Summary of Data Analysis for Physiological Measures of the CoBALT Connects Expressing Vibrancy Project

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Introduction

The Expressing Vibrancy Project conducted at the McMaster LIVELab aimed to use quantitative measures to help define 'vibrancy' and its implications in future cultural plans. This study included ratings on tablets as well as the measurement of physiological indices in a subset of the participants. We collected the physiological data while participants watched a series of eight video tours of Hamilton areas. In order to measure what our participants thought about the videos, we used a measure of brain activity called electroencephalography (EEG).

Communications between neurons (the cells that make up gray matter in the brain) underlies all human thought. Neurons communicate through tiny electrical currents. Each of these electrical currents is very small, but when groups of neurons are communicating together, they create electrical potentials that are large enough to be measured on the surface of the scalp, a measurement that is called electroencephalography or EEG. In each of our test sessions, we placed an EEG cap containing seven sensors on the head of each of ten participants. The sensors were connected with long wires to EEG amplifiers, which recorded the signals.

In addition to EEG, we also used a number of other measures to infer how people felt while watching the video clips. These measures included Heart Rate (the number of beats the heart makes per minute), Breathing Rate (the number of breaths a person takes per hour), and a measurement derived from the variability of the heartbeat, called LF:HF (the ratio of sympathetic activation of the heart to parasympathetic, detailed later).

Combining all these measures, we hoped to provide greater insight into the definition of vibrancy from real citizens that extended beyond the typical survey data that has historically been available.

Data Collection and Initial Analysis

Encephalography (EEG)

EEG signals on the surface of the scalp are very weak - they are usually measured in microvolts, which are millionths of a volt (for comparison an AA battery generates 1.5 volts). Since the signals are so small, it is easy for them to be overwhelmed by sources of interference, for example poor electrode connections, movements of the participants, even excessive eyeblinks. Each of these is many tens or hundreds of times larger than an actual brain signal. These interfering signals are called EEG artifacts. Our first task was to search through the recorded data for artifacts. If a participant had too many artifacts, we eliminated their data from analysis. Out of the 78 participants from whom we measured EEG, 50 participants passed the first test and their data was examined in more detail (See Figure 1 for a sample of artifact-contaminated data; See Figure 2 for a sample of cleaned data). This rate of artifact in EEG data is typical for studies of this kind.

Even after eliminating the noisiest data, it is unavoidable that some artifacts still exist in the EEG data – after all everyone has to blink from time to time! Therefore, the second step in the data analysis is to go through the EEG recorded during each three minute long video and select out the segments that are completely free from any artifact. This is done by a computer algorithm that scans the data for artifact signatures and removes them when it finds them. After this, we are left with 50-80% of the original data for each participant.

Heart Rate

The heart is a very powerful electrical muscle, and the electrical current it produces is also measurable on the surface of the body, similar to EEG potentials. As the heart beats, it polarizes and depolarizes in a stereotypical way, which, when plotted, gives us the iconic heart rate pattern that most people are familiar with. However, one's heart rate is not constant over time. Heart rate changes depending on the situation, one's emotions, one's feelings, etc.

Applying this to the experiment, we collected participants' heart rates over time while they watched each of the eight video clips to determine if watching the clips affected their heart rates. We did so by applying a gel-padded electrode to each participant, on his or her V5 line near the left pectoral muscle. This measure is also referred to as an electrocardiogram (ECG). Similar to EEG, occasionally a participant's data needs to be removed if there are too many artifacts in the recording. A similar algorithm to that used for EEG is used to filter the ECG data, and after filtering, we were left with 50 participants whose data we could analyze. We can examine different aspects of heart rate, as described in the next section.

Heart Rate Variability (HRV)

Even though two participants may have the same heart rate of 60 beats per minute, they may, in fact, have a completely different pattern of beating because the time between each heartbeat may not be consistent. The time between two successive heartbeats represents the inter-beat interval (IBI). The changes across time in these IBIs is referred to as Heart Rate Variability (HRV). HRV can be analyzed in the frequency domain to provide a measure of the effects of the autonomic nervous system on the heart. These effects come from two independent branches of the autonomic nervous system – the sympathetic and parasympathetic branches, which are both responsible for your involuntary responses. The parasympathetic branch becomes more active when you are calm and relaxed, signaling your body that it can do the kinds of things that are appropriate when you are not in danger, such as sleep or digest your last meal. The sympathetic branch becomes active when you are nervous or in danger, releasing adrenaline and preparing your body for an emergency action. Your actual state at any given time is a function of the balance of the activation of these two branches.

Low Frequency (LF) heart rate variability represents the cumulative effects of both the parasympathetic (rest and digest) and sympathetic (fight or flight) nervous systems. High Frequency (HF) heart rate variability represents the effects of only the parasympathetic nervous system. Since the LF:HF is the ratio of these measures, some elementary math shows that it provides a measure of the sympathetic nervous system. This means that the LF:HF ratio could be a measure of how excited or aroused a participant is as a result of what they are doing/watching. HRV measures were extracted from our inter-beat interval data using a computer algorithm.

Breathing Rate (BR)

Breathing rate was measured from the respiratory sinus arrhythmia (RSA), which is a signal contained in the ECG (heart) rate measure. The ECG signal fluctuates as a result of an individual's breathing. Therefore, as one breathes in and out, there is a measureable fluctuation in heart rate that can be calculated and analyzed, allowing us to measure exactly how fast one's breathing is over a given period of time.

