ABSTRACT

THE LATERALIZED READINESS POTENTIAL AS A NEURAL INDICATOR OF RESPONSE COMPETITION IN BINARY DECISION TASKS

by Mary E. Frame

Two experiments used the lateralized readiness potential (LRP) to establish a neurological basis for response competition between decisions involving subjective preferences. Affectively-valenced pictures and monetary gambles were used as stimuli in binary decision tasks in Experiment 1 and 2, respectively. The results of Experiment 1 provide evidence that the LRP is capable of measuring preparatory motor activity underlying the dynamic accumulation of subjective preference in the premotor cortex. The experiment revealed that there was more response competition that occurred when participants chose between stimuli with greater similarity as seen by a reduced amplitude LRP as well as a Gratton dip preceding the decision response. Contrary to our hypothesis, we did not see increased response competition when participants chose the riskier gamble. Future directions and proposals for improved methodology of Experiment 2 are discussed.

THE LATERALIZED READINESS POTENTIAL AS A NEURAL INDICATOR OF RESPONSE COMPETITION IN BINARY DECISION TASKS

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Table of Contents

List of Figures

List of Appendices

Introduction and Background

Some of the earliest models of decision making were developed by economists and sought to understand how humans choose subjectively optimal choice alternatives, known as normative models of decision making. Although these normative models provided the foundation of studies of decision making, eventually it was realized that humans often make decisions in a manner which is suboptimal (Johnson & Busemeyer, 2010). In response to the shortcomings of normative models, descriptive models were developed to better capture how people actually make decisions rather than modeling how they should make decisions. Descriptive models simply attempt to predict final choices without specifying the underlying cognitive processes. Although descriptive models were initially useful in stimulating early research and provided an explanation of many real world decisions, they were insufficient to account for several perplexing phenomena and did not offer insight into the process of stimulus perception and evaluation that lead to the chosen option. For example, descriptive models historically have been unable to fully account for reversals in preference elicitation (Johnson & Busemeyer, 2005) as well as accounting for the similarity, attraction and compromise effects observed in multiattribute and multialternative decisions (Roe, Busemeyer, & Townsend, 2001).

In recent years there has been increased focus on computational models of decision making. These models attempt to improve upon the foundation of research set up by normative and descriptive models of decision making. One of the defining characteristics of these models is that they focus on the motivational, affective, cognitive, and neural processes that are involved from the time choice stimuli are presented to the time a person makes a decision (Johnson & Busemeyer, 2010). Models such as Decision Field Theory (DFT) recognize that, rather than coming to an instantaneous choice when stimuli are presented, people evaluate components of information and combine these pieces of information about the options over time and accumulate preference until a decision threshold has been met, at which point a decision will be made. By examining the cognitive processes that lead ultimately to a decision and structuring models accordingly, process models have increased predictability over previous decision making models. Thus, modeling the cognitive processes allows computational models to overcome the limitations of previous normative and descriptive models of decision making.

Indirect evidence was the basis for making inferences about the underlying cognitive processes in early studies using computational models. According to DFT, for example, the decision threshold is an internal criterion that governs the quantity of evidence that is dynamically accumulated. The decision threshold can be manipulated indirectly through instructions that emphasize how quickly or accurately participants make their decisions. The threshold is adjusted according to the importance of the decision and the urgency with which the decision must be made. The decision threshold is lowered when the instructions emphasize the importance of making a quick decision. Lowering the decision threshold allows the decision to be made quickly with less evidence. At the behavioral level, there is a simultaneous reduction in reaction time and accuracy. By contrast, the opposite effect occurs when instructions emphasize the importance of making an accurate decision. Raising the decision threshold requires the accumulation of more evidence and increases accuracy and reaction time as a result.

More recently, there has been a concerted effort to measure the cognitive processes more directly using process tracking (Johnson, Schulte-Mecklenbeck, & Willemsen, 2008). Process tracing methods are direct measures that have been employed to a better understanding the cognitive processes underlying decision making (Rosenbaum, 2005). For example, eye and mouse tracking have been employed to explore how people obtain and utilize information about choice alternatives in real time (Franco-Watkins & Johnson, 2011; Krajbich, Armel, & Rangel, 2010. However, looking at dynamic movements has helped researchers better understand the cognitive processes that drive them by using a more direct measure. Response dynamics has been used to track the dynamic accumulation of preference that is embodied in the trajectory of one's arm movement towards the decision options. Movement is continually updated by cognitive processes over time, potentially making movement tracking an excellent way of studying dynamic cognitive processing en route to an overt behavioral response (Goodale, Pelisson, & Prablanc, 1986).

Many process tracing techniques rely on the assumption that cognition consists of continuous neuronal process that overlap and co-occur with each other (Spivey & Dale, 2006). In particular, the response dynamics methodology postulates that cognitive processing stages are continuous and that the brain continually sends processed perceptual information to future stages of processing housed in attentional and motor areas of the brain. This assumes that over time preference can accumulate and be updated as a motor response is prepared and even activated and reversals in preferences can be elucidated as a participant moves to a decision outcome. New information can be perceived and processed after a motor response has begun and can continue to change and shape motor activations as new information is evaluated. This is referred to as continuously cascading processing (Freeman & Ambady, 2009). This processing flows gradually into motor outputs as opposed to accumulating in separate processing stages and collapsing before motor activation occurs (Dale, et al., 2007). Tracking responses throughout the decision process provides greater resolution than traditional measures, such as reaction time. Unlike reaction time, the response trajectory in mouse tracking reveals moment-to-moment changes in preference. A linear trajectory is indicative of strong preference for the chosen alternative, whereas a curvilinear trajectory is indicative of response competition.

Methods for examining continuous movements such as arm movement tracking and mouse tracking have been used to study a variety of cognitive phenomena, including, but not limited to, language processing (Spivey & Dale, 2006), categorization of visual stimuli (Dale, Kehoe, & Spivey, 2007), gender and race categorization (Freeman, Ambady, Rule, & Johnson, 2008; Freeman, Ambady, Midgley, & Holcomb, 2011), gender related stereotyping (Freeman & Ambady, 2009), and implicit preferences in decision making (Koop & Johnson, 2013). These methods have also been used to look at information acquisition processes in decision making (Franco-Watkins & Johnson, 2011) as well as dynamically indicate subjective preferences (Koop & Johnson, 2012) including competition among choice options and even reversals in preference (Koop & Johnson, 2011). It has also been established in previous literature that motor systems do not reflect discretely completed cognitive processes but are involved in the decision making process itself (Song & Nakayama, 2009).

An important methodological bridge between response dynamics and cognitive neuroscience needs to be formed in order to test the assumption that motion is an embodiment of a continuous flow of processing in the brain while a stimulus is being evaluated. One way to form this bridge is to directly measure preparatory motor activity via electroencephalography (EEG), which measures aggregate neural activity of electromagnetic scalp potentials in high temporal resolution. Perhaps the most direct neurological marker of preparatory motor activity is the lateralized readiness potential (LRP). This methodology was successfully used by Freeman et al. (2011) to demonstrate continuous perceptual and motor processing in social categorization tasks. Because of EEG's superb temporal resolution it is optimal to use this technology to examine cognitive activities in decision tasks since these processes often occur over the course of milliseconds. Although the scope of this initial project is merely to examine the motoric activity associated with the cognitive processing underlying preferential choice, information gleaned from these studies may be subjected to further analyses by examining perceptual or attentional activation throughout the decision process. Due to the high degree of temporal resolution, we used EEG in the two experiments reported below to record the preparation of motor activity in the brain. Dense array EEGs (between 128 and 256 channels) also provide a greater dispersion of electrodes and allow for excellent spatial resolution as well (Ryynanen, Hyttinen, Laarne, & Malmivuo, 2004).

As stated above, we will be using EEG to examine the neural underpinnings of preferential choice. EEG measures changes in electromagnetic fields on the scalp generated by ensembles of neurons. In cognitive neuroscience one common approach to understanding cognition as it relates to different trial types is to examine time locked averaged waveforms called event related potentials (ERPs) (Luck, 2005). ERPs measure changes in electrical activity in brain tissue; these changes occur as a result of a specific event, whether caused by an external stimulus or an internal cognitive event (Luck, 2005). An ERP is constructed by averaging EEG data across segments of trials that have a time locked relationship to a measured event such as the stimulus or response onset. This serves to cancel out random EEG noise that is not part of the neural and cognitive activity pertaining to the task (Fabiani, Gratton, & Federmier, 2007). In general, ERPs have a much smaller peak (a few microvolts) when compared to raw EEG data (tens of microvolts) since they involve extricating the signal (brain activity during a specific cognitive process) from the noise (other electrical activity in the brain involved in separate functions) (Fabiani, Gratton, & Federmeier, 2007). A particular strength of this type of research for studying cognitive processes is that ERPs provide a continuous measurement of brain activity while the specific cognitive activity of interest is occurring (Eimer, 1998). In contrast, reaction time measures or accuracy measures only gauge the accumulation or the discrete outcomes of cognitive processes.

The lateralized readiness potential (LRP) is a specific type of ERP that represents a preparatory motor response in the hemisphere contralateral to the hand of response movement or planned response movement (Smulders & Miller, 2011). These potentials are recorded at cortical areas involved with controlling finger movement known as C3' and C4' since they are very near C3 and C4 on an international 10-20 system electrode map (Jasper, 1958). It should be noted that an actual motor response is not required in order for an LRP to occur. However, LRPs preceding an overt response have higher amplitudes than LRPs where a response is withheld (Smulders & Miller, 2011). The hemisphere contralateral to the hand of response produces a greater level of premotor activation compared to the ipsilateral hemisphere which still produces neural activity, but to a lesser degree. This dominance of the contralateral hemisphere is not complete but rather is proportionally more dominant than ipsilateral hemispheric activation (Miller, 2007). The LRP examines hemispheric activation relative to one another but is unable to isolate the activation of either hemisphere individually. If an experiment is properly constructed though, the subtractive calculation of the LRP effectively removes all nonlateralized generic activity, making it a pure measure of motor cortex activation. Additional details and specific calculations for the LRP are included in Appendix D.

Certain qualities of the lateralized readiness potential indicate competitive pull between response options. A lower amplitude LRP is indicative of a greater degree of competition between the chosen and alternative option at the time the decision is made. When an alternative response is strongly primed or activated, there may be a negative dip, known as a Gratton dip immediately following the stimulus onset. Generally, this Gratton dip only occurs when a participant accumulated enough preference for the eventually foregone alternative that they have a premotoric response to choose that option. A Gratton dip is largely indicative that the foregone alternative was nearly the chosen one and only occurs when response competition is particularly strong (Gratton, et al. 1988). The magnitude of the Gratton dip and timing of the overt response wave in previous literature have been interpreted as indicators of the strength of response competition. Most often this is seen with reaction time tasks involving a correct response and a competing incorrect response. However, there is a significant gap in this literature since previous studies of the LRP have not examined this response competition in cases of preferential choice.

Response latency with LRP depends strongly on the level of competition between possible responses. Longer latencies occur when responding to stimuli between which there is a great deal of competitive pull (Coles et al., 1985). The final response is delayed due to the mutual inhibition of concurrently activated responses. This increased latency illustrates simultaneous motor and perceptual processing during gradual accumulation of evidence and is diagnostic of a longer information extraction period preceding response activation (Miller, 1988). For these reasons, the LRP is a strong candidate for measuring the neurological underpinnings of response competition in subjective preference decisions.

Overview of Experiments

In the present paper, two experiments were designed to provide convergent validity of the response dynamics approach using the LRP as a neurological indicator of response competition. Specifically, we examined the LRP as it relates to subjective preference of negatively and positivity valenced images and the subjective preference of risky versus safe gambles in a gain only domain. The stimuli for these studies are based upon on previous work from Koop & Johnson (2013) who behaviorally examined motoric evidence of response competition during subjective decision tasks. One cognitive process preceding preferential decision outcomes that is yet to be tested is the set of specific neural mechanisms leading to the preparation of motor responses which may also demonstrate this competition. By examining the amplitude of the lateralized readiness potential and the presence or absence of a Gratton dip in different conditions, we were able to examine competitiveness of response options under various manipulations of the stimuli. Through these two experiments we determined that there is parity between the apparent cognitive conflict in the planned motor activity before a choice is ultimately made.

