AN ERP STUDY OF THE NEURAL CORRELATES UNDERLYING HYPOTHESIS GENERATION AND WORKING MEMORY

A Thesis
Presented to
The Academic Faculty

by

Shereen Farooq

In Partial Fulfillment
Of the Requirements for the Degree
Bachelor of Science in Neuroscience in the
School of Biological Sciences

Georgia Institute of Technology
May 2020

AN ERP STUDY OF THE NEURAL CORRELATES UNDERLYING

HYPOTHESIS GENERATION AND WORKING MEMORY

Approved by:

Dr. Rick Thomas
School of Psychology
Georgia Institute of Technology

Dr. Audre Duarte
School of Psychology
Georgia Institute of Technology

ACKNOWLEDGEMENTS

I would like to thank Dr. Rick Thomas for allowing me to be an undergraduate research assistant in the Decision Processes Lab so that I could gain a better understanding of the research process and learn how to apply my classroom knowledge in a laboratory setting. I would also like to thank the graduate students in my lab, David Illingworth, Sweta Parmar, and Chris White for their wonderful advice and mentorship over the last two years. I would also like to thank the other members of the lab who have supported me along the way. Finally, I would like to thank my mom and dad for their unconditional support and encouragement, without which I would not be here today.

TABLE OF CONTENTS

LIST OF FIGURES

Page

ABSTRACT

Hypothesis generation is the process by which individuals formulate explanations for data found in their environment and evaluating the accuracy of each hypothesis generated is known as a probability judgement. Previous research in decision making has linked hypothesis generation to working memory. This experiment aimed to measure the neural correlates underlying working memory during hypothesis generation in a decision making task. EEG technology was used to measure neural activity and the signals of interest were P300 and CDA. Participants were trained to learn a number of cause-effect relationships between stimuli. Later, participants were asked to make judgements about which causes may have been responsible for an observed effect by remembering the locations of relevant causes in a briefly displayed visual array. The results demonstrate that probability judgements were negatively correlated to the number of relevant hypothesis. The results also show that the peak P300 amplitude did not reveal any significant differences between the 'Effect' cues, and the peak P300 amplitude was greatest for Cue 4 which had a total of three relevant hypotheses associated with it. This work can be used to better understand how working memory underlies our everyday decision making.

INTRODUCTION

Decision making is a higher-order cognitive process that allows individuals to make choices, conduct judgements from a set of alternative possibilities, and arrive at conclusions in order to guide behavior (Turner, 2003). This process is vital to everyday problem solving, and significant research has been performed in the fields of psychology, medicine, and business in order to better understand how it occurs. Individuals make decisions based on a multitude of factors, some of which include using heuristics, logic, or intuition to come to a resolution (Kahneman, 2011). The process can be influenced by both internal and external factors such as an individual's knowledge in a specific area or situational elements like time pressure or high-stakes situations (Scott and Bruce, 1995). Finding solutions to everyday problems relies on a specific aspect of decision making, known as hypothesis generation.

Hypothesis generation is a process necessary for everyday problem-solving as it allows individuals to make sense of patterns in data. Evaluating the accuracy of each hypothesis you develop is known as a probability judgement. For example, imagine you're a doctor and a patient enters your office complaining about chest pain. As the patient is describing their symptoms, you run through various possible diseases in your head until you finally settle on the potential cause of the chest pain, and you conduct a probability judgment on each hypothesis you develop to determine if it is correct. As demonstrated by the example above, hypothesis generation is a daily occurrence because we are constantly generating explanations from environmental data.

The theorized framework for hypothesis generation assumes that three primary processes are involved: retrieving memories from storage (retrieval), sustaining retrieved hypotheses in consciousness (maintenance), and lastly making decisions (judgement) (Thomas, Doughtery, and Buttaccio, 2014). During the judgement phase, a probability judgement is rendered for the likelihood that the hypothesis generated is the correct one. If the initial hypothesis is judged to be incorrect, that information is fed back into working memory (WM), and a new hypothesis can be generated (Thomas, Doughtery, and Buttaccio, 2014). Both hypothesis generation and probability judgment can be constrained by cognitive load, timing pressures, primacy bias, and individual differences in working memory (Dougherty and Hunter, 2003). These limitations can result in either choosing incorrect hypotheses or evaluating correct hypotheses as incorrect.

With the advancement of non-invasive brain imaging technologies, researchers have recently begun to investigate the link between neurophysiological characteristics and decision making. The main methodologies for conducting these correlational studies are functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and magnetoencephalography (MEG) (Heekeren, Marrett, and Ungerleider, 2008). These technologies allow researchers to outline a neurobiological model of decision making that connects multiple regions of the brain for a system-wide view (Heekeren, Marrett, and Ungerleider, 2008). However, there has currently been little work done to link hypothesis generation, a specific facet of decision making, to neurophysiological processes.

Currently, one way of understanding this cognitive process is through computational models such as *HyGene* (Thomas et al., 2008). *HyGene* integrates theoretical frameworks from long-term memory, working memory (WM), and judgement and decision making (Thomas et al., 2008). It operates on three key principles: 1) environmental data serves as a retrieval cue to prompt hypothesis generation from long-term memory, 2) the number of hypotheses that can be actively maintained in WM is constrained by cognitive limitations and task features, and 3) hypotheses maintained in WM are used as inputs in the comparison process to derive probability judgements (Thomas et al., 2008). However, in order to better understand the overall model of hypothesis generation, it is important to correlate the process with neurobiological data.

EEG technology would make it possible to gain a better understanding of the exact timing of hypothesis generation to see if it matches the *HyGene* computational model of decision making. We plan to use EEG because the temporal resolution is in the millisecond range which makes it useful for studying decision making which occurs very quickly. This work has potential applications of providing researchers with information on how working memory and decision-making work together to allow us to make decisions in our daily lives.

EEG studies use event related potentials (ERPs) which are waveforms that occur in a specific range at a specific time. The ERPs of interest for this study are P300 and contralateral delay activity (CDA). The P300 ERP is evoked when a stimulus representation is updated in working memory (Polich, 2007). The P300 is characterized by a positive going peak in the 250-500 ms range and consists of two components, P3a and P3b (Polich, 2007). The P3b component is of particular interest for this study as it has been linked to memory processes, and it has been suggested that it's evoked with updates to working memory (Beydagi et al., 2000). Previous research on CDA has found that the amplitude increases according to the number of items maintained in visual working memory (VWM) (Luria et al., (2016). The CDA asymptotes at about 3-4 items which is a common estimate of VWM capacity and is correlated to individual working memory capacity (Luck and Vogel, 2013). Researchers can use previously defined ERPs to help determine the underlying neural activity during specific task-based studies. Combining these methods will help us fill the gaps in decision making research by correlating neurophysiological activity with hypothesis generation and help us understand the role of working memory in this process.