Similarly to HRV, a computer algorithm extracts this information from the recorded ECG signal for later analysis.

Data Reduction and Further Analysis

Encephalography (EEG)

When recording EEG, we measure the voltage at each of the seven electrodes 512 times each second. Therefore, over the 24 minutes that the participant is watching the videos, we collect about 5.1 million points of data, or 250 million points altogether for all 50 participants. As you can see from the figure showing the 'clean' data (Figure 2), there is not a lot that you can learn by just looking at the raw EEG data about what a person might be thinking or feeling. Our next task, then, is to perform data reduction, to transform the millions of raw points of data into only a few numbers that we can use to compare the responses to the different videos.

There are generally two different methods for reducing EEG data: Event Related Potentials (ERP) and Spectral Activity. ERP analyses are best suited to very short stimuli of under 1 second that are repeated many tens or hundreds of times. The spectral analysis characterizes EEG in terms of rhythmic activity across different frequency bands. Usually we examine five different bands: delta (1-4Hz), theta (4-8Hz), alpha (8-14Hz), beta (14-25Hz), and gamma (25-35Hz). The spectral activity analysis is more appropriate for the present data.

What we look at is the amount of EEG power in each band. In 'healthy'/'normal' brains, increased power in the lower bands (delta, theta, alpha) is generally associated with sleep, drowsiness, or relaxation. The power in these bands will decrease as a person becomes more engaged or aroused. Power in the higher bands (beta, gamma) increases during certain tasks that require more concentration.

For our data analysis we examined the EEG power people generated to each different video (8) for each electrode (7), dividing the EEG power up into each frequency band (5). Across the 50 participants, this reduces our 250 million data points into 8x7x5x50 points (Videos x Electrodes x EEG frequency bands x Participants) or 14,000 data points. These will then be further reduced by taking the mean across the 50 subjects, leaving us with only 280 data points to interpret.

The results of the analysis on the three lower bands were very similar, and are shown in Figure 3. Each street video has a different position along the X-axis (horizontal), using the following order, which was the order in which the videos were presented:

1. Barton
2. Concession
3. Dundas
4. James
5. Locke
6. Ottawa
7. Waterdown
8. Westdale

It is immediately obvious that there are different amounts of power in these bands for each video. We analyzed this for the three lower bands and found differences across the videos in each band ($p<0.001$ for delta, $p=0.001$ for theta, $p=0.013$ for alpha).

It appears that (similar to heartrate; see next section) there is a rising trend to the power in these bands across the videos. This is a significant linear trend for both delta and theta, and probably means that our participants were becoming more relaxed as the videos progressed, which would make perfect sense.

However, it is also evident that this general trend is interrupted in all three bands analyzed for videos 3 (Dundas St.) and 6 (Ottawa St.). Both have decreases in power below the rising trend. This result is supported by the significance of the higher order trends (quadratic and above) in all three bands, indicating that there is a significant deviation from the linear trend. A decrease in power for these two videos indicates that there is something in them that somehow aroused or engaged the participants more than the other videos. There are of course many different elements in the videos that could be responsible for this effect and it is impossible to say without further experimentation what in particular caused the participants to become more engaged for these two videos.

For the higher EEG bands there was no statistical effect of video presentation on the EEG power; however there was a significant two way interaction between electrode and video.

What this essentially means is that although the total amount of power in all the electrodes did not change significantly from video to video, the pattern of power across the electrodes did change from one video to the next. Studying Figure 4, which shows the beta and gamma power, it is not clear that these changes were isolated to videos 3 and 6, so the effect we are looking at may not be the same effect that is evident in the lower bands. Figure 5 shows how the power is distributed across the scalp for the delta band, separately for each video. The pattern of distribution is the same for each video but the amount of power changes for each video, generally increasing but with exceptions for videos 3 and 6. In Figure 6, we show the same plot but for the beta power band – here we see no differences in total power between the videos, but there is a subtle change in the way the power is distributed across the scalp between videos that is difficult to detect just by looking at the graph but is being picked up by the statistical analysis. Again, further experimentation would be required to figure out exactly what is causing this effect.

Heart Rate (HR)

After the Heart Rate (HR) was collected and filtered, we tested the averages for statistical significance using a One-Way Repeated Measures ANOVA. This initially showed a highly significant result ($F(7,343)=4.181$; $p<0.01$) which indicates that the mean heart rates differ between videos; however, this analysis also showed a significant linear trend ($p=0.005$; See Figure 7) which we speculate may have been the result of participants becoming tired or more relaxed over the course of the study, just as we found with the EEG data. One way to handle this is to mathematically 'remove' the linear trend from the data. After this linear trend was removed, the ANOVA was repeated and the indications of a difference in mean heart rates between neighborhoods remained ($F(7,343)=1.779$; $p=0.091$; See Figure 8), but was no longer quite statistically significant, indicating that different streets might not have had strong effects on HR.