Experiment 1: Mapping the Basics of the LRP in a Decision Task

Primary Predictions Experiment 1

For Experiment 1, our prediction was that trials with stimuli that are more similar in regard to valence would have a longer latency for stimulus locked LRP than trials which have more dissimilar valence values (i.e. one image is rated as substantially more pleasant than the other), which would be indicative of a longer deliberation process and a longer time to reach a point of decisional certainty. Also we predicted that similarly valenced trials would exhibit a lower amplitude LRP and possibly even a Gratton dip, indicating greater response competition. When images have highly disparate valence values we expect a higher amplitude LRP, indicating a greater degree of decisional certainty as manifested in the linear response trajectories found in previous response dynamics work.

Experiment 1 Method

Experiment 1 Participants.

We collected data from 26 undergraduate introductory psychology students, who were recruited from the psychology department SONA subject pool and participated for partial course credit. Participants self-selected into experiments from larger pool of experiments available at Miami University.

Experiment 1 Stimuli.

The stimuli used in this experiment were drawn from the International Affective Picture System (IAPS, Lang, Bradley, & Cuthbert 2008). The IAPS consists of over 1000 photographs that have been well normed (by approximately 100 participants for each picture) on three dimensions of emotion: affective valence (or pleasantness), arousal, and dominance. All three scales are rated on a scale ranging from 1 to 9. Previous research has validated that affective valence ratings are reasonably comparable to preferences in choice tasks (Koop & Johnson, 2013). Before the experiment trials, participants completed five practice trials to become familiarized to the range of pleasantness typified in the experimental trials; none of the images used in the practice trials were repeated in any experimental trials. We selected 80 pictures for a total of 40 binary choice trials presented in random order. This block of 40 trials was repeated four times for a total of 160 trials. We varied the similarity between the two choice stimuli in regard to pleasantness ranging from highly similar to highly dissimilar (mean difference = 2.12, ranging from 0.4 to 4.65 points of valence difference) while controlling for arousal level (mean = 4.35 for left hand stimuli, mean = 4.37 for right hand stimuli, values ranged from 3.28 to 5.36 across trials). To create segmentations with EEG, we discretize trials as either high or low similarity based on the valence difference of the images within each trial. Differences at or above the median value of 2.12 were classified as dissimilar whereas valence differences below 2.12 were classified as being similar. Within each trial the arousal level the arousal level between stimuli differed by no more than 0.26 and across all trials there was an average difference of .1 between left and right hand stimuli arousal levels (Details of pictures used as well as valence values are listed in Appendix A: IAPS Stimuli). Since the standard deviation of arousal level ranges from between 1.5 and 2.5 depending on the image (Lang et al., 2005), the standard we have set is substantially below one standard deviation and essentially controls for arousal.

In addition to our primary stimuli, we used the Edinburgh Handedness Inventory (Appendix B) to measure dominant handedness. This inventory consists of 10 items which can be scored on a scale from -100 to 100, with -100 indicating extreme left hand dominance and 100 indicating extreme right hand dominance. A score of 0 on this scale is reflective of ambidextrousness. The inventory asks how often participants use either hand for a certain task, such as “Throwing”. Participants can respond that they either always or usually use their left or right hand or use both equally.

Experiment 1 Procedure.

After signing up for the experiment, participants were emailed instructions detailing important pre-experimental preparations that included a link to a short video explaining the EEG netting process. The instructions informed participants that they should come to the experiment with clean hair, a clean face and have all facial jewelry and make-up removed. Also, they were required to sign an informed consent document in person at the beginning of their assigned timeslot before being permitted to begin any experimental tasks. After obtaining informed consent, participants underwent the netting procedure. After measuring the circumference of the participant’s head, we soaked an appropriately sized net in a mild electrolyte solution and requested that the participant wash his or her face. The net was applied to the participant by an undergraduate or graduate student who has taken a course in proper procedure for applying a Geodesic sensor net. After placing the net on the participant, they were led into the room where the actual experiment was conducted. Instructions for how to respond to stimuli were articulated to participants twice, once verbally before the experiment begins, during which participants were given an opportunity to ask the researcher questions about how they were to respond to stimuli in the task, and the instructions were then reiterated in writing when the experiment began.

Stimuli will were arranged vertically in the center of the screen. Participants were told to choose whichever image they preferred by pressing a button using their left hand if they wanted to choose the image presented on top and press a different button with their right hand if they wanted to choose the image presented on the bottom. Unfortunately, due to the sensitivity of the EEG equipment to voluntary and involuntary movements, which often distort the mapped electrical activity, we were unable to have participants respond to the stimuli in exactly the same manner as was done in previous studies using mouse tracking. Participants’ arm and hand movements inadvertently generate artifacts in the EEG data. Artifacts such as those generated from muscle activity and bodily movements generally have larger amplitudes than general cognitive activity (Eimer, 1998) and trials with excessive artifacts are removed from analysis. Ocular artifacts such as eye blinks are detected at specific electrode sites and can more easily be removed from data than motor artifacts. Also ocular artifacts can reliably be removed without compromising the underlying waveforms containing cognitive activity. For this reason participants' movements were restricted to choosing between stimuli pairs using a button press of either the left hand for one option or right hand for the alternative option.

Arranging the stimuli vertically prevents overlap of lateralized sensory activation with the LRP (Praamstra, 2007). Praamstra (2007) found that stimuli presented horizontally, with one image more on the left or right side of the screen causes a pattern of lateralized sensory activation called the N2cc which overlaps with the LRP. However, this N2cc becomes essentially invisible when stimuli are presented vertically instead, allowing us to more clearly examine the lateralized motor preparation elucidated by the LRP exclusively without interference from lateralized sensory processes. At the conclusion of the experiment the net was removed, participants filled out a short handedness questionnaire (Appendix B: Handedness Form), and were thanked and debriefed.

Experiment 1 Analyses and Results

Experiment 1 Behavioral Analyses

Examining behavioral information before discussing our primary EEG findings allowed us to determine if our planned manipulations worked as we intended. Verifying that the behavioral effects are present is a necessary condition for connecting the neurological activity to the overt behavior. The final sample size for all behavioral and EEG analyses for Experiment 1 were N=25 for the stimulus locked analyses and N=26 for the response locked analyses. Mean handedness across participants was (M = 52.31, SD = 44.19), indicating that the sample was predominantly right handed. On average, participants chose the right picture (M = 52.2 percent of trials, SD = 5.07) slightly more than the left picture (M = 47.8 percent of trials, SD = 5.07), *t*(25) = 2.225, *p* = .035. There was no significant relationship between handedness of participants and whether the right option was chosen more, $r^2 = .045$, *t*(25) = -1.067, p = .296. The average valence of chosen images was significantly more positive (M = 5.72, SD = .197) than the valence of unchosen images was (M = 4.22, SD = .196), *t*(25) = 19.507, $p < .001$. This confirms our assumption that more pleasant images would be more preferable to participants. To check whether similarly valenced trials induced more response competition, we tested how consistently participants chose the more pleasant image when both images were dissimilar in pleasantness (M = 87.42 percent of trials, SD = 10.61) versus more similar in pleasantness (M = 74.52 percent of trials, SD = 8.93), *t*(20) = 5.433, $p < .001$. It appears that it was easier to distinguish the more pleasant option when the image valences were dissimilar, lending behavioral support that our manipulation was successful.

Average median reaction time across participants was (M = 1183.423, SD = 284.65). There was substantial variability in reaction times across participants as evidenced by the rather large standard deviation. Median reaction time information was used to determine the segmentation windows since average reaction time values are heavily weighted by longer trials and may not be representative of the bulk of a person's trial data. Information about reaction time across participants is essential for creating a proper segmentation window for EEG analyses. In particular, when choosing a time frame after stimulus onset, one must consider a window that is large enough to include any waveforms of interest, but that is not so long that for a number of participants it includes the baseline of other trials as this can dramatically distort the waveforms in a grand average. For this reason, the segmentation window was set from 200 milliseconds before stimulus onset to 700ms after stimulus onset to prevent this from occurring.

In order to form ERPs based on averaged wave forms, it is important to verify that response latencies were consistent across blocks. It is essential that the cognitive activity occurring for participants in later trials is similar to the cognitive activity for earlier trials since they will be averaged under that assumption. For each participant, a one way ANOVA was performed to see if there were differences across blocks in (1) log transformed reaction time, (2) frequency with which participants chose the more positive image, and (3) whether participants chose options with either hand proportionally across blocks. The first series of ANOVAs for reaction time indicated that all but one participant showed a significant block effect for reaction time, which is to be expected, with later blocks of trials having on average shorter reaction times than later trials. Fortunately, there appeared to be no differences in the pattern of responding across blocks. Participants were consistent in responding across blocks with regards to the valence of pictures chosen (average p value = .867) and the location of the chosen picture (left vs. right; average p value = .945), suggesting there was no strong evidence of fatigue.

Next, we examined whether greater response competition would be reflected in longer reaction times in the similarly valenced condition compared to the dissimilarly valenced condition. Note that due to the strong positive skew of reaction time values, the following t-statistics associated with reaction time were reported based on log transformed reaction time values, but means and standard deviations were reported in the original units (milliseconds). Participants responded slower on trials in which the valence of the images was highly similar (M = 1719.35, SD = 494.08) versus trials in which the valence of the images was more disparate (M = 1458.06, SD = 361.06), indicating greater decision difficulty, $t(25) = 8.319$, $p < .001$. This manipulation check further supports the effectiveness of the valence similarity manipulation.

Preprocessing of EEG Data Experiment 1

Before EEG data could be analyzed, some major preprocessing needed to be conducted to remove gross ocular artifacts distorting the cognitive activity occurring in the raw EEG. Ocular artifacts were removed from the EEG data using Independent Components Analysis in EEGLab, a Matlab add-on. Before exporting the data files to EEGLab, a filter (.1 Hz highpass) was applied to the data and multiple markers were added to indicate events which were exported from EPrime to the original Netstation file such as when the stimulus was first visible and when participants made a response. These highpass filtered files were exported to a previous Netstation file type which is readable by EEGLab. Once the files were in EEGLab the proper electrode map layout was applied to the channel data so electrical activity could be displayed over a spatial map of the head. In our experiment the correct channel mapping was an EGI Hydrocel Electrical Geodesic net with 257 channels (256 active channels and a reference electrode). Before running ICA, channel information was re-referenced to the reference electrode (Jung, Makeig, Westerfield, et al., 2000). According to this method, one does not necessarily even need to re-reference the electrodes, however, since averaging to the reference is a linear transformation it does not change the components relative to one another.

To help illustrate how using ICA changes the data by removing artifacts without compromising the structure of the data, an example has been created to illustrate a few of the steps involved in ICA (Appendix E) with data from this project. Using the response locked data file for Participant 6 in Experiment 1, Figure 1 in Appendix E illustrates the original form of the data after it has been run through a highpass filter to remove large DC drifts generated by the amplifier. The large peaks in the data are ocular artifacts generated by blinking. The electrodes at the front of the net are extremely sensitive to activity from ocular musculature as well as retinal electrical activity, causing these deflections to be more extreme than normal cognitive activity. ICA mathematically deconstructs the waveforms, which are the sum of a nearly infinite number of sine waves, into the most prominent component parts. Often eyeblinks occur as their own component using this method. To determine if a component is an eyeblink, one must examine where eyeblinks occur in the data. It is useful to compare the same time range with the component activity waveforms (Figure 3, Appendix E) and determine which component appears to have co-occurring deflections at the same time the blinks occur. In order to remove the component, one can look at a topographic plot of the component and other nearby components using a topographic heat map (Figure 2, Appendix E). Eyeblink components appear with a great deal of activity (in red) around the eye area and almost no activity (lack of activity indicated in blue) on the rest of the scalp. In the example for participant 6 in experiment 1, this is seen with component 8. After removing this component, one can then look at the EEG data at the same time as before (Figure 4, Appendix E) and see that the structure of the data is unchanged with the exception of the large eyeblink deflections being removed. Using this method, we are able to preserve many trials that would otherwise need to be removed and use them for analyses.