Therefore, the overall purpose of this project is to determine the underlying neural correlates of hypothesis generation and working memory. We plan to study this by correlating

P300 and CDA with working memory activation as a result of a hypothesis generation task. Our main hypothesis is that probability judgements from the hypothesis generation task will be negatively correlated to the P300 peak amplitude such that as the probability judgments decrease, the P300 amplitude increases. We also predict that the P300 amplitude will be greatest for the task cue that has the largest number of relevant hypotheses associated with it as this cue will have the most updates to working memory. We also predict that if a target subset in the working memory task is determined by the relevant hypotheses generated, the CDA amplitude will increase as the number of hypotheses generated increases. Finally, we predict that the probability judgements will decrease as the number of relevant hypotheses increases.

LITERATURE REVIEW

Hypothesis generation is a process necessary for everyday decision making because it allows individuals to make sense of patterns of data in the environment. Previously, one of our only reliable methods of understanding this cognitive process was through computational models. However, recent advancements in non-invasive neuroimaging technologies have allowed researchers to investigate the link between decision making and neurophysiology (Heekeren, Marrett, and Ungerleider, 2008). Yet, little work has been done to correlate hypothesis generation, a key process in decision making, to neurobiological data. In order to alleviate this gap, we aim to conduct an event related potential (ERP) study of the neural correlates of working memory in hypothesis generation via a causal learning task.

When the brain is making decisions, cortical areas are spatiotemporally linked to create long-range global networks. The discovery of the association between cortical areas has led to studies focusing less on investigating an individual part of the brain and increasingly taking a systems-wide approach to understanding complex cognitive tasks (Jin, et al., 2006; Anokhin, et al., 1999; Razoumnikova, 2000) such as hypothesis generation. One method by which researchers focus on gaining a system-wide understanding of the brain is through electroencephalography (EEG).

Consistent oscillations in varying frequency bands in the EEG data are a way of understanding the functional integration of various brain areas. For example, a recent study looked at the mechanism of voluntary focused attention and how it correlated to theta and gamma bands in EEG (Anokhin, et al., 1999). Another study by Razoumnikova studied alpha, beta, and theta bands during experimental convergent and divergent thinking (2000). Convergent thinking occurs when mental operations converge on only one task solution. Divergent thinking occurs when many new ideas are generated in response to a mental task, implying more than one correct solution. Both of these studies found that most of their significant correlations between cognitive processes and EEG coherence were observed in the theta band. In other words, the theta frequency band was present when there was synchrony between brain regions which demonstrates spatiotemporal linkage between cortical areas. However, these studies are limited in that the frequency bands tell us nothing about the specific timing of activation of the cognitive processes studied. Individual stages of information processing cannot be parsed out. Rather, they just provide a global view of the magnitude of activation in response to a specific task. Therefore, while these studies have been important in determining that EEG is a viable method by which to study higher order cognitive processes, they leave gaps in our understanding of the timing of neural correlates. A different methodology must be employed to gain an understanding of the spatiotemporal organization of the brain during a hypothesis generation or decision-making task.

One of the first experiments in the literature to attempt to correlate neural data with hypothesis generation was a study conducted by Jin et al. (2006). This study used EEG to investigate whether different brain activities can be correlated during hypothesis generation via averaged cross-mutational information (A-CMI) values. A-CMI allows researchers to investigate linear and non-linear properties of functional connectivity between electrode pairs. However, this method does not directly estimate spatiotemporal communication. Rather, the A-CMI value quantifies transmission of information statistically, a method that can introduce error. These errors can occur because the A-CMI values are an indirect measure of neural activity. Another interesting point to note is that this study made no previous predictions as to which brain areas would be coupled, making it much more of an exploratory study rather than one with set predictions of an outcome. Our study will focus on using ERPs rather than the A-CMI method and will have a predisposed hypothesis planned out. This is important because we will know exactly what signals to look for to determine the underlying neural correlates that are present during hypothesis generation.

A better method of understanding neural correlates underlying hypothesis generation than the neural oscillations and A-CMI values described above is to look at ERP signals. These ERPs have millisecond temporal resolution which is important for precise quantification of the timing of cognitive processes such as hypothesis generation (Friedman and Johnson, 2000). The ERP waveform can be used to measure three unique features: 1) amplitude for information about neural activation, 2) component latency to understand the timing of activation, and 3) scalp distribution which gives information about the overall pattern of activated brain areas (Friedman and Johnson, 2000). Neural oscillations are unable to provide us with information about the precise timing of activation which is important when looking at fast occurring cognitive processes such as decision making, and A-CMI values cannot directly measure spatiotemporal communication. Therefore, when combined with large electrode arrays, ERPs make for a powerful tool that can be used to give researchers a better understanding of cortical activity.

ERPs allow researchers to determine the cortical activity underlying complex cognitive tasks. Previous studies have used ERP signals from EEG studies of decision making and working memory to better understand the cortical spatiotemporal organization of the brain (Gevins, et al., A., 1997; Gevins, et al., 1998; Rohrbaugh, et al., 1974). For example, in a seminal paper in the literature, Rohrbaugh et al. used EEG and the P300 ERP component to look at working memory in decision making (1974). Similarly, in later research, high-resolution EEG was used to study ERP signals in response to cognitive load, task difficulty, and types of processing (Gevins, et al., A., 1997; Gevins, et al., 1998). This technique allows researchers to elucidate more complex information from an experimental paradigm than other neuroimaging techniques. However, these studies are not without their limitations. One of the drawbacks of ERP research is the number of trials and participants needed to gain meaningful data from continuous EEG recordings (Beres, 2017). Research has found that a minimum of 40 trials per condition may be needed to gain a comprehensive understanding of the ERPs being studied which can lead to further issues by increasing the overall length of the study (Kaan, 2007). Long experiments can cause tired participants leading to poor concentration and paying less attention to the task at hand. Limitations such as participation numbers, long studies, and variations in EEG preprocessing techniques can lead to gaps in the literature that must be addressed.