Individual streets were then compared by repeated paired t-tests (see Figure 9). The table shows the p-value (significance) of the respective t-tests. When considered in isolation, values below 0.05 mean that the means were significantly different from each other and this difference was unlikely to have happened by chance. Values above 0.05 indicate that the means are likely not significantly different for that pair. For example, the mean heart rate was significantly different between Locke and Ottawa ($p=0.015$); however, the mean heart rate was not significantly different between Locke and Waterdown ($p=0.395$). Note that as this data is exploratory, and we did not correct for multiple comparison. If we had, then none of these differences would have reached conventional levels of significance.

There were no significant effects of income, age, sex, or ethnicity on mean heart rate trends.

Without more experiments, we can only speculate on the causes of these differences in heart rate across the videos. Short-term fluctuations in heart rate are mediated by autonomic arousal, potentially indicating some difference in stress levels for the participants while watching the videos. Familiarity with the neighbourhoods by the participants could also have affected their responses, by activating prior memories of the places.

Heart Rate Variability (HRV)

The means of the LF:HF ratios were tested for significance using a One-Way Repeated Measures ANOVA. The initial analysis showed that the differences in means between videos was near significance ($F(7,343)=1.815$; $p=0.083$; See Figure 10); however, this analysis also showed a highly significant linear trend ($p<0.01$), indicating that arousal increased over time. We speculate that this was likely due to fatigue or anxiety as the session progressed. After this linear trend was removed, the ANOVA was repeated. The effect of street was not significant ($F(7,343)=0.646$; $p=0.718$).

There were no significant effects of income, age, sex, or ethnicity on LF:HF trends.

Breathing Rate

The data is presented as the average number of breaths per second for a participant ($n=50$; See Figure 11). The means of the breathing rate data was tested to see if they differed significantly between videos using a One-Way Repeated Measures ANOVA. This showed that these means were very close to being significantly different between street videos ($F(7,343)=1.928$; $p=0.064$; $a=0.1$). Interestingly, unlike heart rate variability and heart rate, there was no linear trend for breathing rate change over the course of the experimental session.

Individual streets were then compared by repeated Paired T-Tests (see Figure 12). For example, the mean breathing rate was significantly different between Barton and James ($p=0.032$); however, the mean breathing rate was not significantly different between Barton and Ottawa ($p=1.00$). Again, because the data was exploratory, we did not correct for multiple tests.

In addition, there were no significant effects of income, age, sex, or ethnicity on mean breathing rates.

Conclusion

Overall, the analyses yielded a number of interesting results. Some reached conventional levels statistical significance, allowing us to make stronger statements about the data, while others showed trends, indicating that they are worth exploring in further research. An important conclusion is that responses to videos shown in this way can have measurably different physiological responses that are consistent across people. Entering this process, CoBALT Connects and the LIVELab team were not certain if this would be the case. While we cannot specifically determine exactly what factors caused the increased sense of engagement for certain videos from this data, the fact that the differences are measurable is very promising. This will allow us to ask further exploratory questions in continuing research on our quest to understand what makes a city ‘vibrant’.

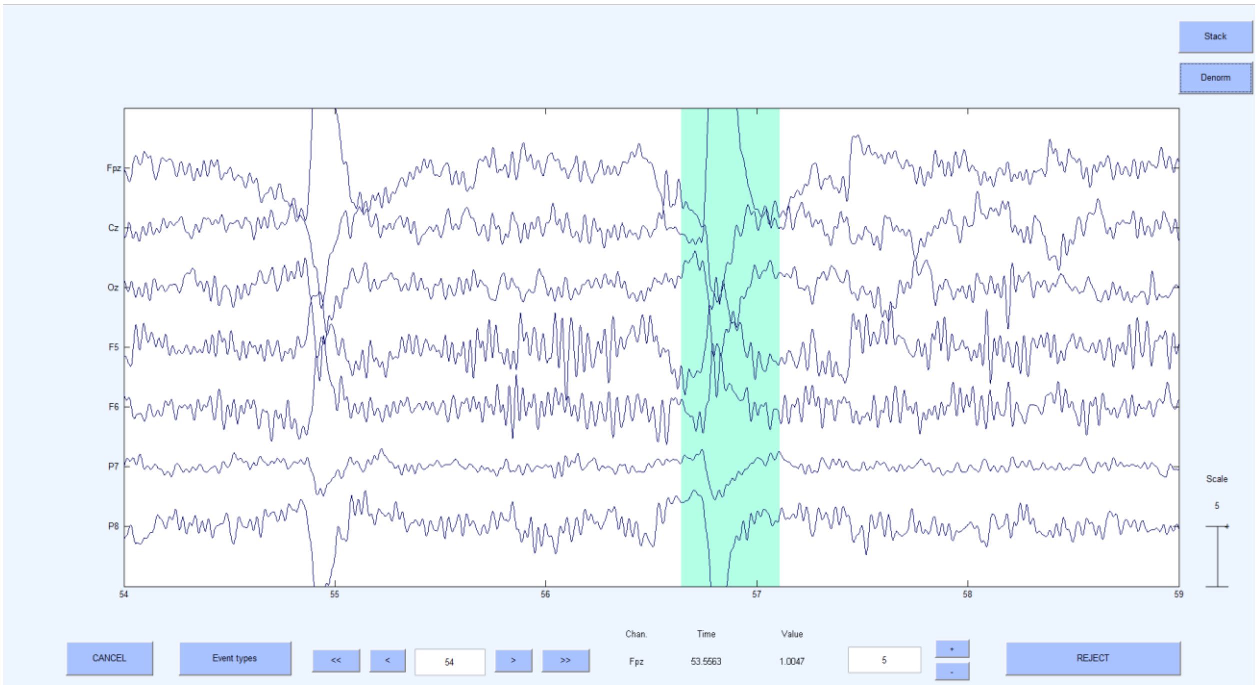

Figure 1: Sample of Noisy EEG Data (Highlighted sample is of an eyeblink)