It was possible to remove ocular artifacts from most participants using ICA with the exception of 1 stimulus locked file. This is most likely due to a high correlation between participant blinking and cognitive activity, making it impossible to reconstruct the waveforms successfully when the eyeblink components were removed. Each of the files, both the raw highpass filtered files, and highpass filtered files post ICA were run through a lowpass filter (55Hz) and were segmented appropriately. After segmentation, Netstation flagged and replaced bad channels and noted bad segments (segments which cannot be analyzed due to indications of movement, facial muscle tension, and ocular artifacts). By using Independent Component Analysis, the number of “good” segments improved drastically. For the Experiment 1 files, the percentage of acceptable segments increased from 87% good to 90% good for stimulus locked files and 85% good to 91% good for response locked trials for all files.

Although ICA was conducted on all files, some files still contained an inadequate number of segments for analyses. Based on the rationale of previous experiments, only participants who had at least 15 good segments in each category were used for averaging and all EEG analyses reported will be conducted on these individuals. Behavioral analyses were conducted on all participants as well as the subsample of participants which had usable EEG although only the behavioral outcomes for those with usable EEG data will be reported here.

All of the usable segments were averaged by category and then a baseline was subtracted. The baseline for all segments, both for those which were response locked and stimulus locked was calculated as the 200ms before stimulus onset. Between each trial, there was a pause of between 1000ms and 1200ms. This pause was inserted between trials so that cognitive activity from preceding trials would not occur during subsequent trials. Generally, a pause of one second is adequate, allowing us to more confidently use the 200ms preceding stimulus onset as a baseline of zero when the cognitive component of interest will not be present. After correcting the baseline for the averaged waveforms, a montage was created taking channels just in front of C3, which is on the left side of the scalp near motor cortex and subtracted the values from channels just in front of C4 on the right side of the scalp near motor cortex. However, instead of simply using one channel minus its homologue, since a dense array net was used for this experiment, to obtain more accurate measure of scalp electrical activity the channel most of interest and the 6 surrounding channels were used in the C3'-C4' montage. Each channel on the right side was subtracted from its homologous channel on the left side and an average reference was used. After this, seven difference waveforms in each category were created from this montage by taking the segments from the left side minus the segments from the right side. This double subtraction method yielded seven LRP waveforms which were then averaged to obtain a more accurate LRP with a smoother curvature for ease of interpretation. Using the double subtraction method, positive polarity deflections indicate a greater level of preference for the selected alternative.

Experiment 1 EEG Analyses

Before determining the onset latency and average amplitude for participants in the similar and dissimilar valence conditions, an average of the baseline was calculated. If calculated correctly, all of the activity in the baseline should average to zero. The average value of the baseline during the 200ms before stimulus onset was (M = $1.94*10^{-8}$, SD =.244) when the valence difference between the images was high and (M = $2.88*10^{-8}$, SD =.319). Both of these values are extremely close to zero, and as confirmed by one way t-tests with a test value of 0, $t(49) = .000$, $p = 1$ for highly dissimilar trials and $t(49) = .000$, $p = 1$ for highly similar trials, the average of the baseline for both waveforms can essentially be interpreted as zero.

LRP Amplitude.

LRP amplitude was measured by taking the average amplitude (instead of peak amplitude) of each waveform in the time where the LRP appeared to be contained. This is a more accurate measure of LRP amplitude since the average of the maximum amplitudes from individual participants is not equivalent to the peak of the grand averaged waveform. Also, peak amplitude values are sensitive to local maxima generated by high frequency components in the signal. By examining the plot of the two waveforms in Figure 1, it is apparent that the LRP is within the approximate range of 220ms before the response button was pressed and lasting a few hundred milliseconds after response selection. The average amplitude in the range from 220ms before the response was made to 200ms after the response was made was significantly higher (M = .478 microvolts, SD = .333 microvolts) when the images were more dissimilar and (M = .289 microvolts, SD = .260 microvolts) when the images were more similarly valenced, $t(104) = 4.57$, $p < .001$. This higher LRP for the dissimilarly valenced images is in line with our initial prediction that there would be less response competition when the subjective value of the stimuli was more dissimilar. Lower amplitude LRP for the highly similar trials indicates greater response competition.

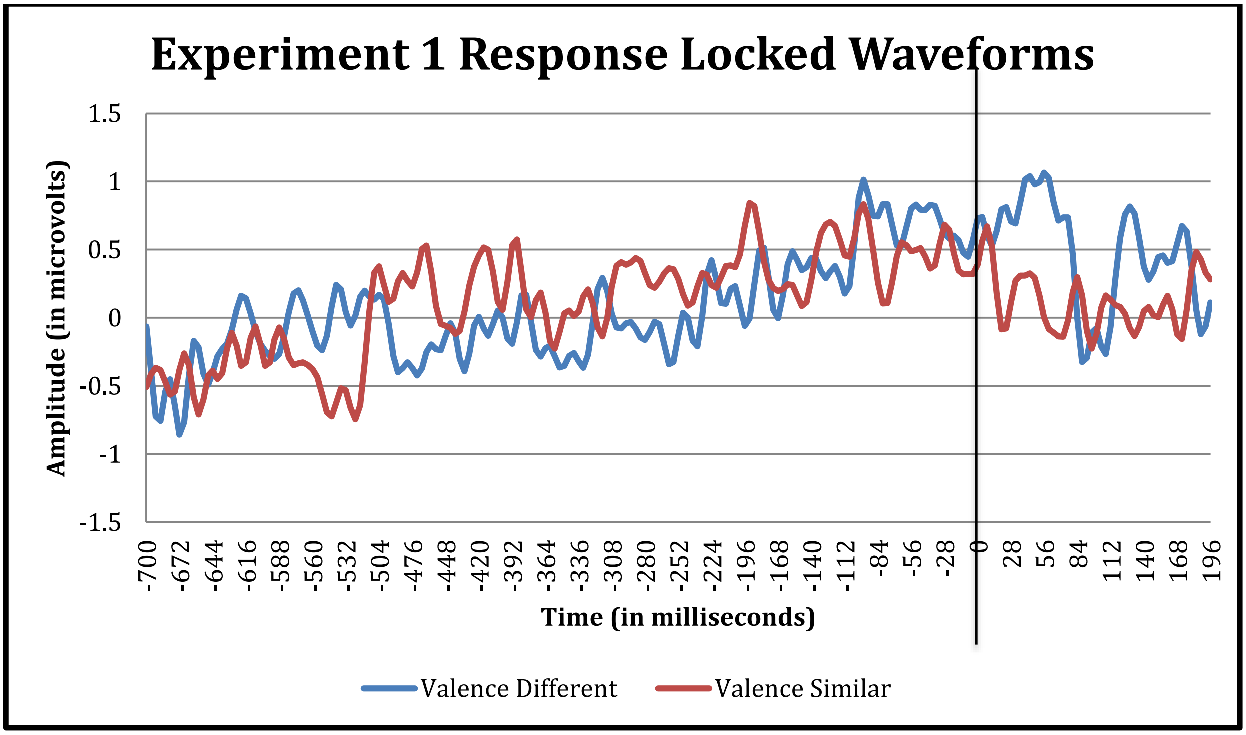

Figure 1. Response Locked Waveforms for Experiment 1. Response selection occurs at time 0 indicated by a black vertical line.

Gratton Dip.

In the time leading up to the LRP there was an apparent negative deflection in the similar waveform that is not present in the differently valenced trial waveform. A paired sample t-test was used to compare the amplitude of each waveform from 580ms before response selection to 508ms before response selection, where the deflection appears to occur. There is a significant difference between the average amplitude in this area for the similarly valenced waveform (Mean = -.426 microvolts, SD = .269) but a much closer to zero average amplitude in the highly different valence waveform (Mean = .057 microvolts, SD = .144). To test if the deflection was significantly different from zero (the baseline) a 1 sample t-test was conducted on each group. For the high difference trial waveform, the deflection did not significantly differ from zero *t*(18) = 1.707, p = .105. However, in the highly similar trial waveform, the average amplitude of the deflection did significantly differ from zero, *t*(18) = -6.905, p < .001.

Based on the location of this negative deflection relative to the onset of the LRP and the average amplitude significantly deviating from the baseline, there is evidence that this is most likely a Gratton dip. As described earlier, a Gratton dip is present when across trials participants have a high degree of response competition. In previous research, this dip has been interpreted as the start of a LRP in the direction of the foregone alternative. This Gratton dip was only present for the high similarity valence group but not for the higher difference valence group of trials *t*(18) = 7.832, *p* < .001. This Gratton dip combined with the lower amplitude LRP for the trials with similarly valenced images indicates a higher degree of response competition, in line with our initial hypotheses.

Onset Latency.

Various methods have been employed by previous researchers to determine the onset latency of the lateralized readiness potential. Two of the simplest methods are to consider the onset latency to be the first consistent stretch of time where the amplitude of the waveform exceeds an arbitrary value (Mordkoff & Gianaros, 2000) or an arbitrary percentage of the height of the peak of the LRP. However, these methods require an arbitrary criterion of some kind, either absolute or relative to peak amplitude respectively and also prone to detecting false onsets. Another method which appears to be more robust is to use a baseline deviation method, to determine the onset latency. Usually this is done by determining when the amplitude of the waveform remains consistently (e.g. for over 50 milliseconds) a number of standard deviations in amplitude above the mean amplitude of the baseline (Osman, Bashore, Coles, Donchin, & Meyer, 1992). By requiring the amplitude to not only reach this threshold, but also remain there over time is helpful to prevent detecting a false onset. Generally this threshold is set at around 2 standard deviations above the baseline.

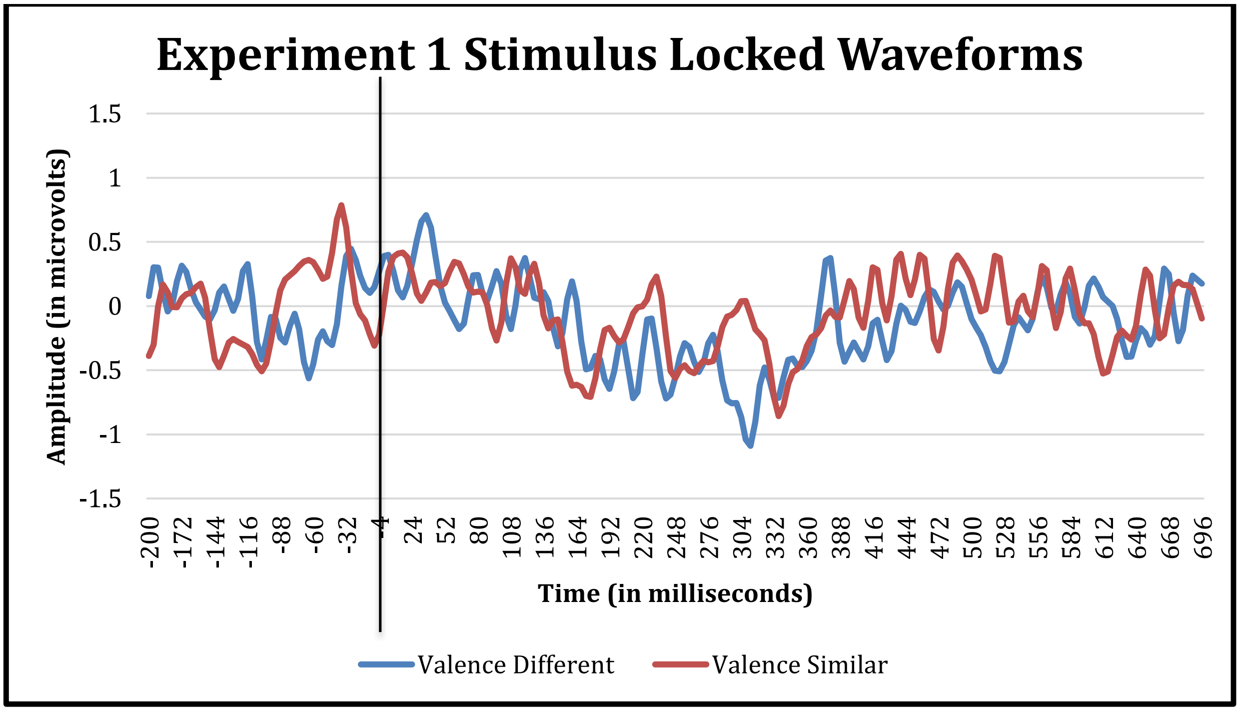

Figure 2. Stimulus Locked Waveforms for Experiment 1. The black vertical line indicates the time at which the stimulus appeared.