Our current study plans to use a visual working memory (VWM) task to understand the underlying neural correlates of hypothesis generation. ERP studies can be used to better understand processes that involve the use of more than one cortical area, and VWM tasks that look to understand the relationship between the frontal cortex and the visual cortex are commonly used in decision making research (Gao, et al., 2011; Downing, 2000; Woodman, Vogel, and Luck, 2001). The interactions between VWM and decision making can be studied using the contralateral delay activity (CDA) signal. CDA is a measure of cognitive load that is found by subtracting the ipsilateral brain wave activity from the contralateral activity. In these studies, researchers correlate the amplitude of the contralateral delay to the number of objects that are held in VWM (Gao, et al., 2011; Woodman, Vogel, and Luck, 2001). Researchers have determined that the amplitude of the CDA should increase as the number of hypotheses held in WM increases (2011). However, there are still inconsistencies in the literature on how CDA amplitude is affected by items held in WM (Woodman, Vogel, and Luck, 2001). These inconsistencies are an issue that must be resolved in order to properly understand the neural correlates underlying hypothesis generation and decision making. Our work aims to understand how CDA amplitude is related to the number of objects in WM by having participants undergo a decision-making memory activation capture procedure. As participants hold a number of relevant hypotheses per the task cue in WM, the CDA amplitude will be measured.

Previous work in our lab has focused on developing a computational model of hypothesis generation known as *HyGene* (Thomas et al., 2008). This model integrates theoretical frameworks from long-term memory, working memory, judgement, and decision making. A novel measure of working memory called the memory activation capture (MAC) procedure (Lange et al., 2014) was integrated with *HyGene* to better study the dynamics of hypothesis generation. The MAC procedure uses a Cause and Effect learning task where certain colored disks represented environmental data, or Effects, and other disks represented hypotheses, or Causes. A correlational study that combines this experimental task with EEG would allow us to better our understanding of the neural mechanisms of hypothesis generation and better understand how working memory plays a role in decision making.

The current study will address these gaps in the literature by conducting an ERP study via EEG with a modified version of the MAC causal learning procedure. The P300 and CDA signals will be used to look at working memory activation and the number of items being held in working memory respectively in order to help us gain a better understanding of the neural mechanisms underlying hypothesis generation and decision-making.

Experimental Design

Participants were responsible for completing a decision-making task on the computer while EEG was recorded in order to determine the underlying neural correlates of hypothesis generation.

This experiment was a modification of the MAC procedure (Lange et al., 2014) and utilized P300 and CDA to provide an indirect measurement of working memory content. The experiment manipulated the number of relevant hypotheses held in visual working memory. The study consisted of two primary stages. The first stage of the study was a training phase in which participants learned the causal relationships between 'Cause' and 'Effect' stimuli. Stimuli were represented as colored disks on the screen. Each 'Effect' disk had specific 'Cause' disks associated with it. The 'Cause' disks represented hypotheses that would be generated in response to an 'Effect' disk. Each Effect could have up to three hypotheses associated with it. The second stage of the study was an elicitation phase in which the participants had to make judgements about potential 'Causes' for a given 'Effect', and the EEG was recorded.

The training phase involved two distinct types of training blocks: a passive training block and an active training block. The training phase of the experiment consisted of three total training blocks wherein a passive training block was always followed by an active training block. The elicitation phase began after the end of the final training block.

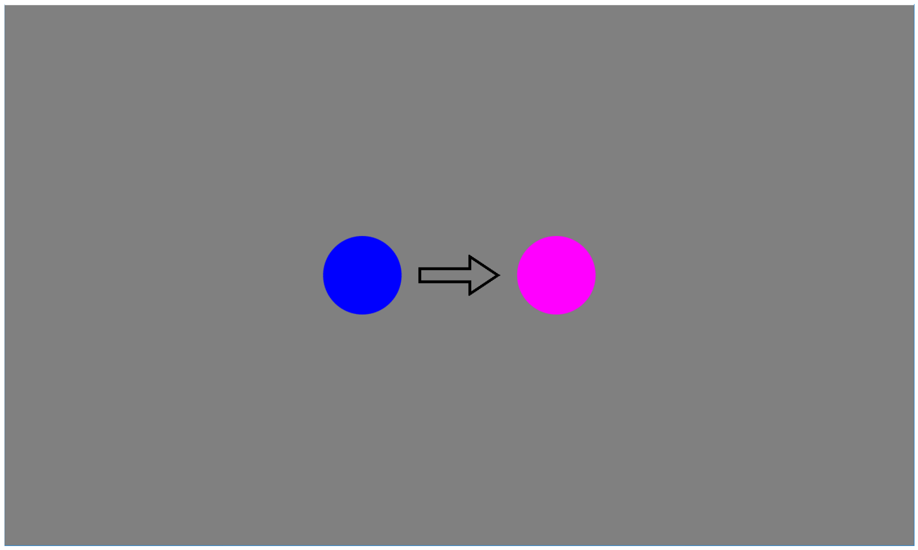


Figure 1: A sample cause/effect cue from the passive training block. The blue disk represents the cause and the magenta disk represents the effect.

The passive training block consisted of an “unblocked” and a “blocked” learning phase. During the “unblocked” passive training block, a single cause cue and a single effect cue appeared on the screen with an arrow pointing from the cause to the effect (Figure 1). The cue remained on the screen for 2,000 ms before being replaced by a fixation cross for 500 ms which was then replaced by another cause/effect cue. Each cause appeared 16 times and each effect appeared 12 times in a random order. In the “blocked” learning phase, all possible cause/effect pairs were displayed in order of the “Effect” cue. Each participant had a training block with at least one unblocked learning phase and one blocked learning phase. The cause/effect cue frequencies per training block are displayed in Table 1.

	Effect 1	Effect 2	Effect 3	Effect 4
Cause 1	12	0	0	4
Cause 2	0	6	6	4
Cause 3	0	6	6	4

Table 1: Cause/effect pair frequencies per training block.

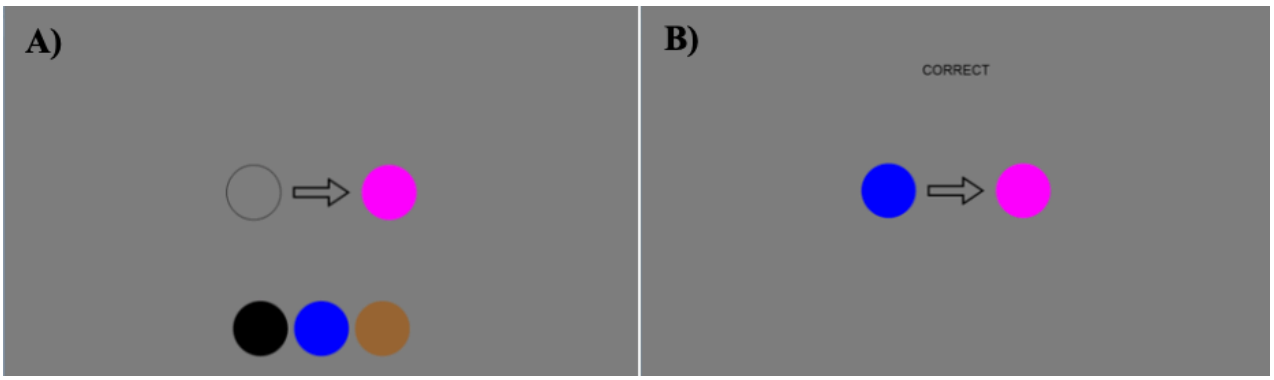


Figure 2A: A sample cause/effect cue from the active training phase. The blank disk represents a potential cause and the magenta disk is the effect. Possible causes are displayed at the bottom of the screen.
Figure 2B: The correct disk is displayed with the word CORRECT at the top of the screen.