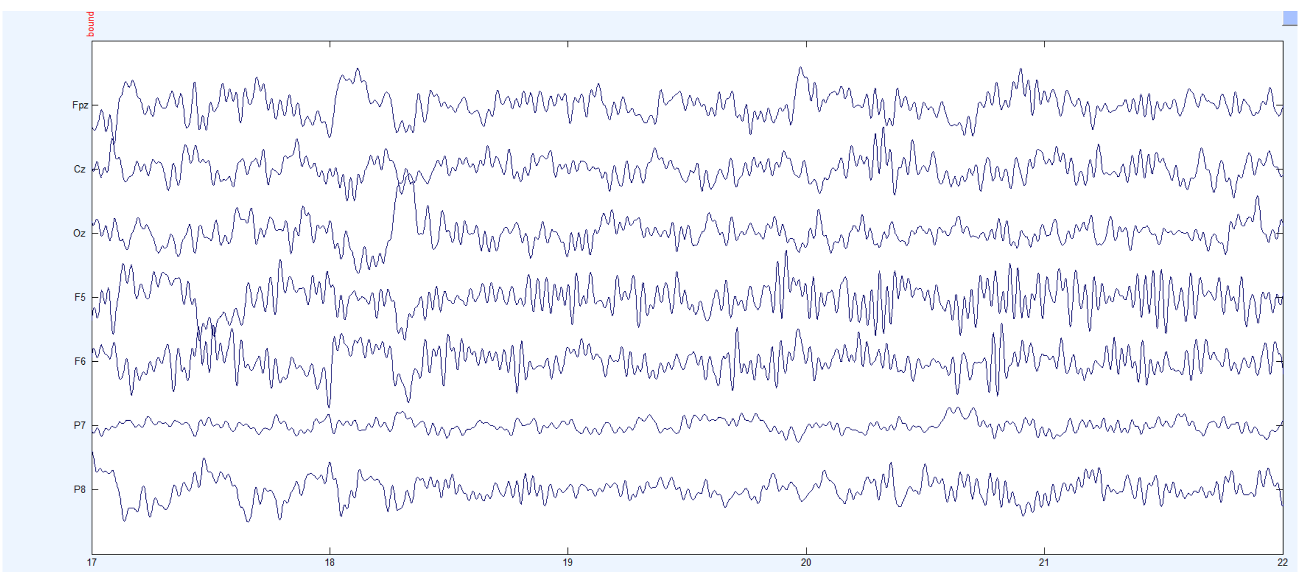

Figure 2: Sample of Cleaned EEG Data

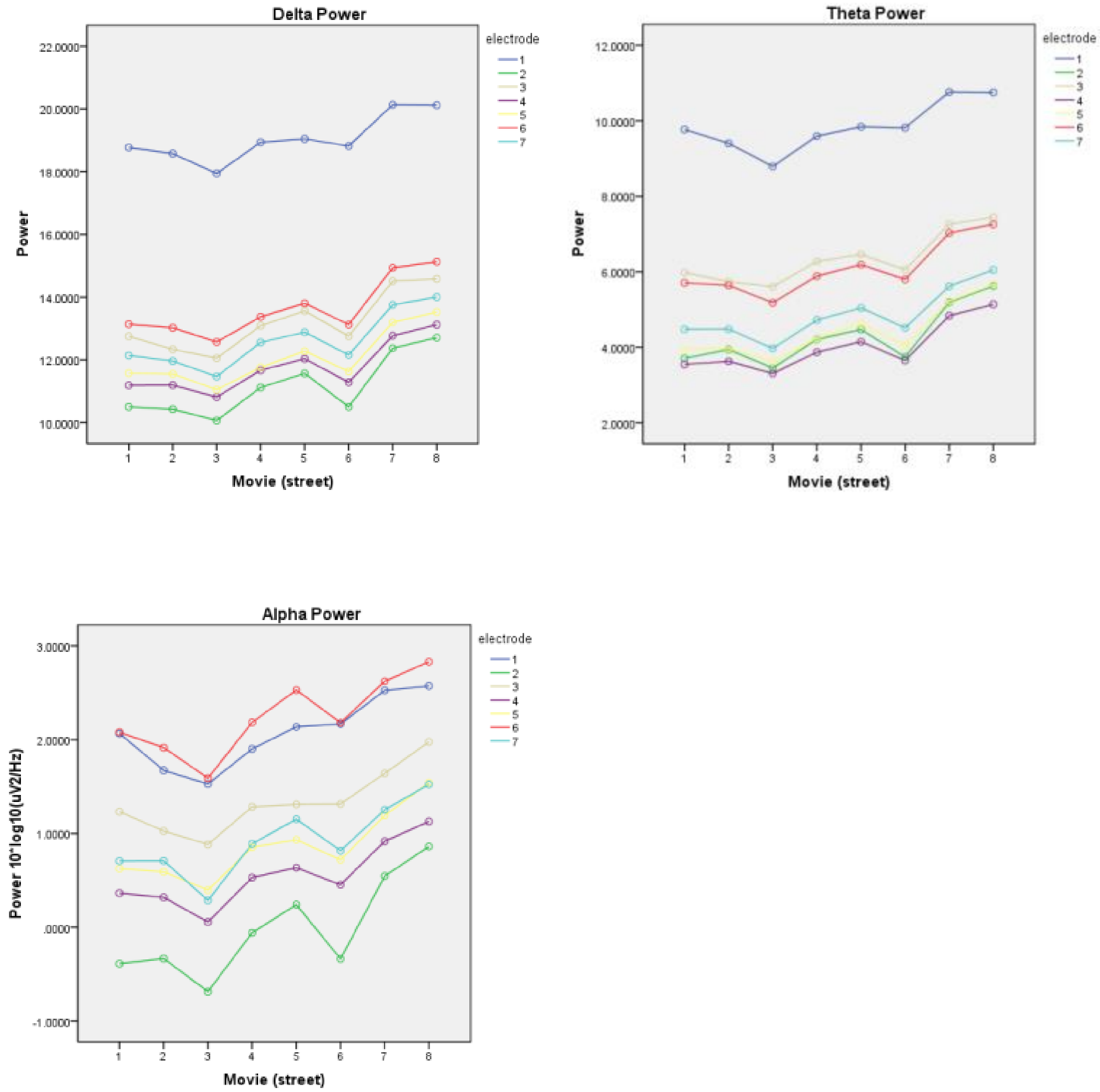

Figure 3: Power in the Lower EEG Frequency Bands (Delta, Theta, and Alpha)

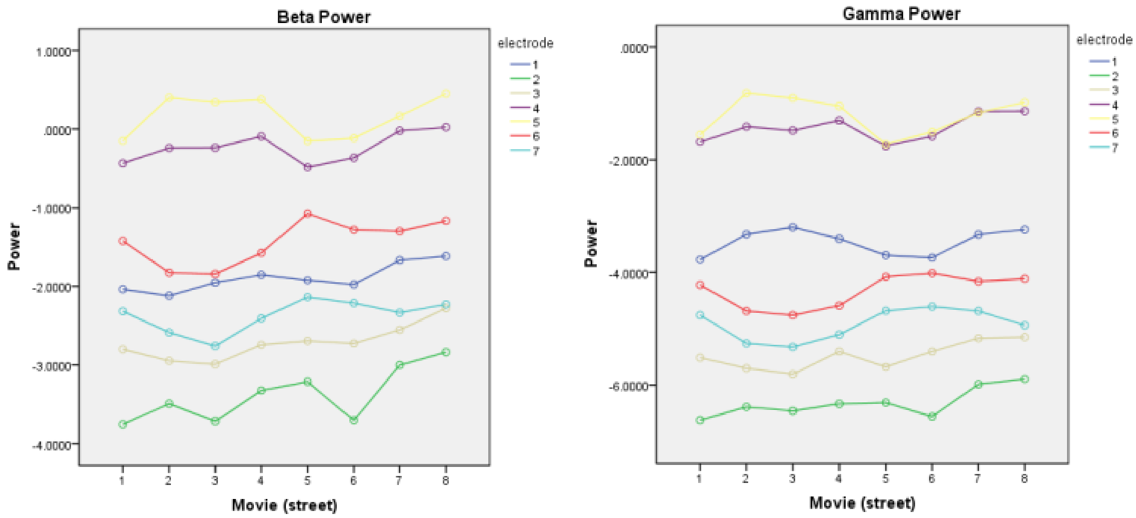

Figure 4: Power in the higher EEG frequency bands

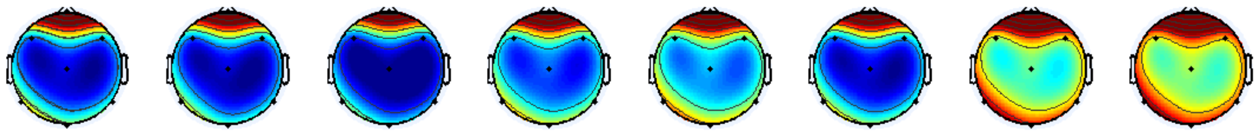

Figure 5: Scalp map of delta band power for the eight videos (Note the general trend for increasing power, except for movies 3 and 8, which show a reduction from the trend)

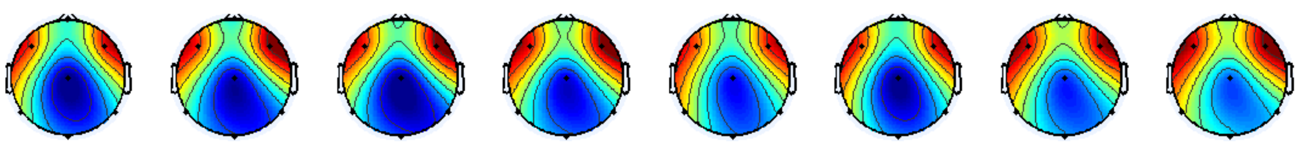

Figure 6: Scalp map of beta band power for the 8 movies (Note the power for all of the movies is about the same, but there is a subtle difference in how the power is distributed across the scalp between movies)