In Experiment 1, the onset amplitude criteria was set at two times the standard deviation of the baseline. This gave us an amplitude threshold of .488 microvolts for the highly dissimilar valence trials and .638 microvolts for the similarly valenced trials. These amplitude values were set as the threshold values for each respective waveform. In the stimulus locked waveform (see Figure 2 above) there appeared to be no consistent point in the data where the averaged waveform exceeded either of these criteria or even lower criteria of 1.5 standard deviations above the mean of the baseline. Onset latency therefore could not be determined. However, this could be due to the highly variable nature of the reaction time data as described in the behavioral analyses above. Despite our inability to determine the onset latency of the LRP potentially due to the highly varied response times across participants averaging to noise, there was a definite pattern seen in the behavioral analyses that indicated that participants deliberated longer on trials where the image variance was more similar.

Although an onset was unable to be detected for the stimulus locked time frame as desired, it is possible to determine the latency relative to the onset of a response. The interpretation of this value must be modified slightly though. Generally the onset latency is understood as the time after stimulus presentation when a preference is accumulated. Relative to response locked logic the onset latency can be understood as the time relative to when a response was actually made that preference began to be accumulated to a criterion where the choice was essentially decided mentally. Basically, we can see this as the time difference between when mentally the participant reached a decision on a mental level relative to when they actually took action to make their response.

The same criteria values were used to determine how soon before responding the LRP began. The highly dissimilar trials reach a threshold that consistently (at least 50ms) remains 2 standard deviations above the baseline starting at 132 ms before the response is initiated and the highly similar trials do not at any point consistently (at least 50ms) remain at least 2 standard deviations above the mean of the baseline. This could be due however to the much higher variance of this waveform in the grand averaged baseline and also the overall lower amplitude of the LRP itself. Since the grand averaged LRP for highly similar trials indicated that there was most likely a large degree of response conflict as evidenced by the Gratton dip and lower amplitude LRP, it is understandable that this high threshold might not have been reached. To adjust for this the onset latency was also calculated using a lower threshold of 1.5 standard deviations above the mean of the baseline for both groups. This threshold was around .4 microvolts, which is a reasonable threshold in LRP research using arbitrary criterion methods of determining the onset of the LRP (Mordkoff & Gianaros, 2000). When this lower threshold was set, the high similarity group had a consistent indicator the preference had been accumulated around 144ms before responding and the high difference trials had consistent preference beginning at around 164ms before responding. Not only did the LRP appear to start later relative to the time of response across trials where the images were of similar valence, but it also terminated more rapidly after the response had been made.

Experiment 1 Discussion

Experiment 1 was designed to exam the convergent validity of response dynamics using the LRP as neurological indicator of response competition in the premotor cortex. According to the response dynamic approach, preference accumulation manifests in the response trajectories toward the selected option. Using the LRP, we were able to determine whether there was analogous motor preparatory activity occurring in the brain, which could map on to dynamic changes in motor responses over the course of a trial in a behavioral experiment.

We hypothesized that cognitive response competition embodied in more curvilinear mouse trajectories would be reflected neurologically as a lower amplitude LRP and potentially a

Gratton dip if the response competition was particularly strong. Previous work with response dynamics indicated that participants tended to move in a less direct and curvilinear path when the two images presented within each trial were of a similar valence to one another, whereas participants tended to move in a much more linear path to the eventual choice when the valences of the images were more disparate. This hypothesis was confirmed in the response locked waveform, indicative of response competition occurring from the time participants came to a mental conclusion about their preference to when a button was pressed to confirm the decision. The average amplitude of the LRP across decisions between similarly valenced images was significantly lower than the amplitude for the more differently valenced images. Also, in the waveform for similarly valenced image trials there appeared to be a Gratton dip which significantly deflected from zero whereas there was no similar dip for the differently valenced trials, indicating overall that there was a much larger mental competition occurring for decisions between two similarly valenced images.

Additionally, it was hypothesized that the LRP onset latency would be delayed for images that were more similarly valenced. Unfortunately, due to high variability in overall response times across participants, the time before participants came to a mental conclusion was highly variable. When participant waveforms were averaged across each other the, first 700ms after the stimulus appeared to never significantly deflect from the variability of the baseline. An LRP could not be determined across participants for the stimulus locked waveform.

Although the onset latency of the LRP could not be determined relative to the display of the stimulus, across participants there was evidence that participants took longer to respond behaviorally during trials where the two images were more similarly valenced. Also, relative to when the behavioral decision was made via action, the beginning of the LRP was delayed (occurred closer to when a physical response was made) when the images were of a similar valence and the LRP terminated sooner after the response was made.

Over the course of trials with similarly valenced images, there was increased competition in premotor areas of the brain. There was preparation of a motor response for the foregone alternative as seen through the Gratton dip. There then was an inhibition of the response following the initial Gratton dip, and a response selecting the chosen alternative. The lower amplitude of the LRP is another indicator of neural response competition during the actual choice. This pattern of evidence seems to support the work of response dynamics, which attempts to use motor activations and trajectories as a measure of cognitive preference and preference reversals. A similar effect to what is assumed in models of response dynamics appears to be occurring neurally as evidenced through the LRP.

Experiment 2: Exploring Response Competition in the LRP for Decision Tasks Involving Risk

The primary goal of Experiment 2 was to determine the robustness of the results in Experiment 1 using gamble stimuli as opposed to affective pictures. Past research using response dynamics has indicated a greater degree of response competition when participants are faced with a decision between a gamble with higher variance (riskier) and lower variance (safer) and choose the risky option than when they choose a safer option (Koop & Johnson, 2013). Our goal was to see if, as was seen with Experiment 1, there was neural support for these behavioral findings indicated by measures of increased response competition in motor preparatory activations.

Primary Predictions Experiment 2

Previous research involving response dynamics found that a typical mouse trajectory proceeds directly to a safer gamble, indicating little response competition (Koop & Johnson, 2013). By contrast, when subjects selected the risky gamble, the mouse trajectory initially proceeded toward the safer gamble before reversing course towards the risky option mid-choice. On the basis of these previous findings, our primary prediction for Experiment 2 was that preparatory motor activity in the brain forms the neurological basis of dynamic preference accumulation as manifested in response trajectories. We hypothesized that that there would be a lower amplitude LRP and possibly a Gratton dip when participants choose the risky gamble, indicating greater response competition. These two elements of the grand averaged LRP waveform would indicate an overall competitive pull toward the safer option when choosing the risky option and thus provide a neurological basis for the curvilinear mouse trajectories found in previous response dynamics work. In addition, we expected to see greater LRP onset latencies in risky trials indicating a longer deliberation process and slower process of reaching certainty about the decision.

Experiment 2 Method

Experiment 2 Participants.

For this experiment we collected data from 32 undergraduate introductory psychology students who signed up from the Miami University psychology department SONA subject pool. Students had the option to select our experiment from a variety of experiments being conducted within the department. After signing up for our experiment, participants were be emailed information detailing the netting procedure and be informed of what they needed to do before the experiment.

Experiment 2 Stimuli.

Each participant chose between 40 gamble pairs that were presented in a random order and repeated in four blocks for a total of 160 choices. Each gamble pair featured one safe option and one risky option and the response mapping was counterbalanced so that the safe option and risky option could be selected with the right hand and left hand half the time and reverse response mapping for the remaining half (A detailed list of gambles is included in Appendix C: Gamble Stimuli). Additionally, it was important to craft the gambles in a manner that would incite participants to pick the risky option and safer options in relatively equal numbers. In order to generate an LRP component, a participant must give a response of a given segment type optimally on at least 30 of the trials; however, more recently ERP researchers have been constructing LRPs with as few as 15 or 20 good trials successfully (Leppanen, Moulson, Vogel-Farley, & Nelson, 2007).

Generally, in binary gamble choice tasks, participants will predominantly (approximately 75% of the time) choose the safer gamble and will rarely choose the risky option. In order for us to compare LRPs for risky and safe gamble choices, it is necessary to make the safe and risky options equally appealing. Using a utility function allowed us to make the risky gambles more attractive by increasing the predicted probability that participants would choose the risky outcome. In addition to making risky gambles relatively equally appealing as safe gambles, which allowed us to elicit participants to select both safe and risky gambles in relatively equal numbers, we also were better able to counterbalance subjectively optimal gamble presentations on the left and right of the screen so that half of the gambles with a higher utility value were on the left side and the other half were on the right side. The utility formula we used, which based on a standard power utility formula (Johnson & Busemeyer, 2010) is listed below:

$$(1) \qquad \mathrm{EU(A)} = \sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{p(a_i)U(a_i)}$$

where x represents the value outcome of x, $\mathrm{U(a_i)} = \mathrm{a}_i^{\alpha}$ represents the subjective value outcome of the ith outcome of gamble A, and $\mathrm{p(a_i)}$ represents the probability of winning the gamble. The parameter α (alpha) is a measure of risk aversion where larger numbers indicate greater risk seeking and smaller numbers indicate greater aversion to risk. We chose a risk averse value of $\alpha = .50$ in our utility equation based on past participants' response patterns which consistently favor safe gambles (Koop & Johnson, 2013).

Experiment 2 Procedure.

Overall, the second experiment required 10 to 15 minutes to complete, which is optimal to maintain low impedance of the electrodes., As in Experiment 1, the same information was emailed to participants regarding the netting procedure. The netting procedure for both procedures was identical as well. After obtaining consent, participants were verbally given the instructions which were then reiterated once the experiment began to ensure that the procedure was clear. Before the experiment, participants were made aware that at the conclusion of the experiment they would be given a payment voucher which they could exchange later in the week for money. It was made clear that they would receive course credit (1 credit hour) for their participation regardless of whether they chose to play their gambles for money or not, and that the monetary reward was a bonus incentive. Payment has been used previously in the literature to motivate participants to sincerely consider which gamble option they would rather play for money (Hertwig & Ortmann, 2000). Monetary incentives such as those used in this experiment have been shown to improve participant effort in judgment and decision making tasks (Camerer & Hogarth, 1999). Other projects in our lab (Koop & Johnson, 2012) and other researchers have used this type of payment procedure as a means of improving the salience of gambles for participants and eliciting more realistic decision making responses. As in Experiment 1, stimuli were arranged vertically in the center of the screen. Participants chose which gamble they would prefer to play later for real money by pressing a button using their left hand if they wanted to choose the top gamble and press a different button with their right hand if they wanted to choose the bottom gamble. All of the gambles were for potential gains (values ranging from \$15-\$95) at a certain probability of success (20%-90%).

At the conclusion of the experiment the net was removed, participants filled out a short handedness questionnaire, and were thanked, debriefed, and given a payment voucher. Participants were given the opportunity to exchange the payment voucher for an opportunity to play five of the gambles they chose during the experiment at a later date with a payout of 1/20 of the monetary value of the gambles presented to them (payout values ranging \$0.75-\$4.75 for each gamble). The outcomes of their choices were based on the rolls of two ten sided dice.

Experiment 2 Analyses and Results

Experiment 2 Behavioral Analyses

Before proceeding with the primary EEG analyses, it is necessary to verify that the experimental manipulations produced the intended behavioral effects. The final sample size for the response locked segments was N = 20 and for stimulus locked segments was N = 18. All descriptive statistics from this point onward are for participants included in the final sampling upon which all analyses were conducted. Mean handedness across participants was M = 56.43, indicating that the sample was predominantly right handed. Participants overall chose the right option (M = 56.04 percent of trials, SD = 5.19) significantly more than the left option (M = 43.90 percent of trials, SD = 5.17) *t*(20) = 5.378, p < .001. However, this was not directly related to handedness. Stronger right handedness did not correlate significantly with choosing the right option more, r^2 = .084, *t*(20) = 1.316, p = .204.

