

THE INTERACTION OF PROBABILITY LEARNING AND WORKING
MEMORY

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**THE INTERACTION OF PROBABILITY LEARNING AND WORKING
MEMORY**

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ABSTRACT

THE INTERACTION OF PROBABILITY LEARNING AND PREFRONTAL CORTEX

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Probability learning is the ability to establish a relationship between stimulus and outcomes based on occurrence probabilities using repetitive feedbacks. Participants learn the task according to the cue-outcome relationship, and try to gain in depth understanding of this relationship throughout the experiment. While learning is at the highest level, people rely on their working memory. In this study 20 participants were presented a probability learning task, and their prefrontal cortex activity was measured with functional Near-Infrared Spectroscopy. It was hypothesized that as participants gain more knowledge of the probabilities they will learn cue-outcome relationships and therefore rely less on their working memory. Therefore as learning precedes a drop in the fNIRS signal is expected. We obtained results confirming our hypothesis: Significant negative correlation between dorsolateral prefrontal cortex activity and learning was found. Similarly, response time also decreased through the task, indicating that as learning precedes participants made decisions faster. Participants used either the frequency matching or the maximization strategy in order

to solve the task in which they had to decide whether the blue or the red color was winning. When they use the frequency matching strategy they chose blue at the rate of winning for the blue choice. When they use the maximization strategy they chose blue almost always. Our task was designed such that the frequency for blue to win was 80%. We had hypothesized that the people in frequency matching and maximization groups would show working memory differences which could be observed from the fNIRS signal. However, we were unable to detect this type of behavioral difference in the fNIRS signal. Overall, our study showed the relationship between probability learning and working memory as depicted by brain activity in the dorsolateral prefrontal cortex which widely known as the central executive component of working memory.

Keywords: Probability Learning, Working Memory, Prefrontal Cortex, Pattern Searching, Central Executive

ÖZ

OLASILIKSAL ÖĞRENMENİN PREFRONTAL KORTEKSLE İLİŞKİSİ

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Olasılıksal öğrenme bir uyarın ve sonucu arasındaki ilişkiyi sunulan geri bildirimler doğrultusunda anlamaya dayanan bir yetidir. Katılımcılar deneyi ipucu ve sonuç ilişkisine dayalı olarak, deney süresince bu ilişkiyi öğrenmeye çalışırlar. Öğrenme en üst seviyedeiken, insanlar çalışma belleklerini kullanırlar. Bu çalışmada 20 katılımcı bir olasılıksal öğrenme deneyine katılmışlardır, ve prefrontal korteks aktiviteleri fonksiyonel Yakın Kızılötesi Spektroskopi (fNIRS) kullanarak ölçülmüştür. Katılımcıların deney süresince verilen geri bildirimler yardımıyla olasılıkları anlayacakları ve çalışma belleklerini daha az kullanacakları öne sürülmüştür. Sonuç olarak öğrenme ilerledikçe fNIRS sinyallerinde düşme beklenmiştir. Sonuçlar beklenen yönde bulunmuştur: Dorsolateral prefrontal korteks aktivitesi ve öğrenme arasında anlamlı negatif korelasyon bulunmuştur. Benzer şekilde, cevap verme hızı da deney süresince düşmüştür. Bu düşme, deney süresince olasılıkların anlaşıldığı ve katılımcıların cevap vermek için daha az vakit harcadıklarını göstermektedir.

Katılımcılar olasılıksal öğrenmeyi uyarıların sıklığını eşleştirerek ya da en fazla kazanan uyarıyı sürekli seçerek gerçekleştirmişlerdir. Mevcut deney mavi kutuların kazanma sıklığı her zaman %80 olacak şekilde tasarlanmıştır. Uyarıların sıklığını eşleştirerek deneyi tamamlayanların ve en fazla uyarıyı sürekli seçerek deneyi tamamlayanların çalışma belleği aktivelerinde farklılık olacağı öne sürülmüştür. Fakat, bu öne sürülen farklılık bulunamamıştır. Sonuç olarak, bu tezde çalışma belleği ve olasılıksal öğrenme ilişkisi, dorsolateral prefrontal korteksten ölçülerek gözlemlenmiştir.

Anahtar kelimeler: Olasılıksal Öğrenme, Çalışma Belleği, Prefrontal Korteks, Örüntü Arama, Merkezi Yürütme

To Mercan

Let science to enlighten your way...

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CHAPTER 1

INTRODUCTION

Our brain is capable of analyzing and evaluating several aspects of events in the environment. One of the most important learning processes involves understanding of probabilistic events and making decisions according to associated feedbacks. Decision-making in an uncertain environment by using cognitive resources such as attention and memory is an indispensable skill. When people encounter a problem with uncertainty and have difficulties in estimating the situation, they rely on their cognitive ability to analyze the event and predict outcomes. In such an uncertain situation, making reasonable choices and trying to find the best consequence is crucial in terms of survival. Analyzing people's behavior in probability learning tasks gives a clue to researchers to understand how people make rational choices. Probability learning has many implications in several areas of economics, evolutionary psychology and neuroscience.

Probability learning research tries to understand how people look for patterns when a task is given, and how people change their responses according to feedback. According to the cue-outcome relationship, a learning paradigm occurs gradually (Knowlton, Squire & Gluck, 1994). In a typical probability learning experiment,

participants are presented few stimuli and asked to choose one of them. One of the stimuli has a higher probability rate for winning. After choosing one option, a feedback (either win or lose) is given to the participant, thus s/he tries to understand which option wins the most according to the feedback. The participant eventually learns the winning probabilities associated with possible options during the experiment trials. Such a probability learning process taps into two different cognitive mechanisms: pattern searching and frequency learning.

Pattern searching: In the process of probability learning, current options and feedbacks are temporarily stored as a chain. By using this chain, people try to find a pattern among the stimuli. This mechanism is called “pattern searching” (Clark, 2004). Clark suggests that human’s innate mechanism to search for patterns constitutes an important survival mechanism which helps dealing with the situations of high uncertainty.