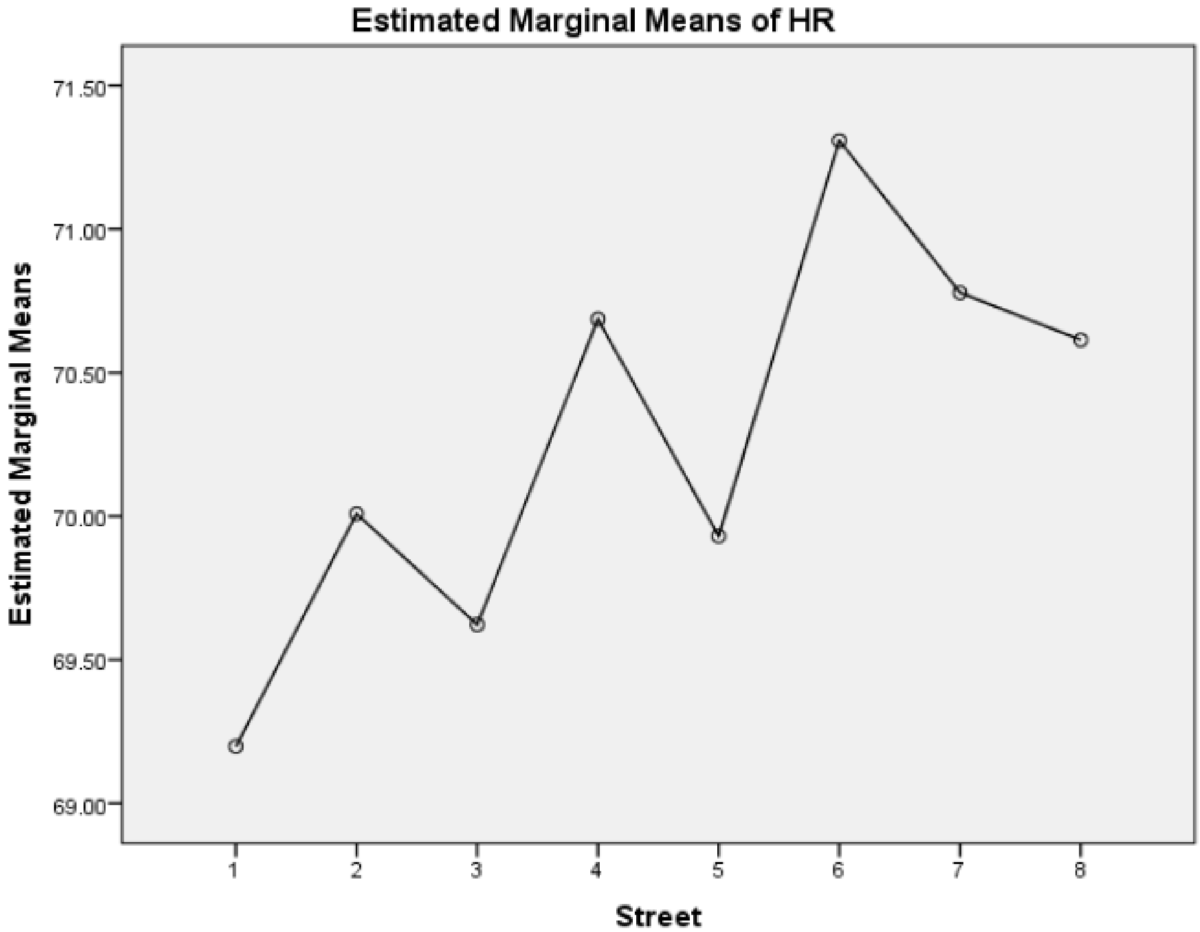

Figure 7: The Estimated Marginal Means of Heart Rate by Street – Pre-Normalization