Overall, participants chose the risky option less often (M = 44.02 percent of trials, SD = 13.72) than one would expect if they responded equally to safe and risky trials, but only by a marginally significant amount *t*(20) = -1.999, p = .059. Participants chose the higher utility (standard of alpha set to .5) on an average 109.57 trials out of 160. Average median reaction time across participants was (M = 3645.24, SD = 3223.5). It is important to note that the standard deviation of the median reaction time was extremely large across participants. The range of median reaction times between participants fell from 900.5ms – 6381.0ms. This wide spread of reaction times should be noted since it greatly affects the stimulus locked analyses for the EEG data. As with the segmentation in Experiment 1, segmentation needed to encompass most of the data across all participants, so the segment was locked as 200ms before stimulus onset and 1000ms after stimulus onset. As with Experiment 1, t-statistics associated with reaction time were reported based on log transformed reaction time values, but means and standard deviations were reported in raw units (milliseconds). There was no significant difference in reaction time across participants when the risky option was chosen (M = 4429.76, SD = 1493.1) versus the safer option (M = 4263.02, SD = 1545.40), *t*(20) = 1.316, p = .203, which indicates that we cannot be certain that there was more response competition before choosing the safe or risky option by examining behavioral measures alone.

One way ANOVAs were used to inspect block effects for (1) log transformed reaction time, (2) frequency with which participants chose the higher utility option, and (3) the proportion of hand.. Reaction time was significantly different across blocks for more than half of participants, with later blocks having a faster average reaction time. As with Experiment 1 though all of the participants did not seem to differ in their pattern of responding indicated by consistent proportion of higher utility gambles chosen (average p value = .926) and hand of response (average p value = .664).

As previously noted, the gamble stimuli were selected based on the predictions of a simple utility model to encourage an equal choice distribution between safe and risky options. Using maximum likelihood estimation, the model was fit to individual-level data in order to determine whether the assumption that α = .50 was reasonable. Individual choice patterns were predicted with an exponentiated version of Luce's choice rule:

$$(2) \qquad \mathrm{P(A|\{A,B\})} = \frac{\mathrm{e}^{\mathrm{EU(A)c}}}{\mathrm{e}^{\mathrm{EU(A)c}} + \mathrm{e}^{\mathrm{EU(B)c}}}$$

where EU(A) is the expected utility from Equation 3 and c is a consistency parameter that governs how deterministically or stochastically an option is chosen. As c increases, the model predicts a higher probability of choosing the option with the higher expected utility. A value of zero indicates the options are chosen in a completely random fashion. Across participants, the average maximum log likelihood across participants was (M = -81.016, SD = 12.11). As an intuitive index of model fit, the log likilhood was transformed into an average predicted choice probability using the following formula,$(\mathrm{e}^{\mathrm{LL}})^{\frac{1}{\mathrm{N}}}$, where LL is the log likelihood and N is the number of choices, in this case 160. Across participants, the average predicted choice was (M = .604, SD = .044), which is better than a chance level of .5, *t*(20) = 10.839, *p* < .001. Upon initial inspection, the model fit may appear somewhat low. However, this is to be expected because response competition strong for certain gambles. We would expect many of the competition inducing gambles to be chosen with approximately equal probability as a reflection of this indifference.

Individual alpha values ranged from extremely risk aversive (α = .05) to slightly risk seeking (α = 1.08). On average, however, alpha was very close to .50 (α =.483, SD = .308), *t*(20) = -.256, *p* = .800. The results indicate that setting up gambles with an expected alpha of .5 seems to be appropriate when looking in the aggregate, but the high degree of variability suggests that the assumption may not have been met for all participants. The consistency parameter measured how deterministically participants chose with their subjective utilities, which on average was (M = 2.2, SD = 1.68) with values closer to 0 indicating a more inconsistent or random decision making. In the case of our data, this moderate level of consistency value indicates that participants generally responded in a non-random manner.

Preprocessing of EEG Data Experiment 2

The raw EEG information was processed in the same manner as in Experiment 1. For a detailed explanation of preprocessing of EEG data and removal of ocular artifacts please refer to the previous section detailing this process. It was possible to remove ocular artifacts from most participants using ICA with the exception 2 files. Using Independent Components Analysis was especially beneficial for the Experiment 2 files in preserving the number of usable segments across all files. The percentage of acceptable segments increased from 66% to 77% for stimulus locked files and 68% to 84% for response locked files.

As with Experiment 1, the number of acceptable segments for averaging was set at 15 per segmentation category. Due to participants differentially choosing either the safe option or the risky option predominantly and neglecting to choose the alternative option unfortunately left many participants' files unusable for ERP analyses.

Experiment 2 EEG Analyses

As with Experiment 1 it was important to determine that the baseline preceding the stimulus onset was on average near zero. The average amplitude of the baseline in the averaged across risky trials across participants was (M = $5.35*10^{-8}$, SD =.218) and across safe trials across participants (M = $-7.32*10^{-8}$, SD =.259). Both of these values are extremely small numbers that do not differ significantly from zero, *t*(49) = .000, *p* = 1 for risky trials and *t*(49) = .000, *p* = 1 for safe trials. This indicates that our average baseline is around zero.

LRP Amplitude.

A longer segmentation window was created for Experiment 2 since on average response times tended to be longer than the response times in Experiment 1. In the response locked waveform (see Figure 3 below) the LRP for both conditions appears to be included within the time window from 460ms before a response button was pressed to 200ms after a response was selected. Average amplitude of averaged risky trials and safe trials was taken during this window as a comparison of average amplitude of the LRP between conditions. The amplitude for the "risky" decisions was significantly higher, (M = .940, SD = .581), in this region than the chosen "safe" trials, (M = .482, SD = .384), *t*(164) = 15.148, p < .001.

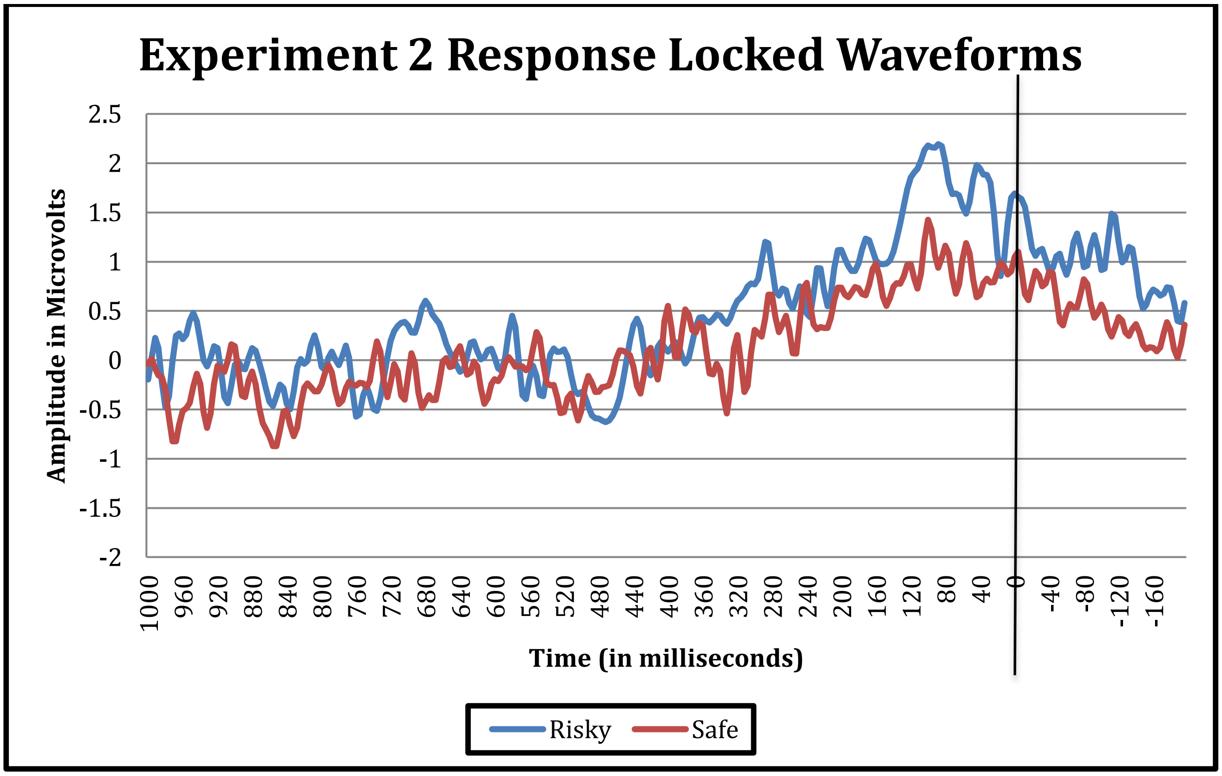

Figure 3. Response Locked Waveforms for Experiment 2. The black vertical line indicates the time at which a response was selected.

Gratton Dip.

The area from 1000ms before stimulus onset to 820ms before stimulus onset appeared to have a slight negative deflection. To determine if this was a Gratton dip that varied across conditions, a one sample t-test was conducted for each waveform to determine if there was a significant deflection from the baseline indicating cognitive activity. In the risky trial waveform, the average deflection in this area did not differ from zero (M = -.064, SD = .258) *t*(45) = -1.685, p = .099. However, the safe trial waveform did have a significantly negative deflection from zero consistent with a Gratton dip (M = -.390, SD = .288) *t*(45) = -9.206, p < .001. Contrary to our hypothesis, the Gratton dip for the safe option was more pronounced than the Gratton dip for the risky option *t*(45) = 6.505, p < .001, a point which is elaborated upon to in the discussion section below.

Onset Latency.

As with Experiment 1, in Experiment 2 the onset latency was defined as the onset of when the waveform consistently reached an amplitude at least 2 standard deviations above the mean of the baseline amplitude. Using this standard, the threshold for the risky waveform will have to be consistently above .436 and the safe waveform will have to be above .518. Using these criteria in the stimulus locked segments, which spanned an area lasting 1000 milliseconds after stimulus onset, did not indicate any time points that were consistently deviating above the mean (see Figure 4 for stimulus locked waveforms). A lower threshold of 1.5 times the standard deviation of the baseline was attempted but this also yielded no point in time of the onset latency. This is most likely due to the variability of the response times across participants as was indicated in the behavioral analyses section.

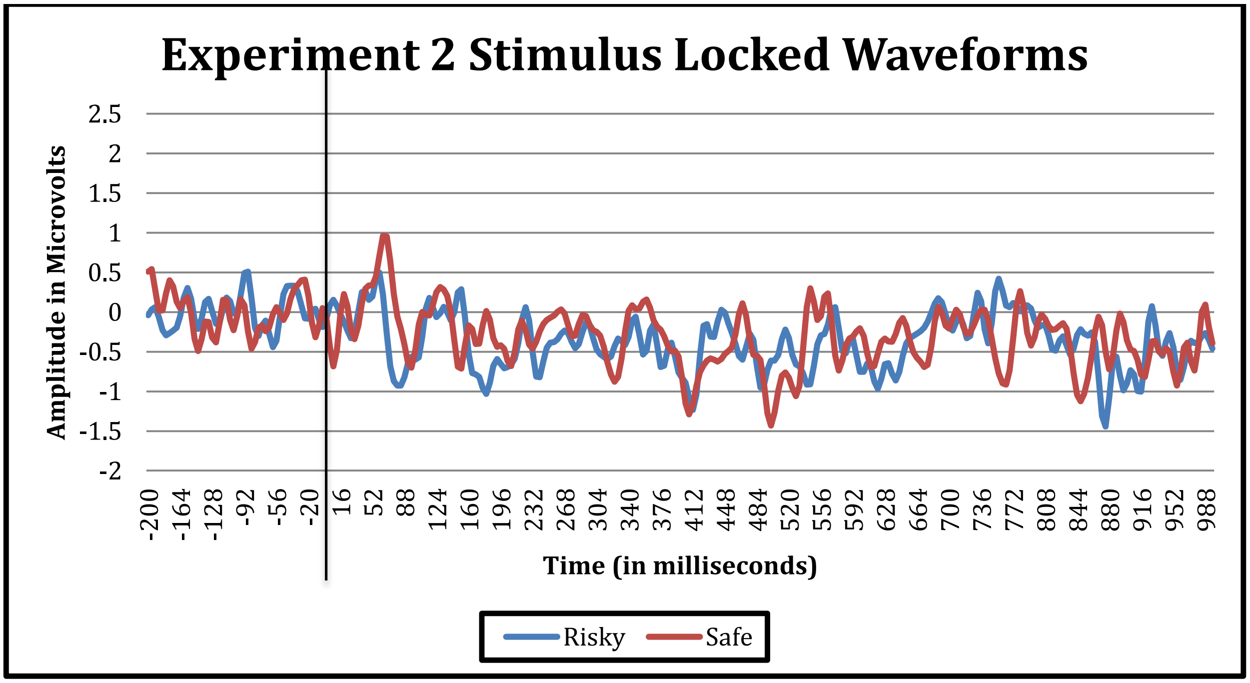

Figure 4. Stimulus Locked Waveforms for Experiment 2. The black vertical line indicates the time at which the stimulus appeared.

