741-758. Doi:10.1017/S0954579400004764

Davidson, R. J., (1993) Cerebral asymmetry and emotion: Conceptual and methodological conundrums, Cognition and Emotion, 7:1, 115-138, DOI: 10.1080/02699939308409180

Deldin, P. J., Keller, J., Gergen, J. A., & Miller, G. A. (2001) Cognitive bias and emotion in neuropsychological models of depression. Cognition and Emotion, 15:6, 787-802, DOI: 10.1080/02699930143000248

Delorme, A., & Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of neuroscience methods*, *134*(1), 9-21.

Fox, N. A., Rubin, K. H., Calkins, S. D., Marshall, T. R., Coplan, R. J., Porges, S. W., Long, J. M. and Stewart, S. (1995), Frontal Activation Asymmetry and Social Competence at Four Years of Age. Child Development, 66: 1770-1784. doi:10.1111/j.1467-8624.1995.tb00964.x

Gable, P. A., & Harmon-Jones, E. (2010). Late positive potential to appetitive stimuli and local attentional bias. *Emotion*, *10*(3), 441.

García-Martínez, B., Martínez-Rodrigo, A., Zangróniz Cantabrana, R., Pastor García, J., & Alcaraz, R. (2016). Application of entropy-based metrics to identify emotional distress from electroencephalographic recordings. *Entropy*, *18*(6), 221.

Grandy, T. H., Garrett, D. D., Schmiedek, F., & Werkle-Bergner, M. (2016). On the estimation of brain signal entropy from sparse neuroimaging data. *Scientific reports*, *6*, 23073.

Grühn, Daniel & Sharifian, Neika. (2016). Lists of Emotional Stimuli. In Emotional Measurement, Herbert Meiselman, ed. pp.145-164.

Guillary SA, Bujarski KA. (2014) Exploring emotions using invasive methods: review of 60 years of human intracranial electrophysiology. *Soc Cogn Affect Neurosci.* 2014 Dec;9(12):1880-9. Accessible at https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4249472/

Hagemann, D., Naumann, E., Becker, G., Maier, S., & Bartussek, D. (1998). Frontal brain asymmetry and affective style: A conceptual replication. *Psychophysiology*, *35*(4), 372-388.

Hagemann, D., Naumann, E., Thayer, J. F., & Bartussek, D. (2002). Does resting electroencephalograph asymmetry reflect a trait? An application of latent state-trait theory. *Journal of personality and social psychology*, *82*(4), 619.

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

Hajcak, G., & Olvet, D. M. (2008). The persistence of attention to emotion: brain potentials during and after picture presentation. *Emotion*, *8*(2), 250.

Harley, Carolyn W. (1987) A role for norepinephrine in arousal, emotion and learning: Limbic modulation by norepinephrine and the Kety hypothesis. *Prog. Neuro-Psychopharmacol. & Biol. Psychiat.* 1987, 11: 419–458.

Hensley, JG. (2010) Serotonin in Mood and Emotion Handbook of Behavioral Neuroscience Volume 21, 2010, Pages 367-378.

Hosseini, S. A., & Naghibi-Sistani, M. B. (2011). Emotion recognition method using entropy analysis of EEG signals. *International Journal of Image, Graphics and Signal Processing*, *3*(5), 30.

Kaplan, D. (2008). *Structural equation modeling: Foundations and extensions* (Vol. 10). Sage Publications.

Keil, A., Bradley, M. M., Hauk, O., Rockstroh, B., Elbert, T., & Lang, P. J. (2002). Large-scale neural correlates of affective picture processing. *Psychophysiology*, *39*(5), 641-649.

Kock, N. (2010). Using WarpPLS in e-collaboration studies: An overview of five main analysis steps. *International Journal of e-Collaboration (IJeC)*, *6*(4), 1-11.

Kortelainen, J., & Seppänen, T. (2013, July). EEG-based recognition of video-induced emotions: selecting subject-independent feature set. In *2013 35th annual international conference of the IEEE engineering in medicine and biology society (EMBC)* (pp. 4287-4290). IEEE.

Kurdi B, Lozano S, Banaji M. R. (2017) Introducing the Open Affective Standardized Image Set (OASIS). *Behav Res Methods*, 49(2):457-470. doi:10.3758/s13428-016-0715-3.

Lang, P.J., Bradley, M.M., & Cuthbert, B.N. (2008). *International affective picture system (IAPS): Affective ratings of pictures and instruction manual. Technical Report A-8.* University of Florida, Gainesville, FL.

Larsen, R. J. (1984). Theory and measurement of affect intensity as an individual difference characteristic. Dissertation Abstracts International, 85, 2297B. (University Microfilms No. 84-22112)

Larsen, R. J. & Diener E. (1987) Affect intensity as an individual difference characteristic: a review. *Journal of Research in Personality* 21(1):1-39.

Lopez-Calderon, J., & Luck, S. J. (2014). ERPLAB: An open-source toolbox for the analysis of event-related potentials. Frontiers in human neuroscience, 8, 213.

MacLean, P.D. (1952). "Some psychiatric implications of physiological studies on frontotemporal portion of limbic system (visceral brain)". *Electroencephalogr Clin Neurophysiol.* 1952 Nov;4(4):407-18.

Mayer, J. D., & Salovey, P. (2007). *Mayer-Salovery-Caruso emotional intelligence test*. Toronto: Multi-Health Systems Incorporated.