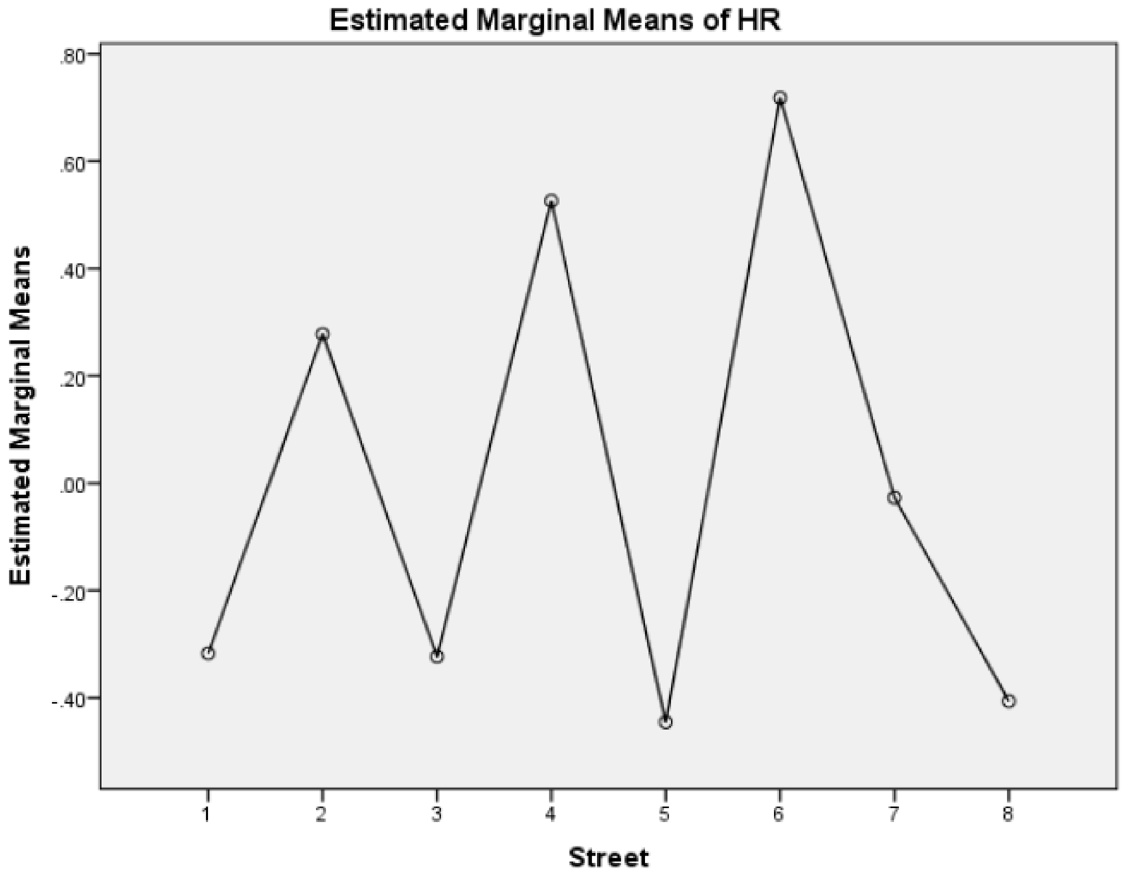

Figure 8: The Estimated Marginal Means of Heart Rate by Street - Normalized

Figure 9: P Values of Paired T-Tests - Average Heart Rate of Participants While Viewing City Streets

	Barton	Concession	Dundas	James	Locke	Ottawa	Waterdown	Westdale
Barton	X	0.213	0.99	0.215	0.741	0.077	0.636	0.883
Concession		X	0.046	0.572	0.082	0.372	0.497	0.139
Dundas			X	0.079	0.751	0.029	0.521	0.876
James				X	0.076	0.729	0.288	0.51
Locke					X	0.015	0.395	0.933
Ottawa						X	0.019	0.016
Waterdown							X	0.329
Westdale								X