Frequency learning: On the other hand, we also keep track of the frequencies of the win/lose situations in order to perform the task successfully. People tend to make their choices according to the most frequent winning option. This mechanism is called “frequency learning” (Cosmides & Toby, 1996).

These two distinct mechanisms have their roots in different brain regions and memory systems. Knowlton, Squire and Gluck’s study (1994) on amnesic patients showed two different knowledge bases are being used in a probability learning task. Through the pattern searching mechanism, participants gain declarative knowledge by trying to associate a relationship between the stimuli and feedbacks. This relationship develops through the task as trials continue. Findings from neurological studies suggested that the pattern searching mechanism is connected to prefrontal cortex, especially to dorsolateral areas which are involved in executive functions.

Pattern searching is one of the executive functions of the working memory (WM) which is responsible for maintaining and manipulating different kinds of information to direct future behavior (Baddeley, 2003). In the past, several studies showed the role of the prefrontal cortex in working memory (Jonides et al., 1993, D'Esposito et al., 1995; Miller & Cohen, 2001; Squire, 2004). In a typical probability learning task, in order to make decisions according to presented trials, working memory is responsible for sustaining attention, storing information and making appropriate selections (Wolford et al., 2004). There are several ways to measure and understand the role of prefrontal cortex on working memory such as lesion studies, studies with split-brain patients and neuroimaging techniques such as fMRI, PET scans and functional near-infrared spectroscopy (fNIRS).

On the other hand, the frequency learning mechanism activates non-declarative memory systems in order to learn event frequencies implicitly. As reported by several studies, the frequency learning mechanism is connected to the basal ganglia (Ashby & O'Brien, 2005, Shohamy et al., 2008; Knowlton, Squire, & Gluck, 1994). Learning the associations between stimulus-outcome processes is a distinct property of the basal ganglia. This mechanism is predominantly associated with procedural learning, a sub type of implicit memory, which is supported by the basal ganglia (Squire, 2004). In this thesis, we were able to quantify the activity of the dorsolateral prefrontal cortex (DLPFC), which is known to be associated with working memory, hence pattern searching rather than frequency learning.

Working memory is an essential component of cognitive processes, since it is placed at the center of complex decision making, attention, manipulation of information. Surrounded by a highly complex environment, human beings are capable of examining complicated relationships, handling difficult tasks, and making correct decisions in daily-life without too much effort. Executive components of working memory are responsible for maintaining such cognitive abilities. Smith and Jonides

(1999) stated five different executive processes which are: “(1) focusing attention on relevant information and processes and inhibiting irrelevant ones, (2) scheduling processes in complex tasks, which requires the switching of focused attention between tasks, (3) planning a sequence of subtasks to accomplish some goal, (4) updating and checking the content of working memory to determine the next step in a sequential task and (5) coding representations in working memory for time and place of appearance” (p.1659). Among these five different executive processes, 1, 4, and partially 5 are relevant for probability learning.

In this study, participants are presented a probability learning task and the activity of their prefrontal cortex during the task is measured with functional Near Infrared Spectroscopy. Both behavioral and fNIRS data from 20 participants are analyzed and the relationship between dorsolateral prefrontal cortex activity and task outcome was examined. Participants’ behavioral responses from the task were categorized into two different behavioral strategies and these strategies are compared in terms of fNIRS signals after learning is achieved.

In chapter 2 a survey of the literature on probabilistic learning and working memory is presented along with neuroanatomical infrastructure. In chapter 3, the methods used in our study are described and data processing procedures are highlighted. Chapter 4 summarizes the results, chapter 5 discusses these results in the light of the current literature, and Chapter 6 gives a brief conclusion over the study.

CHAPTER 2

LITERATURE REVIEW

In this section the relationship between prefrontal cortex and working memory tasks, and probability learning task mechanisms will be briefly explained.

1. PROBABILITY LEARNING

An example probability learning task is composed of a binary choice of stimuli. For instance a set of cards is composed of cards showing two different shapes: a triangle and a square, and the subject is asked which shape is the winning choice. After one of the shapes is chosen, a feedback is given regarding the correctness of the choice. If the probability of presenting a triangle is 70%, and a square is 30%, for 250 trials, 175 times the triangle is the correct choice, and 75 times the square. During the trials the only information regarding the upcoming choice is former feedbacks. The subject does not know the probabilities of the winning choice. Thus, participants try to determine their next answer depending on preceding trials within a block. At first sight, this task may look like an issue of gambling or simple guessing. However, by using previous feedbacks people develop a well-formed strategy in order to win. People rely on the proportions of the alternative stimuli and recall the probabilities. Thus, the task embodies a learning process (Volz, 2004). The most commonly used probabilistic learning task, the “Weather Prediction Task”, was designed by Gluck and Bower in 1988 (cited from Gluck, Shohamy & Myers, 2010). In this task,

subjects are presented four cards which all have different geometric shapes depicted on them and asked to make a prediction whether it is going to rain or shine. Each card has different probabilities so the subjects are required to uncover the hidden probabilistic rule to be successful. Subjects establish some strategies while learning the rule. These are discussed in the following.

In a probabilistic learning task, one can choose the most winning option repeatedly or can choose among stimuli according to estimated frequencies of winning. Therefore the subject may exhibit different behaviors. The former one is called the *maximization strategy*, and the latter one is called *frequency matching strategy*. People tend to use frequency matching more than maximization, even though maximization lets people win more (Siegel, 1964). Siegel gave the formula for calculating the expected probability as:

$$E(X) = P_1*(C_1) + P_2*(C_2),$$

where P is the frequency of subjects' responses, C is frequency of the stimulus, so $P_1 + P_2 = 1$, as well as $C_1 + C_2 = 1$.