Since the LRP was contained in the response locked segmentation, the latency of the LRP as a measure of time of onset prior to the physical response was analyzed for Experiment II. With a criterion of 2 standard deviations over the baseline, the onset of the final decision occurred 364 milliseconds before a response was made for the risky trials and 244 milliseconds before a response was made for the safe trials. After the response was made the safe LRP terminated and returned below criterion level sooner, a pattern similar to the similarly valenced trial LRP in Experiment 1.

Experiment 2 Discussion

Previous research using response dynamics determined that a greater degree of response competition occurred when participants chose a risky option when faced with a binary gamble choice. Experiment 2 was designed to corroborate the results of previous studies with neurological evidence from premotor cortex to determine if there was analogous response competition in premotor neural activity when choosing risky gambles that would not be present when choosing safe gambles.

For Experiment 2, a similar pattern of predictions was made. We expected that the LRP amplitude would be significantly larger when participants chose the safe gambles, mirroring the more direct and linear path from start to choice in previous response dynamics work. A higher amplitude LRP indicates that there is less response competition when participants make their choice. It was also expected that risky gambles might also show a Gratton dip in addition to having a lower amplitude LRP, indicating an even higher degree of response competition. Somewhat surprisingly, the amplitude of the LRP when participants chose the risky gamble was significantly higher than the amplitude of the LRP when the safer gamble was chosen. Also, there appeared to be a Gratton dip for the safe waveform but not for the risky one, indicating a greater degree of response competition when participants chose the safer gambles, not the risky ones.

Based on our initial hypothesis, these results would seem counterintuitive since they are exactly the opposite of initial predictions. One would expect based upon the behavioral model that participants would choose the option which elicited more response competition less often than the option they showed stronger preference for. However, participants chose the safe option more frequently than the risky option even though it provoked stronger response competition. Initially gambles were categorized as “risky” due to having a lower variance compared to the “safe” alternative within each trial. As was explained in the method section, the “risky” trials were made more appealing by using a much higher expected value for certain trials. Although most participants do not take the time to calculate the exact expected values for each gamble, they were able to intuitively grasp which risky trials were objectively much better to choose since the expected values were dramatically higher. To determine if the gambles were in fact changed from what we initially conceptualized as “riskier” became in fact the “safer” gambles, we will look at the riskiness of the gambles using the coefficient of variation (Weber, Shafir, & Blais, 2004), which will take the differences in expected value into account to determine which gamble should be classified as “risky” within trial. We will re-segment this data based upon trials with larger vs smaller coefficient of variation values and re-interpret the results as well as run a follow up study that will systematically vary gambles based on the coefficient of variation as opposed to variance.

In addition to a lower amplitude LRP for risky trials we also anticipated that there would be a later onset latency of the LRP. However, like with Experiment 1, there was an excessive amount of variability between participants in regard to response time, and the resulting stimulus locked LRP (with 1000ms following stimulus onset) essentially averaged to noise that did not significantly deflect from the baseline. Unlike the first experiment, the second experiment did not show any significant difference in reaction time when participants chose the risky versus the safe option. However, the response locked waveform revealed that the LRP for the risky option actually began earlier before a response was made compared with the LRP for the safe option, which began closer to when a response was made. The delayed latency of the safe option LRP follows the same pattern as one would expect from more deliberation and response competition, indicating that our experimental manipulations may have led to a reversal of our expected effect.

It is important to note that this contrary pattern of results could be due to manipulations made to the stimuli with the second experiment as well as methodological differences. For the first experiment, LRPs were segmented based on the similar valance and dissimilar valence conditions. In Experiment 2, the LRPs were segmented based on the *choice* of the "riskier" or "safer" option *within* each trial, leaving the choices more free to vary. This design was done to better mimic the previous work done with response dynamics where there was a riskier and a safer gamble done within trial. Behavioral models of decision making have been designed to deal with participants choosing predominantly safe gambles, but with ERP logic, one needs participants to respond at least 20-30 times with each hand to each type of gamble. For this reason, all of the risky gambles needed to be made more appealing by drastically increasing their expected values relative to the "safer" alternative. Although the variance of these gambles were still higher than the safer counterparts, it is possible that the differences of the expected values of the gambles relative to the variance caused participants to subjectively view the "risky" gambles as "safe" gambles, thus explaining the seemingly counterintuitive results.

Additional analyses will need to be conducted in order to reach a final conclusion regarding the results of Experiment 2. We were able to successfully demonstrate that the LRP could be used to determine response competition in subjective preference of monetary gambles through the response locked waveforms. It appears that our results show greater response competition when choosing a safe gamble rather than a risky gamble, as indicated by lower amplitude LRP and the presence of a Gratton dip, in direct opposition of previous research using response dynamics. However, due to manipulations on the initial gambles, which contain a larger spread of expected values to make risky gambles more appealing, a final conclusion cannot be determined until analyses are done to define risk through the coefficient of variation rather than variance of the gambles. We anticipate that by using this more accurate measure of riskiness, there will be more motor preparatory response competition when choosing the risky gamble as opposed to the safe gamble.

General Discussion

The overarching goal of this project was to determine if preparatory motor activity through the LRP could be used as a direct measure of response competition in binary preferential choices. Also, we were interested in determining if these findings would provide convergent validity for past work which utilized response dynamics to measure underlying cognitive processes in binary decisions. Our results indicate that it is possible to utilize the LRP as a measure of response competition for subjective preference as well as the more objective traditionally used categorization task paradigms. Although more work needs to be done to explore the other various cognitive and perceptual processes that contribute to decision making behaviors to determine if there is continuous or discrete cognitive processing in the brain, the data gleaned from these studies may be used to gain even greater insight into the neural mechanisms that underlie essential cognitive functioning. The measurable differences in response competition in motor preparatory response is suggestive to support the methodology of tracking dynamic movements as a window into the neural processes that underlie decision making.

There is a larger, significant debate in neuroscience research over processing models of brain activity, specifically whether neural processing is discrete, where each stage of processing must finish before the next can begin (Sternberg, 1969), or whether neural processing should be modeled continuously where another stage of processing can begin before the previous processing stage is complete (McClelland, 1979). If discrete models are to be assumed there should be no temporal overlap among stages of processing. The completion of a certain process initializes the next process in serially proceeding manner (Sternberg, 1969). Response preparation according to these models doesn't begin until the stimulus is fully identified and partial information could not be used to prepare a response (Miller, 1982). In the case of discrete models it is essential that total reaction time from stimulus onset to response is equivalent to the sum of all individual component stages. Discrete models do allow for partial perceptual information to be used by concurrent or even subsequent stages of processing and as information accumulates, responses become increasingly constrained given the constantly updating data (Coles, et al., 1985). Initially, many response possibilities are activated, and as perceptual processes continue and partial information is processed, these possibilities shrink in number until a response is executed.

In addition to purely discrete and continuous models, there are some assertions that cognitive processing involves a combination of both continuous and discrete processes, and assert that continuous and discrete are opposite ends of a continuum of potential information processing models (Miller, 1988). There are also multiple partially discrete models of cognitive processing. These models assert that initially full information must be perceptually processed before continuing to the next stage, but partial information can go through each stage in a continuous manner. Initially some information will go through discrete stages, but additional pieces of information can go simultaneously thorough different stages, but ultimately go in the same order through each stage. There may also be a specific order to what partial information transfer occurs, for example information about a stimulus' global shape versus specific details (Miller, 1982). This might be considered a partially discrete model since perceptual information is continually being used to influence responding, but that these chunks are generated in a specific order or are processed in an ordered manner.

The next stage of understanding the cognitive processes underlying decision making will involve brain imaging to investigate other perceptual and attentional processes that influence subjective preferences at a neuronal level, essentially allowing us to probe into the black box and discover if there is evidence for continuous cognitive processing in brain activity. One of the eventual goals of future projects is to eventually look deeper into this data for neural evidence of continuous processing during decision making using EEG. Other researchers have examined this question as well using LRP and have found evidence that perceptual processing continues to accumulate as participants prepare a motor response in social categorization tasks (Freeman et al., 2011).

Although answering the question of this debate is not the primary hypothesis of this analysis and write up, by collecting EEG throughout the decision process, we will have enough temporally precise data to be able to isolate other components such as perceptual activity. Eventually, we may be able conduct analyses to help determine if there is overlap present between perceptual, motor, and other cognitive processes such as working memory, lending support to the assumption of response dynamics that motor processes can be used to measure fluctuations in subjective preference over time. Future studies may be used to test some of the assumptions made by models of decision making which presume continuous and overlapping neural processes.

Limitations and Future Directions

By using even just pictures in Experiment 1 and simple gambles in Experiment 2, we noticed a highly variable length of response time. This prevented us from obtaining accurate onset latencies for the LRPs across participants since the grand averages of the segmentation window across participants averaged to near noise levels. One solution may be to use varying onset windows and average across subsegments of participants as was initially proposed. However, it may be difficult to determine if this is the most appropriate thing to do in regard to matching participants based on cognitive strategies. Also due to how variable these median response times were, it may not be appropriate to simply divide the sample in two, but there may in fact be numerous subsegments that would need to be made, particularly since the distribution of reaction times was not bimodal. If the distribution of reaction times had been bimodal for either experiment, having two onset windows would have been reasonable (our initially proposed solution to this potential problem). However, the distributions were unimodal but with an extremely large spread of values. Instead of bisecting the sample, individual LRPs will be generated to examine differences in onset latency. This will first be done within the initial onset window of 700ms for Experiment 1 and 1000ms for Experiment 2, but may expand this to larger windows for participants where this would be appropriate.

As the behavioral results indicate in Experiment 2, although we were able to optimize the parameters of the utility equation, this may not be the most predictive model to use with these gambles. The utility model used in this experiment is a commonly used standard but it does assume that outcome values are weighted subjectively but probability values are weighted objectively, hence the adjustment parameter alpha to weigh outcome but no similar parameter is used for probability. It is in fact possible that participants not only subjectively weigh the outcome values upon viewing but may also weigh probability values subjectively as well. It would be useful for us to test alternative models of utility to get a better fit of participant’s risk aversiveness or to use a different mathematical model to conceptualize decisions involving risk such as a diffusion model.

Despite trying to draw greater preference to riskier gambles, which previous literature and experimentation have illustrated are chosen much less than a "safer bet", around half of participants had a bias toward choosing either mostly safe or mostly risky gambles. One way which was discussed to prevent this problem of subjects responding exclusively to risky or to safe gambles was to vary the displayed gambles to participants based on each subject's individual risk averseness. However, one major disadvantage of this method of gamble generation is that it would make it impossible to measure overall electrophysiological trends across participants since grand averages cannot be created when each participant is presented with a completely different set of stimuli. However, given an adequate number of trials, it would be possible to model differences within a single participant for when that individual chooses a risky option versus a safe option.

As explained in the discussion for Experiment 2, using variance as a measure of risk is probably not appropriate for this study given the manipulation to the expected values of some of the risky gambles. We initially theorized that a higher variance alone was adequate to determine if a gamble was riskier within a trial. However changing the gambles in our task to make risky gambles more appealing caused greater variability of the expected values. As such, the coefficient of variation would have probably been more appropriate to use (Weber, Shafir, & Blais, 2004). In our past research using response dynamics, due to the low variation in expected value for gambles, it was appropriate to use variance as the operational definition of risk (Koop & Johnson, 2013). Analyses will be run to determine which gambles may actually be the "riskier" ones by measuring the coefficient of variation. We plan to run similar analyses to those run in Experiment 2 but using groupings and segmentation based using the coefficient of variation to classify our "risky" and "safe" gamble groups. One limitation of this planned re-analysis is that we did not initially conceptualize risk this way and therefore did not control these values during the initial crafting of the gambles. In addition to running analyses on the current data set, we will plan a follow up study which will systematically vary these gambles to systematically capture coefficient of variation as a measure of risk, rather than simply considering the higher variance gamble the risky one. Also it may be useful to attempt to mirror Experiment 1 more faithfully by having different trial types (i.e. similar risk between gambles versus highly disparate risk between gambles) rather than having a safer and riskier option within each trial.