In the active training block, a blank 'Cause' disk was displayed with an arrow pointing to an 'Effect' disk, and three potential 'Causes' were displayed on the bottom of the screen (Figure 2A). The participant had to indicate with a keyboard click which 'Cause' disk they thought was correct for the 'Effect' disk displayed. In this training block, each cause appeared 16 times and each effect appeared 12 times. During the first active training block, participants had 5,000 ms to respond. In subsequent active training blocks, the time limit was reduced to 1,500 ms. After a response was submitted, the blank disk was replaced by the correct cause and participants were told if their selection was correct (Figure 2B). Participants had to complete three rounds of passive and active training blocks before moving on to the elicitation phase of the experiment.

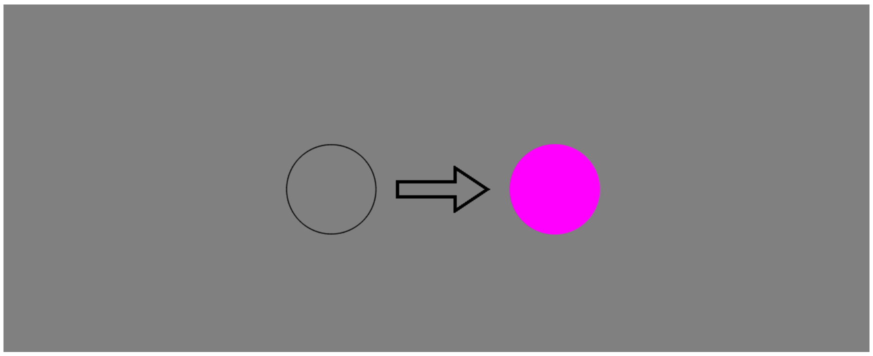


Figure 3: *A sample cause/effect conditionalization cue from the elicitation phase.*

The elicitation phase tested participants ability to generate hypotheses. During this phase, a blank ‘Cause’ disk was displayed with an ‘Effect’ disk (Figure 3). The conditionalization cue appeared on the screen for 1000 ms and was then replaced by a fixation point for 400 ms. After the interstimulus interval was displayed, an array with 12 colored disks representing possible causes appeared on the screen for 400 ms. All the potential ‘Causes’ for the ‘Effect’ displayed were located on the same side of the screen. This colored disk array was followed by a retention period of 1000 ms. The retention period is responsible for the maintenance and recall of stored information in working memory. After the retention period, a blank visual array appeared on the screen (Figure 4). This second array consisted of blank disks located in the same positions as the colored array seen previously. Participants were required to select all the blank disks that were hypothesized to correspond to the possible ‘Causes’ of the ‘Effect’ displayed. At the end of the trial, participants had to make a probability judgement on the accuracy of one of their selected hypotheses. The probability judgment ranged from 0-100. The elicitation phase occurred in blocks of 48 trials, with 12 trials for each possible effect. There were three blocks for a total of 144 trials.

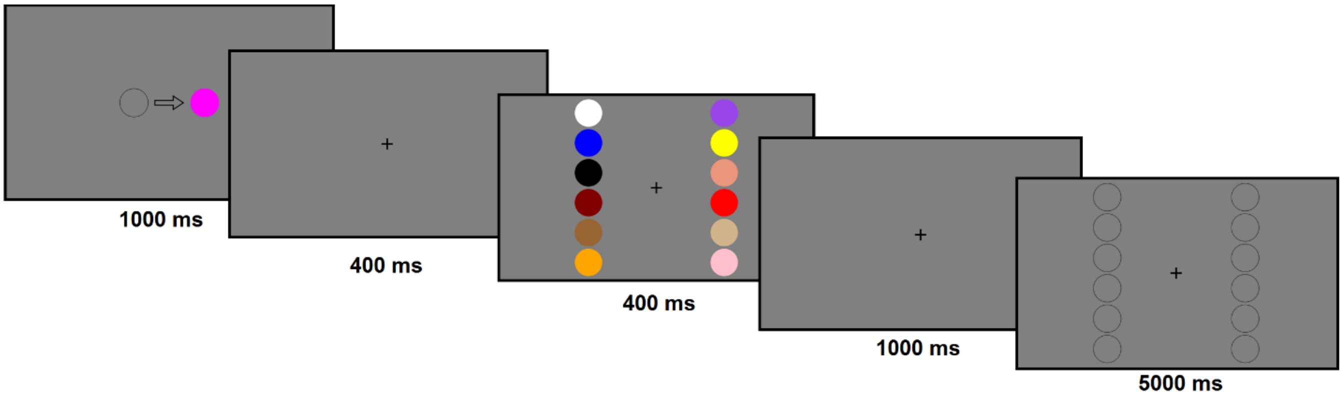


Figure 4: Outline of the elicitation phase from cue onset to hypothesis generation. Participants must select the blank cues corresponding to the colored disk that they predict to match the effect cue.

EEG Acquisition and Analysis

EEG was recorded using an EGI 400 series Geodesic EEG System. Stimulus presentation and data recording were controlled by PsychoPy software (Peirce, 2007). EEG data was continuously recorded at 1000 Hz. Offline analysis of EEG data was conducted in MATLAB 2019a with the EEGLAB (Delorme and Makeig, 2004) toolbox. Offline data analysis was conducted on nine data sets that had low impedances.

Continuous EEG data were down sampled from 1000 Hz to 256 Hz and re-referenced offline to the average of the left and right mastoid electrodes. Data was bandpass filtered between 1 – 40 Hz. Channel locations were assigned to the electrodes. Artifact rejection was conducted to filter out noise from the data and remove eye movements. The data were epoched between -100 ms before cue onset to +1000 ms after cue onset. Each epoch was baseline corrected to the average of the whole. Then, an independent component analysis (ICA) was run on all head electrodes to examine for any additional sources of noise in the data and conduct trial rejections.