For example, if C1 is .30, and C2 is .70, in a **frequency matching strategy**, P1 is approximately .30 and P2 is .70 (because the subject tries to match the frequencies according to their estimates). In this case, the chance for a successful outcome is $E(X) = (.30*.30 + .70*.70) = .58$. On the other hand, in a **maximization strategy**, the subject exclusively selects the stimulus which is presented most: $E(X) = (0*0.3 + 1*0.7) = .70$.

Other than the frequency matching and maximization strategies, there is another strategy called "overmatching". In this strategy participants try to match the frequencies however they select the most frequently winning stimuli more than its frequency, but they also do not maximize this behavior. Over matching strategy can be concluded as a transient strategy between the frequency matching and the maximization strategies.

Although success increases when the subjects use maximization, many studies found that in probability learning experiments subjects use the frequency matching strategy more than the maximization strategy (Vulkan, 2000). The subjects seem not to be satisfied with the highest possible success rate, 0.70, and they have a fallacy to believe that there might be a better way to guess the winning stimulus: uncovering a hidden pattern of occurrence of difference choices. This underlying mechanism is called pattern searching.

The pattern searching mechanism is consists of decisions based on past experiences, mainly from previous feedbacks, in order to find a pattern within the stimuli. People's tendency to search for patterns was discussed in the "Gambler's Fallacy Theory". Tversky and Kahneman (1972) described this fallacy as a cognitive bias resulting from representativeness heuristic since people think that any probability of a short sequence of event must be similar to the long version of it fed by previous experiences. Thus, when people are asked to consider a sequence of heads or tails they believe that a sequence of H-T-T-H-T-H is more likely to be than T-T-T-H-H-H. However, the results of the previous coin flipping have no effect on the landing of the next coin. People conclude that way, since they do not consider every event as independent. Another example for this came from Yellot (1969). In this study it was proposed that people have troubles for understanding the sequences are random. Thus they designed the experiment as for the trials whatever the participants chose that is, feedback was always "correct". At the participants' after-experiment interviews it was reported that they searched for a pattern and found it at the last trials of the experiment. However the task was designed to be so.

During the course of the experiment, the subjects' general tendency to search for a pattern indirectly leads to uncovering the frequencies of the the winning stimuli. Because at the debriefings after the experiment, they were found to guess the winning probabilities approximately correct (Yellot, 1969). However, once the winning probabilities are learned, people do not change their strategy into

maximization for higher profit, but they keep using the less profitable frequency matching strategy instead. Several studies have been performed to understand this irrational behavior of people. It might be possible that people have a general tendency to explain events with predefined complex patterns rather than every single event occurring randomly: In Gal and Baron's (1996) study, they asked participants whether they knew the events in the probability learning task are independent. Although all subjects confirmed they knew still they failed to use the optimal strategy which is maximization. Most of the participants used the frequency matching strategy. The participants reported that "Even though the probability of green coming up does not increase after several red—I always have a feeling it will" (p. 92).

The urge to explain events with predetermined patterns may even have developmental roots: For example, a study of probability learning conducted with children yielded interesting results (Derks & Paclisanu, 1967). Very young children used the maximization strategy, while children of 5-7 ages used frequency matching. Older children had already learnt to associate events and this fact resulted in more complex learning rules.

Wolford et. al (2004) studied people's tendency to look for patterns and use of the frequency matching strategy. The authors proposed that as an outcome of pattern searching, people tend to use the frequency matching strategy even when they were told that the stimuli are presented randomly. Thus they designed an experiment that participants would clearly understand that the probability task has random sequence (for other probability tasks, even when the task was random, participants could not clearly understand the case and looked for a pattern). If the participants believed that the stimuli are random, then they were expected to apply the maximization strategy. Participants who were presented obvious random sequences gave up frequency matching and did maximization in order to increase their success in the task. They understood the sequences were random and did not look for a pattern. It can be concluded that pattern searching results from people's perception of randomness

even randomness doesn't exist. This perception may not be completely unfounded, because frequency matching causes exploration of the non-winning choice every now and then, which leads to a more adaptive behavior in case the task changes and probabilities are reassigned.

One interesting study (Koehler & James, 2009) used a follow-up questionnaire after a probability learning task. In the questionnaire, two strategies of probability learning tasks were described and subjects were asked to choose a strategy that would result in winning more. It was found that although more people used frequency matching strategy in the experiment in comparison to maximization, the number of people rating maximization as a better strategy was higher. Thus, the authors concluded that probability matching is a readily stored strategy rather than maximization. When explained openly, the subjects were able to understand maximization was a better strategy but they failed to implement this strategy in the experiment before explanations. Taylor, Landy and Ross (2012) examined the importance of explanation of tasks in probability learning. They found that when the task was explained explicitly, subjects used maximization, whereas when explanation was not given they tended to use frequency matching.

There are several other factors that affect learning and behavior in a probability learning task. For instance, feedback may include emotional stimuli (Thomas & LaBar, 2008). Photographs of unpleasant animals as outcomes of the task provide aversive feedback. When compared with neutral outcome stimulus; participants who were fearful of these animals performed worse, used less complex strategies and could not learn at the initial phase. Other participants who were not fearful to those animals used more complex strategies and they showed greater knowledge of the task. Thus, individual differences in terms of emotions also have an impact on strategy use. Another important factor of strategy choice rests on the number of trials (Shanks, Tunney & McCarthy, 2002). In a series of experiments, 300 and 1800 trials were presented to different groups of participants. In the first experiment only half

of the participants maximized their answers, while in the second, 2/3 of the participants showed maximization behavior.