There are numerous routes for future studies which can be taken using this data as well as the proposed follow up study involving systematically manipulating trial types based upon differences of expected values over the variance between gamble options to gain more parity in regard to structure and manipulation with Experiment 1. In particular, it may be of interest to model the EEG data on a single trial level. Although the nature of the LRP explored in this study was dependent on averaged waveforms across trials, diffusion models of decision making indicate that there is importance in studying decision making at the single trial level since preferences can evolve across time. However, a single trial level LRP may be unnecessary as it may be possible to model individual participant LRP data with a diffusion model. Some models of decision making have assumptions about the neural processes that underlie decision making and these assumptions may be used in part when constructing the models. However, it may be of greater use to further examine the neural processes that underlie each decision over time to better inform these mathematical models of decision making so that neural activity assumptions are unnecessary and avoidable.

Another route of analyses might be to look at spectral properties of the EEG data. Since we did not choose to filter out high frequency waveforms, it may be possible to examine segments of raw EEG data during the decision deliberation and execution process and examine the bands of electrical activity (such as periods of high theta and gamma synchrony) during various portions of the decision process to better determine when participants are consciously aware that they are accumulating preference for an alternative.

As alluded to earlier, the data collected in this experiment may be able to contribute to larger bodies of research including a longstanding debate in cognitive neuroscience about whether processing is discrete or continuous. EEG is temporally precise and by isolating a variety of components we should to be able to model various cognitive activities on a participant by participant level. Of interest would be to examine potentials associated with evaluation of perceptual stimuli. If there is simultaneous co-activation of these perceptual evaluations in time with fluctuations in premotor activity indicative of accumulating preferences, this would lend support to the notion of continuous cognitive processing or partially discrete processing.

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Appendix A: IAPS Stimuli

Trial	PictL	PicDesL	ValL	ArousL	PictR	PicDescR	ValR	ArousR	High ValR	H/L Sim	Emt P/N	Val Diff	ArousDiff
1	1350	Pig	5.25	4.37	1630	Fawn	7.26	4.45	1	H	PP	2.01	0.08
2	2150	Baby	7.92	5	2141	Grieving Fem	2.44	5	0	L	PN	5.48	0
3	2304	Girl	7.22	3.63	2305	Woman	5.41	3.63	0	H	PP	1.81	0
4	2700	Woman	3.19	4.77	2457	CryingBoy	3.2	4.94	1	H	NN	0.01	0.17
5	2490	Man	3.32	3.95	2550	Couple	7.8	3.99	1	L	NP	4.48	0.04
6	2702	BingeEating	5.21	3.92	2630	Male	6.35	3.92	1	H	PP	1.14	0
7	2332	Family	7.64	4.3	2331	Chef	7.24	4.3	0	H	PP	0.4	0
8	2312	Mother	3.71	4.02	1600	Horse	7.37	4.05	1	L	NP	3.66	0.03
9	7550	Office	5.27	3.95	5040	Venusfly trap	5.39	3.75	1	H	PP	0.12	0.2
10	9390	Dishes	3.67	4.14	9220	Cemetary	2.06	4	0	H	NN	1.61	0.14
11	9341	Pollution	3.38	4.5	7580	Desert	7.51	4.59	1	L	NP	4.13	0.09
12	8205	Waterskiing	6.62	4.17	8320	CarRacer	6.24	4.27	0	H	PP	0.38	0.1
13	7472	Grapes	6.25	4	2521	ManW/Dog	5.78	4.1	0	H	PP	0.47	0.1
14	2442	Drying Hair	6.17	4.04	9010	Barbed Wire	3.94	4.14	0	L	PN	2.23	0.1
15	1900	Fish	6.65	3.46	2722	Jail	3.47	3.52	0	L	PN	3.18	0.06
16	2715	Smoking	3.28	4.35	2900.1	CryingBoy	2.56	4.61	0	H	NN	0.72	0.26
17	2122	Tongue Out	5.15	4.59	2055.2	ManInPool	6.4	4.45	1	H	PP	1.25	0.14
18	7046	Pill	4.18	4.14	1750	Bunnies	8.28	4.1	1	L	NP	4.1	0.04
19	7520	Skyline	3.83	4.57	9008	Needle	3.47	4.45	0	H	NN	0.36	0.12
20	9031	Mud	3.01	4.82	9090	Exhaust	3.69	4.8	1	H	NN	0.68	0.02
21	7200	Brownie	7.63	4.87	9041	ScaredChild	2.98	4.64	0	L	PN	4.65	0.23
22	7220	Pastry	6.91	5.3	7135	CarDamage	3.17	5.36	0	L	PN	3.74	0.06
23	3300	DisabledChild	2.74	4.55	7352	Pizza	6.2	4.58	1	L	NP	3.46	0.03
24	7507	Painting	6.25	3.54	7545	Ocean	6.84	3.28	1	H	PP	0.59	0.26
25	2341	Children	7.38	4.11	2690	Terrorist	4.78	4.02	0	L	PN	2.6	0.09

26	6562	Attack	3.19	5.08	5970	Tornado	4.14	4.88	1	H	NN	0.95	0.2
27	6800	Gun	4.01	4.87	6311	DistressedFem	2.58	4.95	0	H	NN	1.43	0.08
28	9080	Wires	4.07	4.36	7410	Candy	6.91	4.55	1	L	NP	2.84	0.19
29	9395	Dishes	3.21	4.22	8050	Rower	6.24	4.31	1	L	NP	3.03	0.09
30	7489	Ferry	6.54	4.49	9445	Skeleton	3.87	4.49	0	L	PN	2.67	0
31	5631	Mountains	7.29	3.86	7290	Fish	4.37	3.87	0	L	PN	2.92	0.01
32	9007	Needles	2.49	5.03	9145	Cow	3.2	5.05	1	H	NN	0.71	0.02
33	7482	Lamb	6.36	4.81	8510	SportCar	7.32	4.93	1	H	PP	0.96	0.12
34	7361	MeatSlicer	3.1	5.09	2346	Kids	7.05	5.28	1	L	NP	3.95	0.19
35	2308	GirlMakeup	5.22	3.82	9000	Cemetary	2.55	4.06	0	L	PN	2.67	0.24
36	9002	Memorial	3.39	4.55	9831	Cigarette	2.95	4.61	0	H	NN	0.44	0.06
37	9290	Garbage	2.88	4.4	6837	Police	4.25	4.5	1	H	NN	1.37	0.1
38	7013	Lightbulb	4.2	4.11	5991	Sky	6.55	4.01	1	L	NP	2.35	0.1
39	5665	Building	6.15	4.02	7023	Garbage	3.8	4.17	0	L	PN	2.35	0.15
40	9280	Smoke	2.8	4.26	1313	Frog	5.65	4.39	1	L	NP	2.85	0.13
Avg			4.91825	4.35075			5.0315	4.37475		20		2.11875	0.101

Appendix B: Handedness Form

Edinburgh Handedness Inventory

Please indicate your preference in the use of hands for each of the following activities/objects by placing a check in the appropriate column.

	Always Left	Usually Left	No Preference	Usually Right	Always Right
Writing					
Drawing					
Spoon					
Open Jars					
Toothbrush					
Throwing					
Broom (upper hand)					
Scissors					
Knife					
Striking a match					

Participant # ___________________

Appendix C: Gamble Stimuli

	alpha =	0.5									
Trial	x1	p1	x2	p2	EV(1)	EV(2)	U(1)	U(2)	Var(1)	Var(2)	Udiff
1	20	0.5	40	0.25	10	10	2.236068	1.581139	100	300	0.654929
2	50	0.4	30	0.5	20	15	2.828427	2.738613	600	225	0.089814
3	60	0.4	40	0.6	24	24	3.098387	3.794733	864	384	-0.69635
4	60	0.6	90	0.5	36	45	4.64758	4.743416	864	2025	-0.09584
5	20	0.7	30	0.6	14	18	3.130495	3.286335	84	216	-0.15584
6	70	0.2	50	0.4	14	20	1.67332	2.828427	784	600	-1.15511
7	50	0.5	30	0.8	25	24	3.535534	4.38178	625	144	-0.84625
8	40	0.3	70	0.2	12	14	1.897367	1.67332	336	784	0.224047
9	95	0.5	65	0.55	47.5	35.75	4.873397	4.434242	2256.25	1045.688	0.439155
10	25	0.7	50	0.4	17.5	20	3.5	2.828427	131.25	600	0.671573
11	30	0.3	70	0.2	9	14	1.643168	1.67332	189	784	-0.03015
12	80	0.4	25	0.7	32	17.5	3.577709	3.5	1536	131.25	0.077709
13	20	0.9	50	0.7	18	35	4.024922	4.949747	36	525	-0.92483
14	35	0.5	45	0.3	17.5	13.5	2.95804	2.012461	306.25	425.25	0.945579
15	90	0.5	80	0.7	45	56	4.743416	6.26099	2025	1344	-1.51757
16	75	0.6	95	0.55	45	52.25	5.196152	5.360737	1350	2233.688	-0.16458
17	60	0.2	40	0.35	12	14	1.549193	2.213594	576	364	-0.6644
18	60	0.5	80	0.45	30	36	3.872983	4.024922	900	1584	-0.15194
19	50	0.5	15	0.8	25	12	3.535534	3.098387	625	36	0.437147
20	40	0.5	20	0.7	20	14	3.162278	3.130495	400	84	0.031782
21	40	0.7	60	0.4	28	24	4.427189	3.098387	336	864	1.328802
22	35	0.5	65	0.3	17.5	19.5	2.95804	2.418677	306.25	887.25	0.539363
23	75	0.35	35	0.5	26.25	17.5	3.031089	2.95804	1279.688	306.25	0.073049
24	40	0.4	70	0.35	16	24.5	2.529822	2.92831	384	1114.75	-0.39849
25	50	0.85	70	0.6	42.5	42	6.010408	5.01996	318.75	1176	0.990447
26	70	0.2	85	0.5	14	42.5	1.67332	4.609772	784	1806.25	-2.93645
27	80	0.2	65	0.4	16	26	1.788854	3.224903	1024	1014	-1.43605
28	90	0.3	35	0.7	27	24.5	2.84605	4.141256	1701	257.25	-1.29521
29	90	0.6	85	0.65	54	55.25	5.6921	5.992704	1944	1643.688	-0.3006
30	45	0.6	55	0.5	27	27.5	4.024922	3.708099	486	756.25	0.316823
31	90	0.45	20	0.9	40.5	18	4.269075	4.024922	2004.75	36	0.244152
32	75	0.5	50	0.9	37.5	45	4.330127	6.363961	1406.25	225	-2.03383
33	70	0.25	60	0.5	17.5	30	2.09165	3.872983	918.75	900	-1.78133
34	70	0.4	95	0.35	28	33.25	3.34664	3.411378	1176	2053.188	-0.06474
35	30	0.5	10	0.8	15	8	2.738613	2.529822	225	16	0.208791
36	20	0.6	60	0.2	12	12	2.683282	1.549193	96	576	1.134088
37	75	0.35	15	0.7	26.25	10.5	3.031089	2.711088	1279.688	47.25	0.320001

38	25	0.35	80	0.2	8.75	16	1.75	1.788854	142.1875	1024	-0.03885
39	30	0.9	70	0.5	27	35	4.929503	4.1833	81	1225	0.746203
40	45	0.5	15	0.7	22.5	10.5	3.354102	2.711088	506.25	47.25	0.643014

Appendix D: Calculation of the LRP

Since LRPs indicate a difference of hemispheric activation, they can be calculated in one of two ways (Smulders & Miller, 2011). The first way, which will be used in the proposed experiments, is double subtraction:

$$(C3'(t)-C4'(t))\text{ left hand} - (C3'(t)-C4'(t))\text{ right hand} = LRP \qquad (3)$$

and the alternative way is:

$$((C4'(t)-C3'(t))\text{ left hand} + (C4'(t)-C3'(t))\text{ right hand}) / 2 = LRP \qquad (4)$$

One advantage of using the double subtraction method (equation 1) of calculating the LRP is that it is able to cancel out other ERPs that are recorded simultaneously in the same location such as the P300 and the N2, successfully isolating the LRP from other components (Smulders & Miller, 2011).