ERPs were analyzed to determine the underlying neural correlates. In particular, the P300 signal was of interest due to its correlation with working memory activation. Electrical activity was averaged across all trials for each subject and the P3b was measured at the Pz electrode (Polich, 2007) starting with onset of the conditionalization cue. The CDA amplitude was also of interest as it is correlated with cognitive load which is based on the number of items held in visual working memory. CDA was measured during the retention period in the elicitation stage starting from +200 ms after the “Effect” cue. CDA was calculated by subtracting the ipsilateral from contralateral activity at the CP5, CP6, P3, P4, P7, and P8 electrodes.

Statistical Analysis

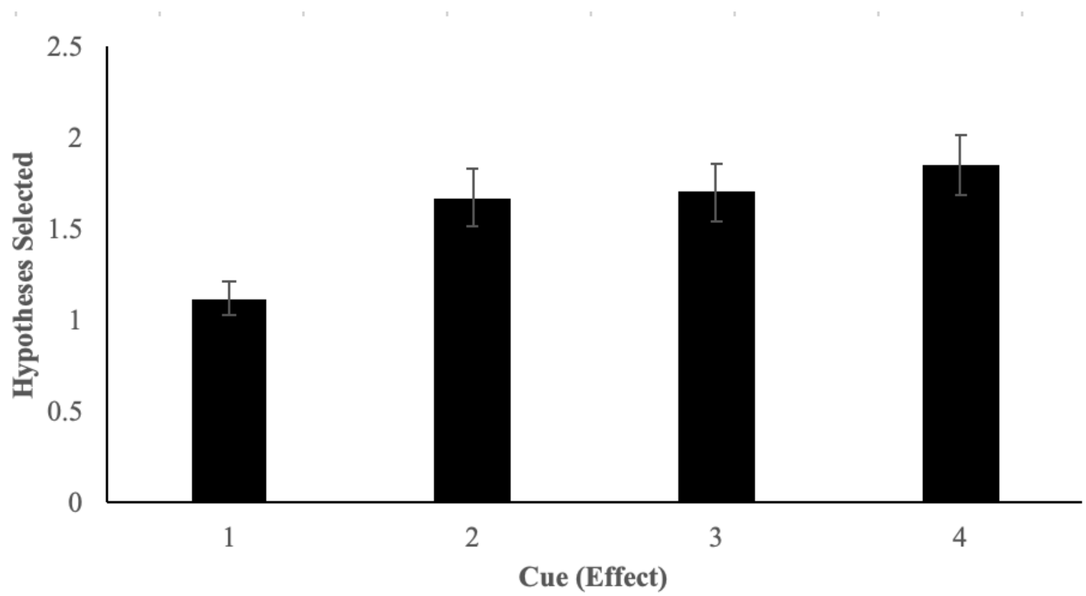
Behavioral data from participants’ responses during the experimental paradigm were analyzed using a log-linear regression model, a repeated measures ANOVA, and two-factor analysis. The log-linear regression model was used to determine the significance of the total number of hypotheses selected based on the ‘Effect’ cue. A repeated measures ANOVA was conducted to determine the significance of the probability judgments based on the ‘Effect’ cue and to analyze the significance of probability judgments by total hypotheses selected. A two-factor analysis was run for an analysis of probability judgements by ‘Effect’ and by hypotheses selected. The interaction of the ‘Effect’ cue and hypotheses selected was also analyzed.

EEG data was analyzed using a repeated measures ANOVA to determine the significance of the peak P300 amplitude between cues.

RESULTS

Behavioral Results

A log-linear regression model was used to examine the relation between the number of hypotheses selected and the ‘Effect’ cue. The relationship between these variables was significant ($G^2(3) = 149.76$, $p < 0.001$). Figure 5 illustrates the number of hypotheses selected per cue. This demonstrates that as the number of relevant hypotheses increased, the number of actual hypotheses selected by the participant also increased. The relationship between the number of relevant hypotheses per cue and the actual number of hypotheses selected by the participant is demonstrated in Figure 6. Participants were more likely to select a greater number of hypotheses when more hypotheses were relevant to the presented Cue.



<u>Figure 5:</u> Hypotheses selected by Effect cue. Cue 1 correlates to one hypothesis, Cue 2 and Cue 3 correlate to two hypotheses, and Cue 4 correlates to 3 hypotheses.

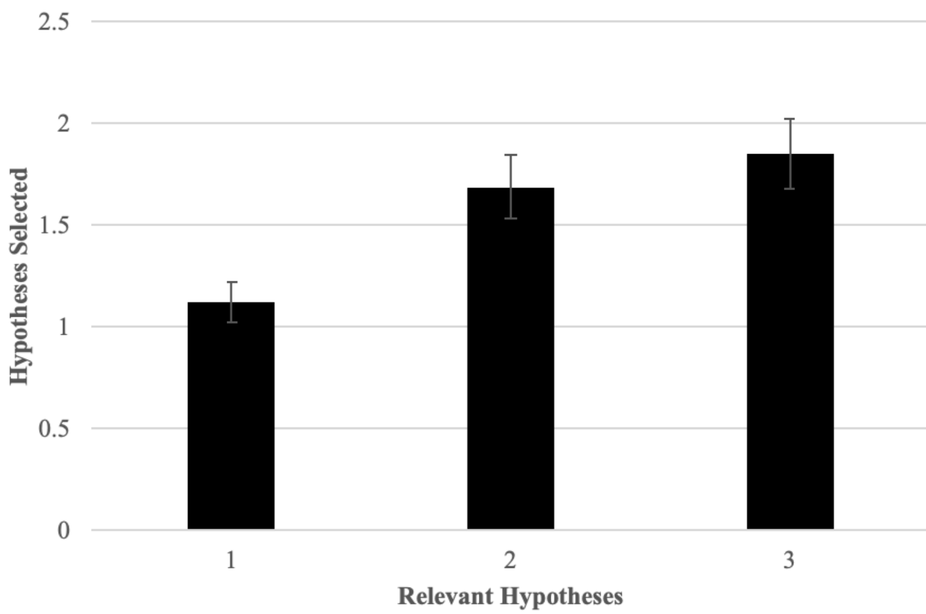
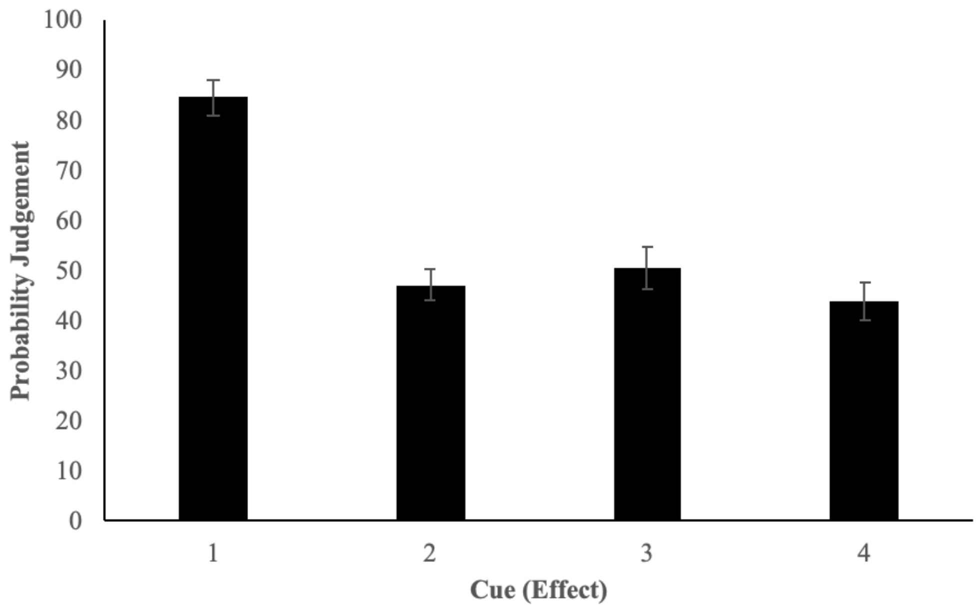