2. PRINCIPLES OF WORKING MEMORY AND PREFRONTAL CORTEX

Holding information for a limited amount of time for future use involves working memory (Baddeley, 2003). Maintaining and manipulating information in order to affect a certain behavior are working memory functions. According to Baddeley's Working Memory Model (1996, 2003, 2007, 2010) working memory has different specialized subsystems called "phonological loop", "visuo-spatial sketchpad" and "central executive". Phonological loop and visuo-spatial sketchpad are called "slave systems" since they are controlled by the central executive. Inputs are provided by perceptual channels like ear and eyes form the knowledge base (longterm memory), and the central executive uses that input and information (Baddeley, 2003). The first subsystem the "**phonological loop**" retains phonological information for a short time and it is similar to sub-vocal speech. The phonological loop has limited capacity as information gets lost over time. Although information can be maintained by help of the repetition, after a certain time what had been heard fades. Evidence for the phonological loop comes from the "phonological similarity effect" that is, letters or words which sound similar in a serial recall list tend to be remembered harder than letters or words that sound dissimilar. There also exists a "word-length effect" such that sequences of shorter letters or words are more easily remembered than sequences of longer letters or words. The phonological loop is very essential in terms of language development, since patients with poor phonological loop have problems with learning new languages although long term memory has been observed to behave normally (Baddeley, Gathercole & Papagno, 1998; cited from Baddeley, 2003). The second subsystem, the "**visuo-spatial sketchpad**" sets up and manipulates visuo-spatial information. This system takes input directly from visual **perception of images**. It has both spatial and visual aspects. Evidence for the distinction between the phonological loop and visuo-spatial sketchpad comes from Brook's task (Goldstein, 2008) which includes 2 different tasks with input coming

from auditory and spatial channels. In the spatial task, subjects were required to answer whether a dot near a big capital letter was placed in the bottom or the top line; in the verbal task, subjects heard sentences and were then asked to determine whether the sentence ended with a noun or not. In each task subjects answered either verbally (saying “yes” or “no”) or spatially (pointing out “yes” or “no”). Subjects performed better when they answered verbally in the spatial task and when they answered spatially in the verbal task; since when they use the same system both for coding and answering the system overloads. These results suggest that these systems are distinct and they work together better when processing is divided between them.

Historically, one of the first tasks designed to understand working memory components was the dual-task paradigm. Baddeley and Hitch (1974) designed a working memory model by analyzing dual task paradigms. The paradigm relies on the fact that when two cognitive tasks compete for the same storage; it becomes harder to perform the task due to overload. What Baddeley and Hitch did was combining digit span and reasoning, so that they would see reasoning was not dependent on short term storage if digit span performance was not diminished. That is, if digit span performance was decreased, reasoning would be dependent on short term storage. Later dual task paradigms became used widely and helped in distinguishing the two slave systems of working memory along with their importance in daily life pointing out that phonological loop was responsible for language learning (Baddeley, 2003; Jackie, 2001).

After Baddeley and Hitch proposed their working memory model, a new sub system was suggested which is the episodic buffer (Baddeley, 2000). It involves episodic or chronological representation of information gathering visual, spatial or verbal information and binding working memory with long term memory. The episodic buffer is also controlled by the central executive system. Evidence of the episodic

buffer comes from tasks involving consciousness awareness, problem solving, chunking, prose recall and rehearsal (Baddeley & Wilson, 2002; Chincotta, 1999).

The main component of the model, called **central executive**, monitors and manipulates both of these systems and the episodic buffer, providing executive control of working memory. It is the function which separates working memory from short term memory (Baddeley & Hitch, 1974). The manipulations performed by the central executive include selecting among the items in order to direct behavior and retrieve information from long-term memory. This system, unlike the other slave systems, does not store information but rather makes working memory select some of the stimuli while ignoring others. Basically it selects which stimulus should we attend to. The first theory of an attention controller in the brain came from Norman and Shallice in 1986 which was called “Supervisory Attentional System” (SAS). Some functions that are included in this system are described as:

“tasks that involve planning or decision making, situations in which the automatic processes appear to be running into difficulties and some form of trouble shooting is necessary, where novel or poorly learned sequences of acts are involved, where the situation is judged to be dangerous or technically difficult, and where some strong habitual response or temptation is involved” (cited from Baddeley, 1986, p.228).

The existence of a SAS is supported by evidence from observed slips of actions as when everyday routines were broken and random generation that occurs when subjects were asked to generate random sequences of letters. However, although Norman and Shallice’s model seems like another explanation of executive function of working memory, and explains working memory with all of its components, the evidence that explains SAS which involve habitual functions are rooted in other neurological systems¹.

¹ WM is rooted in prefrontal cortex, habitual behaviour is rooted in basal ganglia.

In the following, we will concentrate on the neurological localization of probability learning and working memory, to show that some of the components in these two cognitive functions overlap in terms of brain areas.

3. NEUROLOGICAL EVIDENCE FOR WORKING MEMORY AND PROBABILITY LEARNING

3.1. Neuroimaging and patient studies of working memory

A variety of behavioral and neuroimaging experiments had been done to investigate executive functions related to working memory. One of the most known experiments for working memory is the n-back task, in which subjects are required to match the stimulus currently presented with the a stimulus n times back. This task relies on monitoring, updating, and manipulation of what had been remembered. The n-back task is related to a variety of executive processes like maintenance of the items for the n-back times before and newly presented ones, matching between new and old items so that the relation would be made within serial ordering, and judging any proactive interference resulting from non-n items. In their article Chatham et al. (2011) found that updating working memory succeeded when basal ganglia learned to implement a gating signal for the item's serial order, maintenance occurred in prefrontal cortex as it learned to bind items in their serial order and lastly they observed activations prefrontal cortex during proactive interference. The n-back task had been found as an effective measure for working memory activation due to the fact that the task involves a very simple, direct manipulation of working memory load (Jeaggi, Buschkuehl, Perrig & Meier, 2010). An example study stated that, patients with frontal cortex damage performed poorly in a two-back task with words, non-words and phonologically similar words than control subjects (Baldo & Shimamura, 2002).