LRPs are often partitioned as either stimulus locked or response locked. When an LRP is locked to the stimulus onset, the time window of focus across participants is the time from the onset of the stimulus to the onset of the LRP (Smulders & Miller, 2011). An LRP may also be locked between the onset of the LRP and the overt response, known as a response locked LRP. The former partition is useful for examining latency of the cognitive activity before the arrival at a decision, including any competition between potential responses. In addition, the latter partition is useful for examining the latency between the commitment to a decision and the actual response. This division can be useful to elicit information about at what stage of processing an experimental manipulation affects.

Appendix E: Example of Removing Eyeblinks with ICA

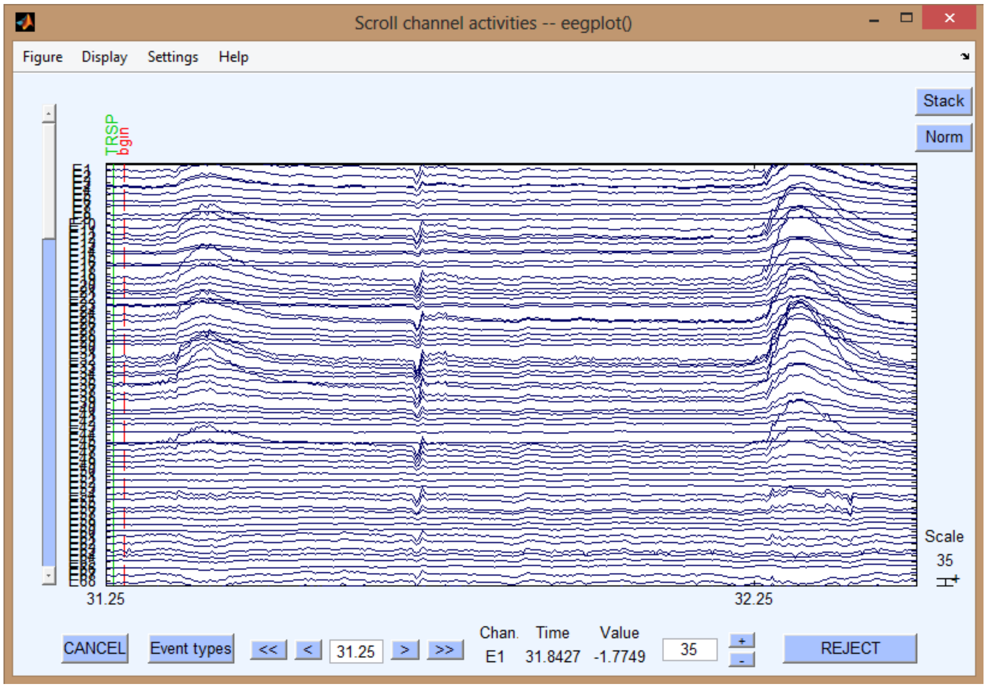


Figure 1: Highpass Filtered EEG Data Before Component Removal (time in window: 31.25 sec - 32.5 sec). The eyeblinks can be seen as large deflections at a much higher amplitude than the rest of the highpass filtered EEG data.

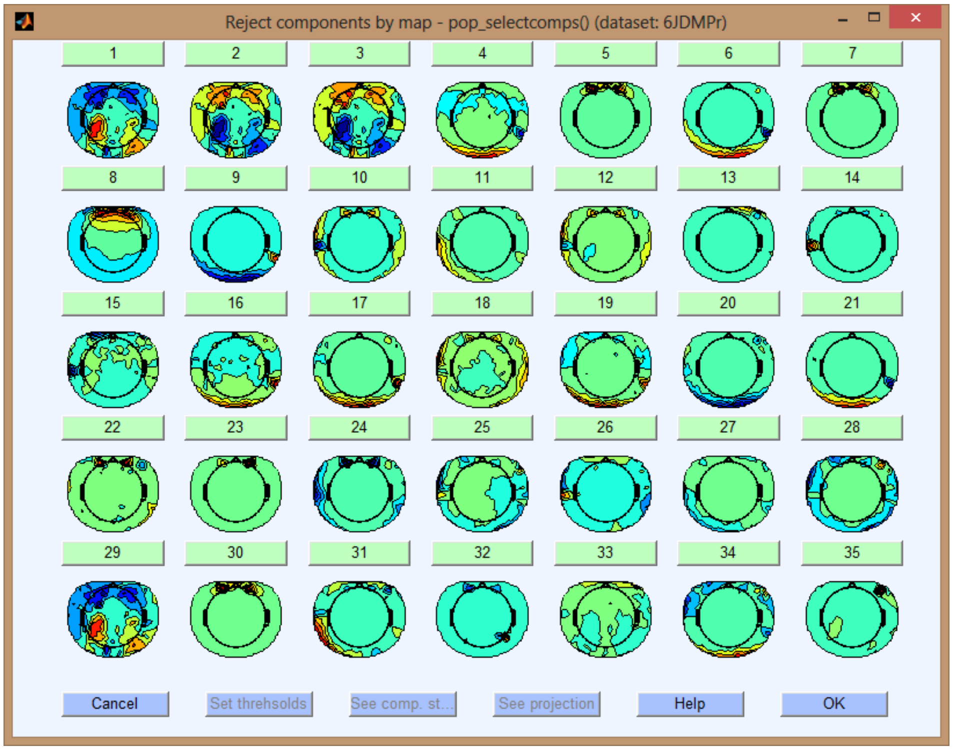
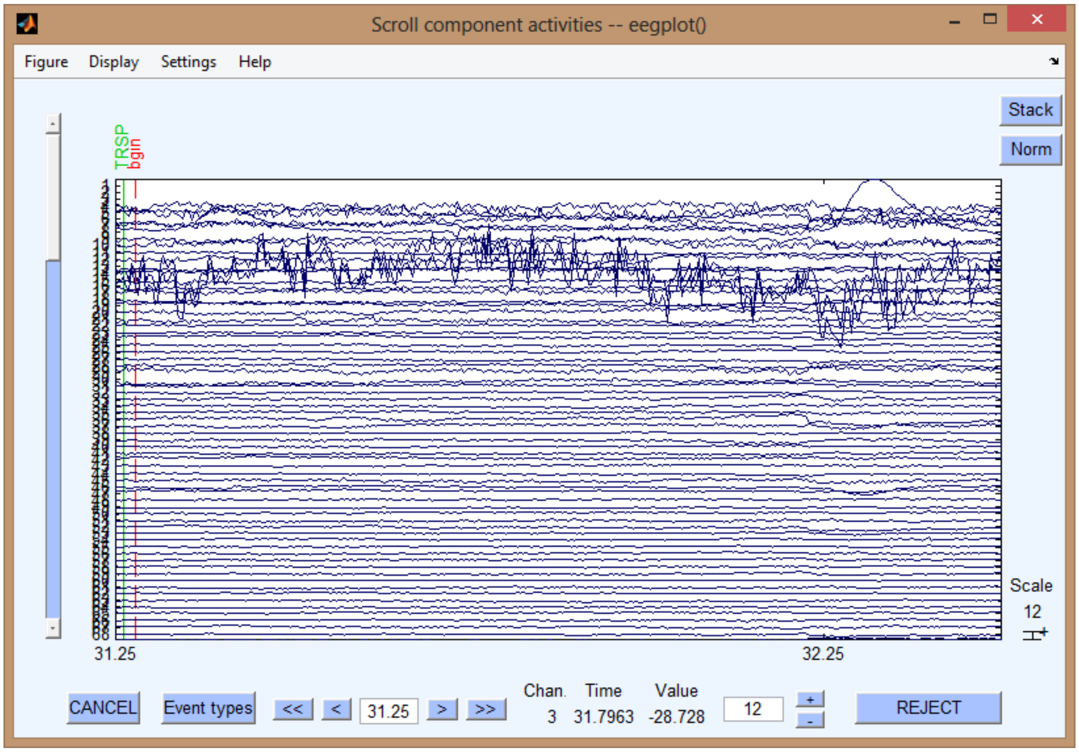


Figure 2: Topographic Map of the first 35 Components. Although it is possible to display 256 components in multiple windows, usually eyeblink components can be found in one of the first 35, although there are some exceptions to this. Note that Component 8 has a great deal of activity in the ocular region, whereas the rest of the head is fairly inactive. This is highly typical of a component usually correlated with blinking.

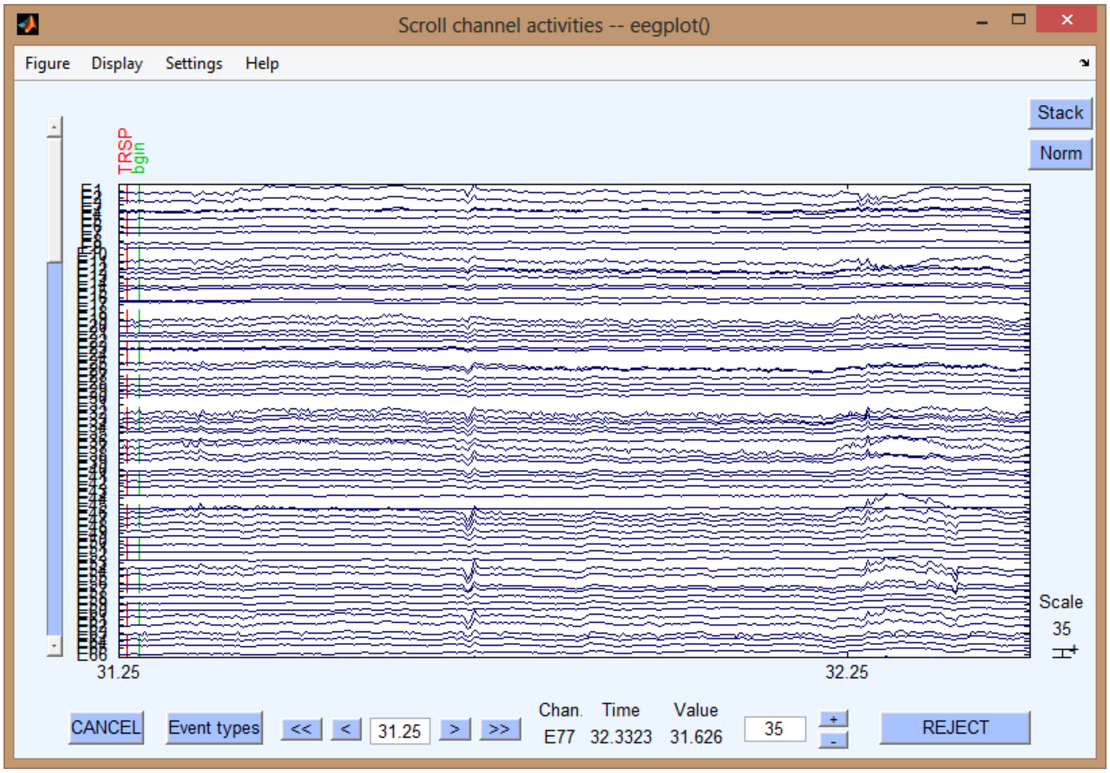


Chan. 3

Time 31.7963

Value -28.728

Figure 3: Component Scroll of Components (time in window 31.25sec – 32.5sec, same as above). Note large deflections on Component 8 occur at the same time as the eye blinks in Figure 1. With this information as well as the topo heat map information, we can conclude that Component 8 is most likely representing blinking activity.



Chan. E77

Time 32.3323

Value 31.626

Figure 4: Highpass Filtered EEG Data Post Component 8 Removal (same time window as previous figures). Note that the eyeblink in this area and others throughout the file are removed without disturbing the cognitive activity recorded in the channels.