Figure 6: Relationship between the average number of hypotheses selected by the participant and the number of relevant hypotheses actually present.

A repeated measures ANOVA analysis of probability judgment by ‘Effect’ cue demonstrated significant results ($F(3, 57) = 46.520$, $p < 0.001$). Post-hoc comparison of the ‘Effect’ cues using the Holm-Bonferroni method demonstrated significant differences between Cue 1 ($M = 84.632$, $SE = 3.51$) and Cue 2 ($M = 47.14$, $SE = 3.06$). Cue 1 also significantly differed from Cue 3 ($M = 50.46$, $SE = 4.07$) and from Cue 4 ($M = 43.96$, $SE= 3.85$). The average probability judgement for the ‘Effect’ cue presented is demonstrated in Figure 7. Participants were more likely to have a higher probability judgement for Cue 1 which was associated with a fewer number of hypotheses. As the number of relevant hypotheses increased with the ‘Effect’ cue, the probability judgements decreased. The one-way analysis of probability judgement by the total hypotheses selected also demonstrated a significant main effect ($F(7, 42) = 154.44$, $p < 0.0001$). The average probability judgment based on the hypotheses generated is demonstrated in Figure 8. Probability judgements shrank in size as the number of relevant hypotheses increased.



<u>Figure 7:</u> Average probability judgement given based on the 'Effect' cue. Probability judgements were given at the end of each trial on a sliding scale. Cue 1 correlates to one hypothesis, Cue 2 and Cue 3 correlate to two hypotheses, and Cue 4 correlates to three hypotheses.

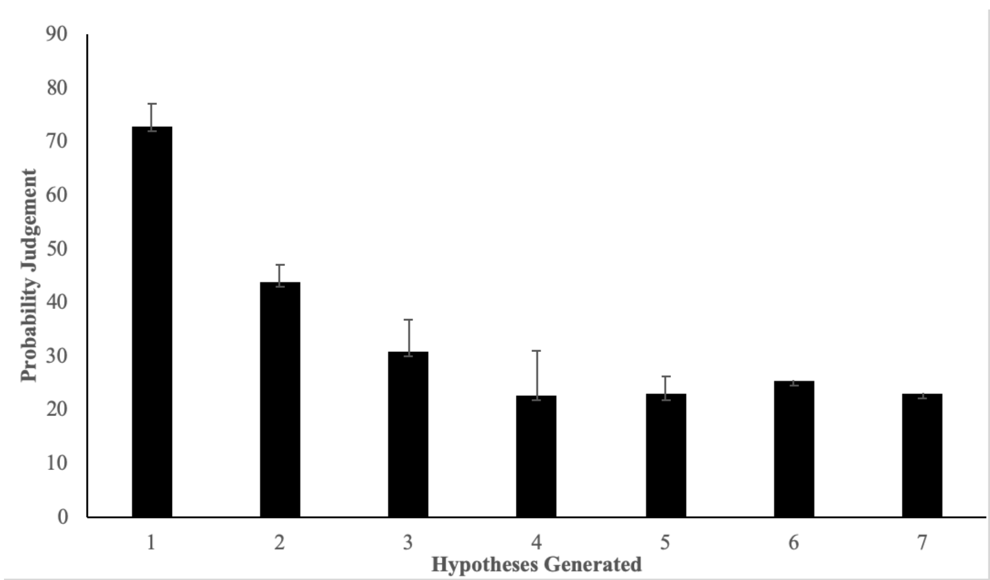


Figure 8: Probability judgement given by total number of hypotheses generated. Participants generated up to seven hypotheses per trial. However, there was only a maximum of three possible hypotheses per trial. Probability judgements were given at the end of each trial on a sliding scale.

A factorial ANOVA of probability judgment by the ‘Effect’ cue demonstrated a significant main effect ($F(3, 57) = 3.11$, $p = 0.0334$), and the analysis of the probability judgements by the hypotheses selected was also significant ($F(7, 42) = 66.54$, $p < 0.0001$). This demonstrates that probability judgements decreased for cues associated with a greater number of relevant hypotheses, and probability judgements were greater when there were fewer hypotheses generated. The interaction between the ‘Effect’ cue and the number of hypotheses selected was also significant ($F(17, 47) = 4.29$, $p < 0.0001$). This illustrates that participants selected the relevant hypotheses associated with the cue presented.

EEG Results

The grand averages of the target P3b ERP for each cue at the Pz electrode are demonstrated in Figure 9. The P3b signal duration occurs from 300 ms to 600 ms. Neural data was averaged from nine subjects with low impedances in order to generate the figure. A repeated measures ANOVA was run for a between cues analysis using the peak amplitude data from nine subjects. There were no significant effects between Cue 1, Cue 2 and Cue 3, or Cue 4 ($F(2, 16) = 0.78$, $p = 0.48$).

Analysis of the CDA signal is currently ongoing in the lab.