Executive control of working memory also has been investigated with experiments on random generation tasks that provide evidence for Norman and Shallice's earlier working memory model. Baddeley also reviewed the random generation task in terms of his working memory model (1986). This task requires participants to generate random sequences of letters or numbers (sequences of numbers like "5, 9, 2, 7, 1" but not like "1,3,5,2,4,6") and relies on different higher order processes like holding task-related instructions in memory, combining information and holding it in working memory, avoiding interference, monitoring output, and shifting response strategy in terms of randomness (Baddeley, Emslie, Kolodny & Duncan, 1998). This task is assumed to be done in two ways; trying to cut off existing schemata within skills and habits and intervening to change ongoing responses by newly generated ones. Baddeley comments that there would have been a tendency for repetitions due to over-learned habits resulting in stereotyped behavior. In order to prevent this behavior, the SAS needed to be activated repeatedly, which would result in manipulation and activity in the central executive component of working memory. The random generation task has been poorly performed by dysexecutive patients (cited from Baddeley & Wilson, 1988; in Baddeley, Emslie, Kolodny & Duncan, 1998) and patients with frontal lobe lesion (cited from Milner, 1982 in Baddeley, Emslie, Kolodny & Duncan, 1998). Another study investigated the random generation task in terms of its psychometric properties in normal adults and schizophrenia patients finding that random generation task was correlated with performance in the Stroop color-word test both in normal and schizophrenic participants. Schizophrenia patients with executive dysfunctions performed poorer than control subjects. This study concluded that the random generation task clearly demands with executive functions as it involves inhibition, updating and monitoring (Peters, Giesbrecht, Jelicic & Merckelbach, 2007).

The Stroop task is another task to examine the central executive part of working memory function. In the Stroop task, participants are required to name the color of a printed color word. The conflict is between the print color and color word (Stroop, 1935). This task again relies on inhibiting an obvious response which is reading out

the word itself rather than naming the color of the print. The word-reading response has to be controlled and inhibited, thus it can be concluded that the Stroop task is an example for an executive task. Pasalich, Livesey and Livesey' study (2010) showed that the Stroop task performance is strongly correlated with other executive functioning tasks.

Evidence for executive functions also comes from patient studies. The 'Dysexecutive Syndrome' is a disorder of planning, organisation, problem solving, setting priorities, and attention (Baddeley & Wilson, 1988). This syndrome is used to be described as a frontal lobe disorder, due to the relationship between the executive control and supervisory function of the frontal lobes. Patients with this syndrome have impaired skills of monitoring and adjusting their behaviour, and their symptoms result from the impairments in central executive which is responsible for attention control and inhibition. Overall, dysexecutive syndrome patients have poor working memory and thus poor planning and reasoning abilities.

Various studies on prefrontal cortex damage showed the importance of this specific brain region in cognitive tasks that rely on the central executive. The effects are most visible when high levels of cognitive control are needed, which is the case for central executive functions. Patients with prefrontal damage lack appropriate social decision making and have severe impairments in daily life. The Wisconsin Card Sorting Task is a task of executive control of working memory, requiring participants to find rules in order to sort the cards. The main point in this task is to apply one rule and then keep track of the rule as it changes according to the feedback. When subjects with prefrontal cortex damage are asked to sort the cards according to some dimensions they fail to do so. Subjects first observe the first rule, however as the rules changes they can't detach themselves from the first rule because of their weakened executive control (Milner, 1963). Another study found that patients with prefrontal cortex damage could not solve is the "Tower of Hanoi task which is a widely used problem solving task (Goel & Grafman, 1994).

Another substantial study on the role of the prefrontal cortex on working memory was conducted on macaque monkeys through spatial delayed-response task (Goldman-Rakic, 1992). In spatial delayed-response task monkeys were presented a cue which can be located at eight different locations. After a delay period, the monkeys were expected to move their gaze to the cue's former location to be rewarded. Neuron-recording analysis showed that different neurons fired for different phases of the task such as cue presentation, delay and response. Some neurons responded only to location, whereas some neurons responded only to delay. Different locations of cues also resulted in different neuron firings in prefrontal cortex. Moreover when the monkeys made an error, different parts of the cortex were activated as if prefrontal cortex itself knew that there was an error. Also several other regions such as primary and secondary sensory and motor cortices in temporal and parietal lobes were active in sustaining the attention phase in the experiment. This activation pattern challenges the assumption that the neural roots of working memory are located exclusively in the prefrontal cortex and rather puts forward the idea that sensory and motor cortexes can sustain activity to encode working memory. Miller and Cohen (2001) responded this by finding by pointing out that the major cognitive role of prefrontal cortex is to sustain attention despite distractions. That is, the ability of prefrontal cortex is to provide focused control over working memory. Goldman-Rakic summarized the activity observed in monkeys' prefrontal cortex as it was not due to "any presence of external stimulus or the execution of the response" (p.114). The activity in the delay phase of the experiment was a result of a mental event between the stimulus and the response. To conclude, a number of studies showed the association between working memory and the frontal cortex.

Baddeley's working memory model suggested two distinct processes of memory, which are: an executive process for memory manipulation and rehearsal process for memory maintenance. A large amount of research examined this functional distinction in terms of anatomical localization (Owen, Evans & Petrides, 1996;

Petrides, 1994, 1996); Owen et al. 1999). Petrides experiments (1995; 1998) of self-ordered delayed-response tasks on monkeys with DLPFC lesion showed that monitoring of information was impaired but maintenance was not since ventrolateral prefrontal cortex is responsible for the maintenance. Thus, Petrides concluded that DLPFC (Brodmann Areas 9 and 46) is responsible for the performance in self-ordered delayed-response tasks.