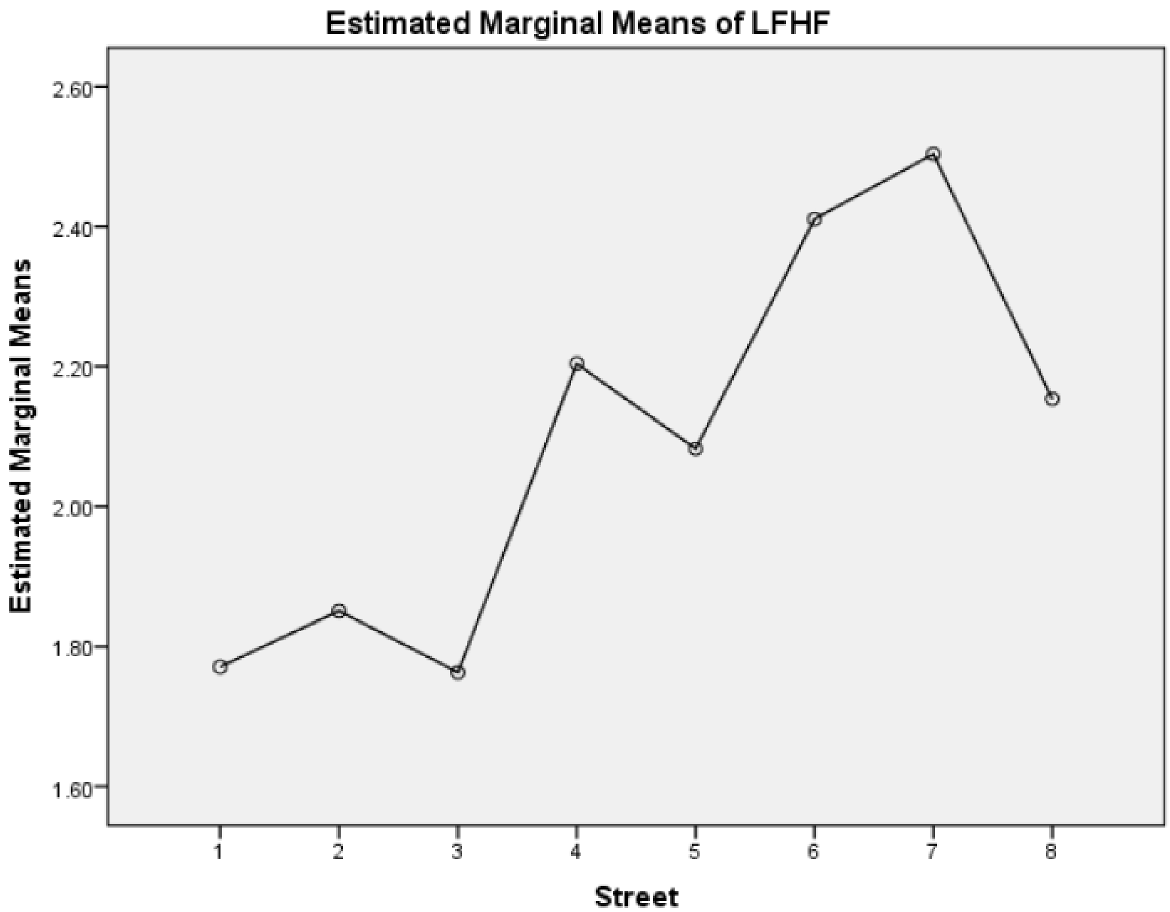

Figure 10: The Estimated Marginal Means of LF:HF by Street – Pre-Normalization (1-Barton, 2-Concession, 3-Dundas, 4-James, 5-Locke, 6-Ottawa, 7-Waterdown, 8-Westdale)

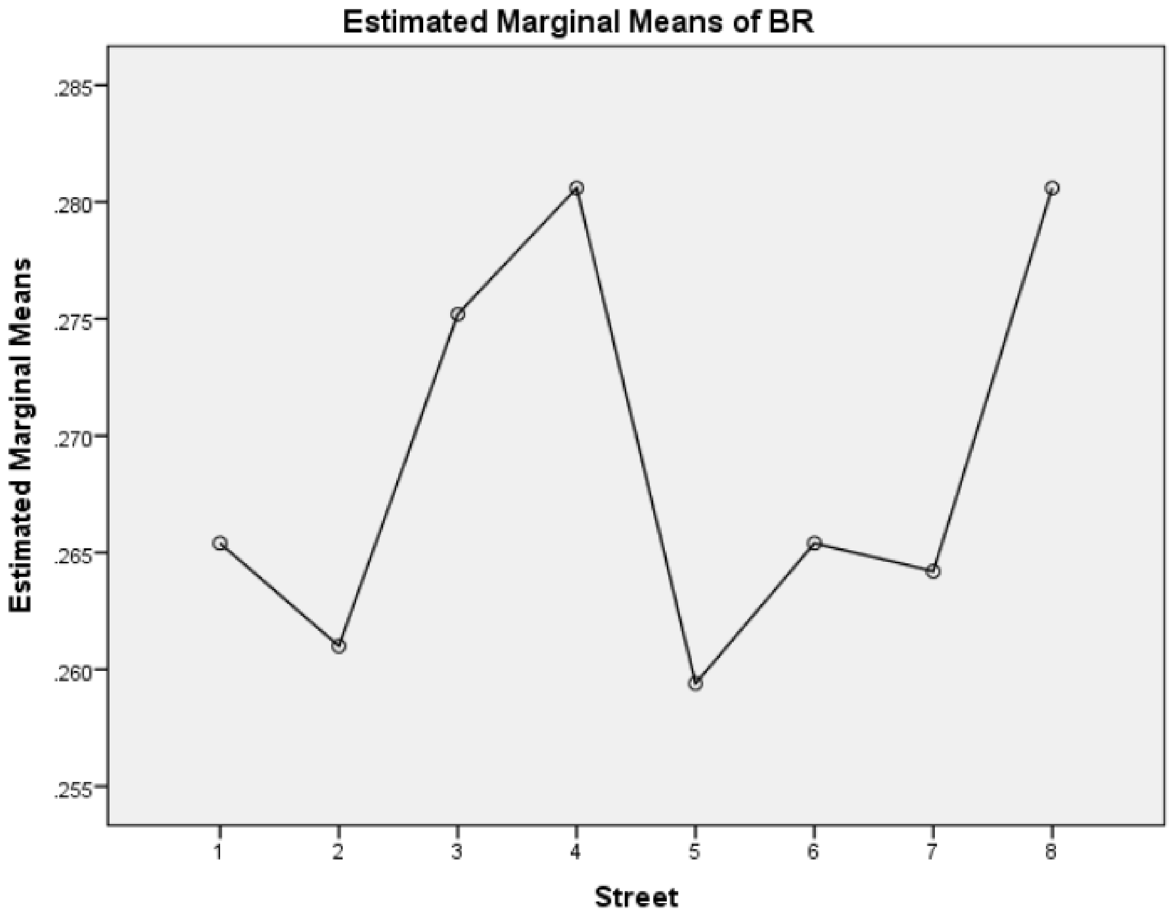

Figure 11: The Estimated Marginal Means of Breathing Rate by Street

Figure 12: P Values of Paired T-Tests - Average Breathing Rate of Participants While Viewing City Streets

	Barton	Concession	Dundas	James	Locke	Ottawa	Waterdown	Westdale
Barton	X	0.597	0.269	0.032	0.576	1	0.899	0.13
Concession		X	0.026	0.024	0.861	0.605	0.697	0.015
Dundas			X	0.43	0.081	0.134	0.205	0.493
James				X	0.053	0.063	0.081	1
Locke					X	0.536	0.57	0.048
Ottawa						X	0.899	0.087
Waterdown							X	0.04
Westdale								X