McIntosh, A. (2018). Neurocognitive Aging and Brain Signal Complexity. *bioRxiv*, 259713.

McIntosh, A. R., Kovacevic, N., & Itier, R. J. (2008). Increased brain signal variability accompanies lower behavioral variability in development. *PLoS computational biology*, *4*(7), e1000106.

Mehrabian, A. (1980). *Basic dimensions for a general psychological theory: Implications for personality, social, environmental, and developmental studies*. Cambridge, MA: Oelgeschlager, Gunn & Hain.

Michalopoulos, K., & Bourbakis, N. (2017, February). Application of multiscale entropy on EEG signals for emotion detection. In *2017 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)* (pp. 341-344). IEEE.

Mocaiber, I., Pereira, M. G., Erthal, F. S., Machado-Pinheiro, W., David, I. A., Cagy, M., ... & de Oliveira, L. (2010). Fact or fiction? An event-related potential study of implicit emotion regulation. *Neuroscience Letters*, *476*(2), 84-88. Polich, J., Updating P300: An integrative theory of P3a and P3b, Clinical Neurophysiology, Volume 118, Issue 10, 2007, Pages 2128-2148, ISSN 1388-2457, https://doi.org/10.1016/j.clinph.2007.04.019.

Morgane PJ, Galler JR, Mokler DJ (2005). "A review of systems and networks of the limbic forebrain/limbic midbrain". *Progress in Neurobiology*. 75 (2): 143–60.

Müller, M. M., Keil, A., Gruber, T., & Elbert, T. (1999). Processing of affective pictures modulates right-hemispheric gamma band EEG activity. *Clinical Neurophysiology*, *110*(11), 1913-1920.

Papez, JW. (1937). "A proposed mechanism of emotion. 1937". *J Neuropsychiatry Clin Neurosci*. 7 (1): 103–12. Accessible at https://neuro.psychiatryonline.org/doi/abs/10.1176/jnp.7.1.103 .

Richman, J. S., & Moorman, J. R. (2000). Physiological time-series analysis using approximate entropy and sample entropy. *American Journal of Physiology-Heart and Circulatory Physiology*, *278*(6), H2039-H2049.

Salovey, P., Mayer, J. D., Goldman, S. L., Turvey, C., & Palfai, T. P. (1995). Emotional attention, clarity, and repair: Exploring emotional intelligence using the Trait Meta-Mood Scale..

Schmidt, B. Hanslmayr, S. Resting frontal EEG alpha-asymmetry predicts the evaluation of affective musical stimuli, Neuroscience Letters, Volume 460, Issue 3, 2009, Pages 237-240, ISSN 0304-3940, https://doi.org/10.1016/j.neulet.2009.05.068.

Schupp, H. T., Cuthbert, B. N., Bradley, M. M., Cacioppo, J. T., Ito, T., & Lang, P. J. (2000). Affective picture processing: the late positive potential is modulated by motivational relevance. *Psychophysiology*, *37*(2), 257-261.

Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal*, *27*(3), 379-423.

Sleimen-Malkoun, R., Perdikis, D., Müller, V., Blanc, J. L., Huys, R., Temprado, J. J., & Jirsa, V. K. (2015). Brain dynamics of aging: multiscale variability of EEG signals at rest and during an auditory oddball task. *Eneuro*, *2*(3).

Sohaib, A. T., Qureshi, S., Hagelbäck, J., Hilborn, O., & Jerčić, P. (2013, July). Evaluating classifiers for emotion recognition using EEG. In *International conference on augmented cognition* (pp. 492-501). Springer, Berlin, Heidelberg.

Soto C. J. & John O. P. (2017) The next Big Five Inventory (BFI-2): developing and assessing a hierarchical model with 15 facets to enhance bandwidth, fidelity, and predictive power. *J Pers Soc Psychol.* 113(1):117-143.

Soto C. J. & John O. P. (2017) Short and extra-short forms of the Big Five Inventory-2: The BFI-2-S and BRI-2-XS. *Journal of Research in Personality*, 68:69-81.

Takahashi, T., Cho, R. Y., Mizuno, T., Kikuchi, M., Murata, T., Takahashi, K., & Wada, Y. (2010). Antipsychotics reverse abnormal EEG complexity in drug-naive schizophrenia: a multiscale entropy analysis. *Neuroimage*, *51*(1), 173-182.

Tonoyan, Y., Looney, D., Mandic, D. P., & Van Hulle, M. M. (2016). Discriminating multiple emotional states from EEG using a data-adaptive, multiscale information-theoretic approach. *International journal of neural systems*, *26*(02), 1650005.

Walter, W. Grey; Cooper, R.; Aldridge, V. J.; McCallum, W. C.; Winter, A. L. (July 1964). "Contingent Negative Variation: An Electric Sign of Sensori-Motor Association and Expectancy in the Human Brain". *Nature*. 203 (4943): 380–384.

Watson, D., & Clark, L. A. (1992). On traits and temperament: General and specific factors of emotional experience and their relation to the five-factor model. *Journal of personality*, *60*(2), 441-476.

Wheeler, R. E., Davidson, R. J. and Tomarken, A. J. (1993), Frontal brain asymmetry and emotional reactivity: A biological substrate of affective style. Psychophysiology, 30: 82-89. doi:10.1111/j.1469-8986.1993.tb03207.x