Rypma, Berger and D'Esposito's (2002) study on prefrontal cortical activity found similar results about the distinction between ventrolateral and dorsolateral PFC activity. To give an example for the different activation process of ventrolateral and dorsolateral PFC, participants were showed three or six letters to remember. For the former one there was activation only in ventrolateral part, however additional activation in dorsolateral part was observed when participants required maintaining more letters (Rypma et al., 1999). In the light of these studies it can be concluded that the monitoring process for temporal ordering has its neural roots in DLPFC, when the fact that temporal ordering is the main aspect of self-ordered delayed-response tasks is considered (Goldman-Rakic, 1992). This process is related to sequencing events and making a decision according to any pattern found. Another finding from Petrides studies was about the lateralization of the DLPFC. Right and left DLPFC were found to be different in terms of their functions, namely a dominancy of left DLPFC for verbal materials, whereas right DLPFC was involved in all monitoring processes. An experiment using letter and fractal (complex geometric designs) n-back tasks also confirmed that, maintenance during tasks resulted in activity of inferior parietal and DLPFC while maintenance and manipulation resulted in activity of dorsolateral and ventral prefrontal cortex, inferior parietal cortex (IPC), insula and Broca's area (Ragland et al., 2002). A more elaborate cortical map distinguishing the components of working memory and identifying their localization was made by Jonides in which DLPFC serves as the main monitoring component, more associated with the central executive, while left IFG and right IFG are related with the rehearsal component of the verbal (i.e. phonological loop) and spatial information, respectively, and finally left and right

dorsal parietal cortex are related with the storage component of the verbal and spatial stimuli, respectively (Jonides et al., 1996; Smith, E. & Jonides, J., 1997).

To sum up the literature on anatomical localization of working memory functions it can be concluded that spatial working memory is localized in the right hemisphere, whereas verbal and object working memory are localized in the left hemisphere. Dorsolateral prefrontal cortex (DLPFC), ventrolateral prefrontal cortex, and parietal cortex are responsible for executive functions, rehearsal and storage respectively. (Smith & Jonides's, 1997; Rypma, Berger & D'Esposito's, 2002; Rypma et. al, 1999).

3.2. Neuroimaging and patient studies for Probability Learning

Probability learning has been largely discussed in the literature. In this section the neural roots of probabilistic learning will be explained.

Strong evidence of probability learning and brain systems mainly comes from lesion and patient studies. Since probability learning has roots in prefrontal cortex (pattern searching), basal ganglia and medial temporal lobe (frequency learning), some patient groups namely schizophrenia, amnesia, Huntington's, and Parkinson's, have been largely investigated (Shohamy, Myers, Grossman et al., 2004; Knowlton et al., 1996; Eldridge, Masterman, & Knowlton, 2002; Koch et al. 2007; Weickert et al.2009). For instance Goldberg (1990) found deficits in problem solving and worse prefrontal planning in schizophrenia patients during a Tower of Hanoi task. Amnesic patients performed as good as control subjects at the first trials of probability learning, however towards the last trials control subjects did better than the patient group (Knowlton, Squire & Gluck, 1994). This study shows that declarative memory (which is absent in amnesic patients) has a role in this type of learning. Early stage Alzheimer's disease patients also showed similar patterns of learning to amnesic patients (Eldridge et al., 2002). However Parkinson's and Huntington's patients could not learn the weather prediction task at all (Knowlton et al., 1996). Patients

with prefrontal cortex damage did not show skin conductance response in the test of real life decision-making when using probabilities (Bechara, Tranel, Damasio & Damasio, 1996). These patients could not make a distinction between good or bad decisions, therefore performed worse than healthy subjects. Although schizophrenic patients showed deficits in executive functions, they performed as good as healthy subjects in a probability learning task. Still, they had problems of recognition of category outcomes, and reasons for their performance might be the result of the fact that their dementia was not clinically significant (Keri et al. 2000).

Several neuroimaging studies have focused on the localization of the activations in the brain during a probability learning task. Fera et al. (2005) showed activations of bilateral dorsolateral and inferior PFC, medial PFC, bilateral anterior PFC, bilateral occipital cortex, posterior cingulate, parietal cortices and bilateral caudate nucleus. In another study presenting probabilistic category learning, brain activations of healthy and schizophrenic patients revealed interesting results (Weickert et. al, 2009). Greater activation of DLPFC and caudate nucleus was observed in healthy subjects; whereas patients showed spread activation in wider areas of the brain, specifically in more rostral regions of DLPFC and cingulate, parahippocampal and parietal cortex. This study pointed out that probabilistic learning might occur without intact frontal-striatal function. Activation differences may result from different conditions like age. Rypma et al's study (2001) on the difference between young and old adult participants in a probability learning task found greater DLPFC activation in younger adults and greater rostral PFC activation in older adults. The difference mentioned here is related to non-declarative memory function distinctions between older and younger populations.

Not only increase of activation but also decrease of activation provides information about the neural roots of probability learning. Koch et al. (2008) designed three probability tasks, all of which differed in terms of their predictability rate. One task has full predictability which means 100% contingency, one has 50% and the other has 69% predictability. In the 100% probability condition, similar to other studies

right lateralized frontoparietal activation was observed. What is interesting is; after the cue-outcome association was learned, activation in DLPFC and dorsal anterior cingulate cortex decreased. This results show that, DLPFC and dorsal anterior cingulate cortex were in charge of the process of learning probabilities. In contrast, for the 50% probability condition, which is the case when one can never learn a relationship between the outcome and the cue, there was no learning effect. That is, there was no decrease of activation for the suggested areas.

The frequency matching and maximization strategies lead to different activation levels and localizations. Studies with split-brain patients showed lateralization of these two strategies. Wolford, Miller and Gazzaniga's (2000) research concluded that the left hemisphere was involved in frequency matching whereas the right hemisphere was mostly involved in maximization strategies. Thus, their conclusion was that neural roots of pattern searching are located in the left hemisphere. However, another split-brain patient study found right hemisphere evidence for frequency matching (Miller & Valsangkar-Smyth, 2004). A study of Wolford, Newman, Miller, and Wig (2004) tried to expand the explanation for this lateralization. In the experiment, three groups of participants were involved in a typical probability learning task where each group of participants were presented different inhibiting tasks, namely a visuo-spatial task, a verbal task and a control task. The purpose of the visuo-spatial task was to interfere with the right hemisphere, and for the verbal task the aim was to interfere with the left hemisphere. Since previous findings suggested involvement of the left hemisphere (responsible for verbal functions) in frequency matching and involvement of the right hemisphere (responsible for spatial functions) for maximization the verbal task should have prevented participants to apply the frequency matching strategy, and the visuo-spatial task should have prevented maximization. The results confirmed the hypothesis. Among 10 students, 7 of them used the maximization strategy in the verbal task condition, whereas it was only one student in the visuo-spatial group and none for the control group. Since the verbal task was the n-back task, and it is a widely known

working memory task, this study is important in terms identifying the role of working memory in probability learning.