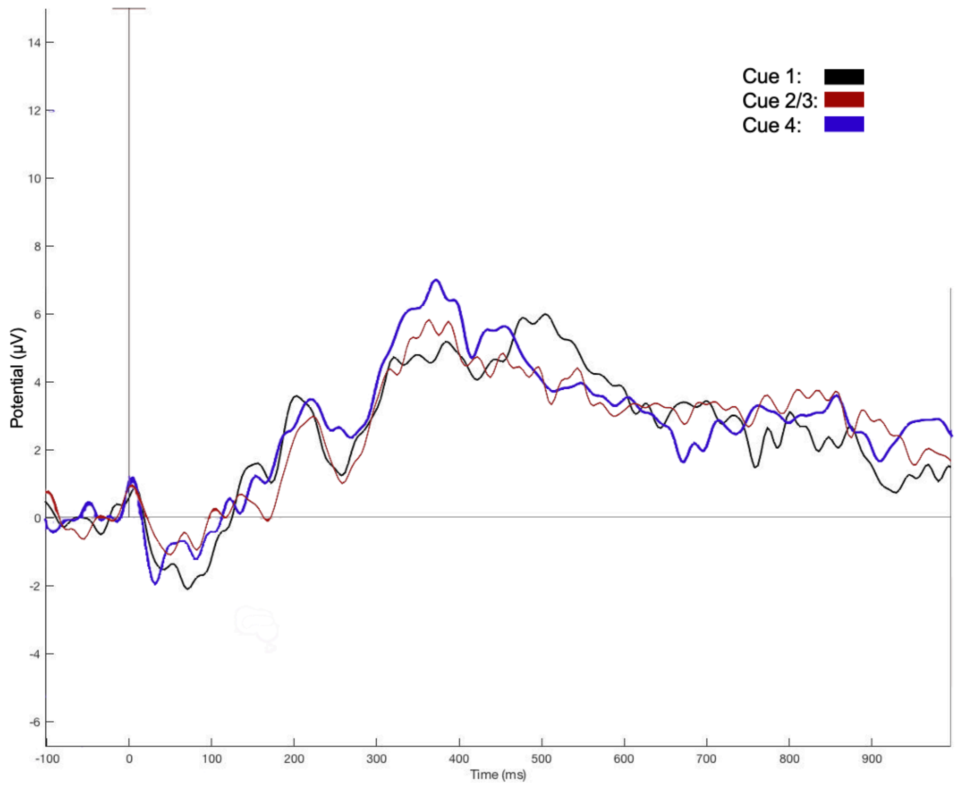


Figure 9: Averaged EEG neural activity for nine subjects at the Pz electrode. The target P3b signal occurs from 300 ms to 600 ms.

DISCUSSION

The purpose of this study was to determine the underlying neural correlates of hypothesis generation. EEG data was collected while participants completed a modified MAC procedure on the computer. One of the hypotheses of interest was that probability judgements will decrease as the number of relevant hypotheses increases. We also predicted that probability judgements from the hypothesis generation task would be negatively correlated to the P300 peak amplitude such that as the probability judgments decrease, the P300 amplitude increases. Another hypothesis of interest was that the P300 amplitude will be greatest for the task cue that has the largest number of relevant hypotheses associated with it as this cue will have the most updates to working memory. Finally, we predicted that if a target subset in the working memory task is determined by the relevant hypotheses generated, the CDA amplitude will increase as the number of hypotheses generated increases.

Overall the results demonstrate that the first hypothesis was supported because the probability judgments were negatively correlated to the number of relevant hypotheses per 'Effect' cue. The second hypothesis was not supported as the peak P300 amplitude did not reveal any significant differences between the 'Effect' cues. The third hypothesis was supported because the peak P300 amplitude was greatest for Cue 4 which had a total of three relevant hypotheses associated with it. Work is currently in progress in the lab to study CDA amplitude further.

Hypothesis Generation and Probability Judgement Behavior

The results demonstrate that probability judgments decrease as the number of relevant hypotheses for a particular 'Effect' cue increase (Figure 7) therefore, hypothesis one was supported. Participants were less likely to judge generated hypotheses as correct for ‘Effect’ Cue 4, which had three hypotheses associated with it. This effect was likely observed because as the cognitive load placed on working memory increases, the likelihood of judging any single ‘Cause’ cue as correct decreases. Furthermore, Cue 1 had the highest probability judgements with only one relevant hypothesis which demonstrates that when fewer items are held in VWM, the ability to accurately judge hypotheses as correct increases.

This finding supports the idea that individual differences in working memory capacity are fundamental to hypothesis generation and probability judgement. These findings also demonstrate that the probability judgement of a single hypothesis is negatively correlated to both the number of alternative hypothesis generated and the span of working memory (Dougherty and Hunter, 2003). This research also provides support to the *HyGene* cognitive model in which individuals with a low working memory capacity are unable to maintain as many alternative hypotheses for inclusion as those individuals with a higher working memory capacity eventually leading to fewer hypotheses generated (Thomas, Dougherty, and Buttaccio, 2014). Thus, a participant’s capacity to accurately judge generated hypotheses as correct is related to their underlying memory constraints which can result in cognitive biases.

Probability Judgements and Peak EEG P300 Amplitude

Hypothesis two predicted that a greater P300 signal would be expected from the ‘Effect’ cues associated with an increased number of hypotheses. This is because lower probability judgements are associated with an increased number of relevant hypotheses, thus more items would be updated in working memory leading to a greater P300 signal amplitude. However, this prediction was not supported as the data was not significant.

This likely occurred because only nine subjects' peak P300 amplitude waveform data was used for the analysis (Figure 9). A one-way ANOVA test can be sensitive to statistical outliers and thus a large sample size is usually recommended. The current sample size was restricted due to high impedances present in the other eleven subjects. High impedances are a technical restriction in EEG studies and indicate a greater resistance to current flow (Teplan, 2002). Thus, a dataset with high impedances will result in a smaller amplitude for an EEG signal and is not recommended to be used.

Hypothesis Generation and Peak P300 Amplitude

The P300 ERP signal is made of two components— P3a and P3b. The current study was particularly interested in the P3b component as it is associated with working memory processes. Research suggests that the P3b component is evoked when expectations of environmental events are updated in working memory (Beydagi, et al., 2000). In other words, as working memory is updated, the P3b component should increase in amplitude.

The results demonstrate that the peak P300 amplitude was greatest for Cue 4 which was associated with three hypotheses. Cue 4 had the greatest number of working memory updates since participants had to generate more relevant hypotheses for this 'Effect' cue than for any other cue. The results demonstrate that increased working memory updates were correlated to an increased P3b amplitude for Cue 4 which supports the third hypothesis. These results are also consistent with previous literature that has found that the P300 amplitude changes in an orderly manner as the number of items that must be remembered, and therefore held in working memory, increases (Beydagi, et al., 2000).