A meta-analysis study by Miller et al. (2005) investigated brain areas associated with probability learning and lateralization of the frequency matching and the maximization strategies in healthy participants. They found activations on DLPFC cortex, the ventrolateral prefrontal cortex, the anterior prefrontal cortex, and the medial prefrontal cortex. Those activations were bilateral; however in the right hemisphere activations were stronger and more extensive. That is participants showed right hemisphere activations for hypothesis forming and making interpretations during the probability learning task. Also, right angular gyrus and right inferior parietal lobule was activated. This study provided both behavioral and neurological evidence for right hemisphere activation in participants who use frequency matching strategies, although when the entire literature is considered there are conflicting results.

Prefrontal cortex is not the only region responsible for probability learning as studies with healthy participants suggest a network that includes caudate nucleus and prefrontal and parietal cortices (Poldrack et al., 2001; Aron et al., 2004). It has been argued that basal ganglia are related to frequency learning and prefrontal cortex is related to pattern searching, although these two mechanisms are somewhat indistinguishable. The studies mentioned above indicated a relationship between working memory, pattern searching and prefrontal cortex within a probability learning task. Since the dorsolateral part of prefrontal cortex is connected to basal ganglia *via* the dorsal striatum area, such a relationship within probabilistic learning is evident. Several studies also confirmed this. For instance; classical probability learning tasks like the weather prediction studies (Knowlton et al., 1994, 1996; Gluck, Shohamy, & Myers, 2002) attribute non-declarative learning to striatum (part of basal ganglia) functions, since patients with striatal dysfunctions have problems in weather prediction tasks. Shohamy et al. (2004) and Poldrack et al. (2001) showed increased activity during the learning phase, but after learning is complete, activity

had decreased. Shohamy et al. (2004) also showed the importance of feedbacks for striatal activity. In Parkinson patients with striatal dysfunction, impaired activity is reported only in the task of probability learning with feedback, but activity was intact in the no feedback version of the task. The no feedback version of the task was different as participants only pressed the “next” button and didn’t make guesses but only observed trials and probabilities. Thus, it can be concluded that the cortico-striatal system is a necessity for feedback based learning. Shohamy et al. concluded in their review that a distinction is necessary where basal ganglia is responsible for learning the associations, and prefrontal cortex is responsible for mediating the performance after the associations are learned.

To sum up, probability learning is composed of two neural systems: First, a frontal cortex based system which is responsible for the central executive function of working memory; second the basal ganglia system which is responsible for procedural memory and learning.

4. THE CURRENT STUDY

The main investigation subject of this thesis is the consolidation of WM during probability learning. Therefore, it had been hypothesized that:

- (1) Due to the utilization of WM resources, DLPFC activity is expected to decrease as the task is learned. After the winning color and probability is learned, the activation in DLPFC is expected to be decreased since there is less need to use monitoring resources to win. If the occurrence of winning choice is increased, DLPFC activity is expected to decrease as well.

- (2) Once the task has been learned, reaction time is expected to decrease because we expect less pattern searching. Negative correlation between reaction time and task performance is expected.
- (3) After learning is achieved, some subjects will use frequency matching strategy while others adopt maximization strategy. Patterns of activity will be examined according to participants' choice of strategy. We hypothesize that frequency matching strategy will induce more PFC activity due to the involvement of the pattern search mechanism related to working memory. Hence DLPFC activity of the maximization group will be lower than that of the frequency matching group. Similarly, reaction time of the maximization group will be lower than that of the frequency matching group because maximization is a more straightforward behavioral response, just involving pressing of the more winning choice.

CHAPTER 3

METHOD

This study was conducted under permission of METU Applied Ethics Research Center. Experiments had been done in METU Campus with students and employees with the fNIRS optical brain imaging device provided by Modeling and Simulation Research and Development Center in METU.

1. PARTICIPANTS

24 (12 F, 12 M) participants are admitted to the study. Subject exclusion criteria were current use of psychiatric medication and a history of neurological disease. 21 of them were students from departments at METU. 8 of them were employees in a company at METU-TECH. Most of the participants (18) lived in a city-dwelling environment and at least one of their parents graduated from high school.

2. INSTRUMENTS

Demographics Form (Appendix A): A set of questions were asked to the participants in order to gather demographic information including age, gender, education and work background, medical history, and socio economic status.

Behavioral experiment: This experiment was created after Erdeniz's study (2007). The probability learning experiment was developed with E-Prime. The images are

drawn on MS Office Power Point, and imported into E-Prime. Stimuli consisted of a picture of 10 red or blue boxes, presented over a black background. The proportion of the boxes' color changed every time the slide was presented. One block consisted of 10 different stimuli (For one block example see Figure 1) and the whole experiment consisted of 25 blocks. The stimuli were assigned once at a time, randomly within a block. However, in the total of 25 blocks their number was balanced. Stimulus with 10 red or 10 blue boxes were never shown, however stimulus with 5 red/5 blue boxes were showed twice.