CONCLUSION

Overall, these results demonstrate that the underlying neural correlates of hypothesis generation are affected by updates to working memory. Probability judgements are negatively correlated to the number of relevant hypotheses associated with each ‘Effect’ cue, and the P300 amplitude is highest for Cue 4 which is associated with the greatest number of hypotheses. However, it is unclear the magnitude of difference among the peak amplitudes of ‘Effect’ cues as the data was not significant. This work can be used to better understand how working memory underlies our everyday decision making. In conclusion, although this research has made strides towards understanding the relationship between hypothesis generation, working memory, and neural activity, further work is needed to fully understand these concepts.

Future Directions

Research is still ongoing in the lab to understand the relationship between the CDA signal amplitude change as the number of generated hypotheses increases.

Future studies should look to repeat this modified MAC procedure with a larger sample size (N > 30) so that EEG traces are not be limited by artifacts. The two main artifacts present in EEG data are subject artifacts which can include body movements, eye movements, heart rate, etc., and technical artifacts such as impedance fluctuation, cable movements, and broken electrode contacts (Teplan, 2002). A large sample size would allow for more in-depth statistical analysis. . Making these changes will ideally demonstrate that updating working memory through generating more hypotheses is correlated to a greater P300 signal amplitude.

Another improvement would be to conduct a similar study in which participants must make probability judgments after every hypothesis generated for ‘Effect’ cues that are associated with more than one relevant hypothesis. This will differ from the present study as participants were only asked to make their probability judgements at the end of every trial.

WORKS CITED

1. Anokhin, A. P., Lutzenberger, W., Birbaumer, N. (1999). Spatiotemporal organization of brain dynamics and intelligence: an EEG study in adolescents. *International Journal of Psychophysiology, 33*(3) 259-273.
2. Beydagi, H., Özesmi, C., Yilmaz, A., Süerd, C., & Ergenoglu, T. (2000). The Relation Between Event Related Potential and Working Memory in Healthy Subjects, *International Journal of Neuroscience*, *105*:(1-4), 77-85.
3. Delorme, A. and Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics, *Journal of Neuroscience Methods, 134*, 9-21
4. Dougherty, M. R., Hunter, J. E. (2003). Hypothesis generation, probability judgment, and individual differences in working memory capacity. *Acta Psychological, 113*(3), 263–282.
5. Downing, P. E. (2000). Interactions Between Visual Working Memory and Selective Attention. *Psychological Science*, *11*(6), 467–473.
6. Electrical Geodesics Inc. (2013). *EGI Net Station 5 Geodesic EEG Software User Manual.* Oregon. Electrical Geodesics Inc.
7. Friedman D., Johnson, R. (2000). Event-Related Potential (ERP) Studies of Memory Encoding and Retrieval: A Selective Review. *Microscopy Research and Technique 51*: 6-28.
8. Gao, Z. Yin, J., Xu, H., Shui, R., Shen, M. (2011). Tracking object number or information load in visual working memory: Revisiting the cognitive implication of contralateral delay activity, *Biological Psychology,* 87:(2), 296-302

9. Gevins, A., Smith, M. E., Harrison, L., McEvoy, L., & al, e. (1998). Monitoring working memory load during computer-based tasks with EEG pattern recognition methods. *Human Factors, 40*(1), 79-91.
10. Gevins, A., Smith, M.E., McEvoy, L., Yu, D., (1997). High-resolution EEG mapping of cortical activation related to working memory: effects of task difficulty, type of processing, and practice. *Cerebral Cortex*, *7*(4) 374–385.
11. Heekeren, H. R., Marrett, S., & Ungerleider, L. G. (2008). The neural systems that mediate human perceptual decision making. *Nature Reviews. Neuroscience, 9*(6), 467-479.
12. Heekeren, H. R., Marrett, S., & Ungerleider, L. G. (2008). The neural systems that mediate human perceptual decision making. *Nature Reviews. Neuroscience, 9*(6), 467-479.
13. Jin, S., Kwon, Y., Jeong, J., et al. (2006). Increased information transmission during scientific hypothesis generation: Mutual information analysis of multichannel EEG. *Psychophysiology 62*(2), 337-344.
14. Kahneman, Daniel (2011). Thinking, fast and slow. New York: Farrar, Straus, and Giroux. ISBN 9780374275631.
15. Lange, N. D., Buttaccio, D. R., Davelaar, E. J., & Thomas, R. P. (2014). Using the memory activation capture (MAC) procedure to investigate the temporal dynamics of hypothesis generation. *Memory & Cognition*, *42*(2), 264-274
16. Luck S. J., Vogel E. K., (2013) Visual working memory capacity: from psychophysics and neurobiology to individual differences*. Trends Cogn Sci*., *17*(8), 391–400.

17. Luria, R., Balaban, H., Awh, E., & Vogel, E. K. (2016). The contralateral delay activity as a neural measure of visual working memory. *Neuroscience and biobehavioral reviews, 62,* 100–108.

18. Polich J. (2007). Updating P300: an integrative theory of P3a and P3b. *Clinical neurophysiology: Official journal of the International Federation of Clinical Neurophysiology*, *118*(10), 2128–2148.

19. Razoumnikova, O. M. (2000). Functional organization of different brain areas during convergent and divergent thinking: an EEG investigation. *Cognitive Brain Science 10*(1) 11-18.

20. Rohrbaugh, J.W., Donchin, E. & Eriksen, C.W. (1974). Decision making and the P300 component of the cortical evoked response, *Perception & Psychophysics 15*(2): 368-374

21. Scott, S. G., Bruce, R. A. (1995). "Decision-making style: the development and assessment of a new measure". *Educational and Psychological Measurement 55*(5), 818–831

22. Teplan, M. (2002). Fundamentals of EEG measurement. Measurement science review, 2(2), 1-11.

23. Thomas, R. P., Dougherty, M. R., Sprenger, A. M., Harbison, J. (2008). Diagnostic hypothesis generation and human judgment. *Psychological Review, 115*(1), 155–185.

24. Thomas, R., Doughtery, M. R., Buttaccio, D. R. (2014). Memory Constraints on Hypothesis Generation and Decision Making. *Association for Psychological Science, 23*(4), 264-270.

25. Turner, L. H. (2003). Decision Making. In J. J. Ponzetti (Ed.), International Encyclopedia of Marriage and Family (2nd ed., Vol. 1, pp. 394-397). New York, NY: Macmillan Reference USA.

26. Woodman, G. F., Vogel, E. K., & Luck, S. J. (2001). Visual search remains efficient when visual working memory is full. *Psychological Science, 12*(3), 219-224.