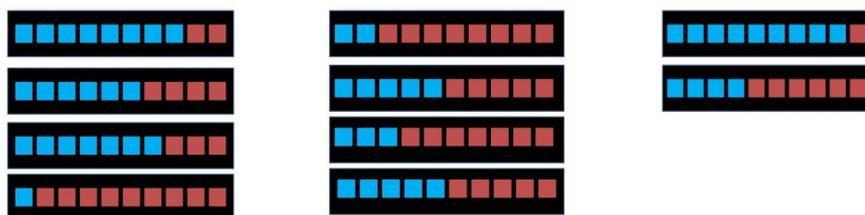


Figure 1. Stimuli within one block of the experiment

After presenting the stimulus, participants' response was recorded in 2 seconds: The participant was expected to decide which color wins. The experiment was designed such that blue wins 80% within a block, independent from the picture in the presented stimulus. The winning stimulus was also randomized with the help of a randomizing program, thus even though it was fixed that blue boxes won 80% of the time, which boxes were winning was random. Feedback was given immediately after the participants make the decision. However, if the subject could not answer in 2 seconds, the response was not recorded and the feedback was indicated as "lost". Participants pressed "m" with their right hand, if they believed red color was winning, and pressed "z" with their left hand if they think blue color was winning. These letters on the keyboard were marked with corresponding color dots. To be successful, participants should suppress the irrelevant stimulus dimension (proportion of red and blue boxes) and generate a rule for the color dimension. Between each block 20 seconds of interval was given and fixation point was shown. Participants hold their hands on the keyboard during the experiment, however in the

intervals between blocks they were allowed to relax and take their hands off the keyboard. General flow of the experiment is shown in Figure 2.

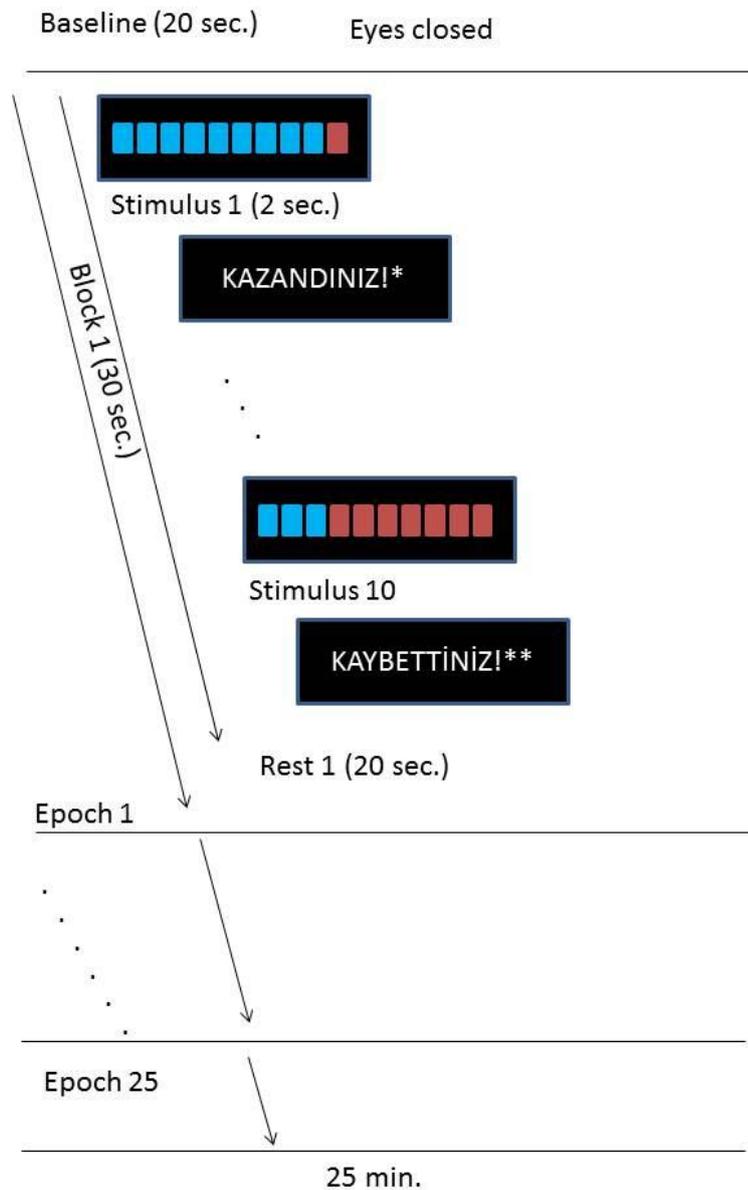


Figure 2. Flow of the experiment. (*: WIN!, **: LOSE!).

Neuroimaging data: Neuroimaging data was collected using the functional Near-Infrared Spectroscopy (fNIRS) Imager 1000 device developed by the Optical Brain-Imaging Lab at Drexel University, manufactured and supplied by fNIRS Devices

LLC (Potomac, MD; www.fnrdevices.com) (Figure 3). fNIRS is a recently developed technique compared to other neuroimaging techniques like fMRI, EEG, or PET. It is used for detecting blood oxygenation changes in the hemodynamic response of the cortex in response to cognitive tasks that involve attention, working memory, target categorization, and problem solving. Because fNIRS is portable, safe, affordable, noninvasive and minimally intrusive in monitoring cognitive activity, more application areas are developing. Using fNIRS for a cognitive task is more advantageous due to its mobility when compared to other techniques like fMRI or EEG, although it has similar spatial resolution with EEG and similar time resolution with fMRI. The Brodmann areas of BA9, BA10, BA46, BA45, BA47, and BA44 which sub-serve attention, executive function and working memory networks can be monitored by the physical principles of light absorption. Findings from studies of working memory and attention are consistent across fNIRS, fMRI and PET (Izzetoglu et al, 2004). Being more tolerable to motion artifacts makes fNIRS even more suitable for research. In order to measure working memory activity from the prefrontal cortex, fNIRS is highly appropriate as it is placed on participant's forehead.



Figure 3. The fNIRS Imager 1000 sensor pad

The fNIRS device used in our study is connected to a control box and this control box is connected to a computer for data collection. Data collection by the fNIRS device is made available to the data collection computer by a special software called “COBI studio software (Drexel University)”. Synchronization of the computer and control

box is made with a serial cable which is responsible for sending online event triggers from E-Prime to the COBI studio software.

The fNIRS device used in our study has 4 light sources and 10 light sensors 2.5 cm apart, placed in a grey plastic rectangular band. Light sources send the infrared signals through the skull into the brain, while light sensors collect the reflected signals coming from the brain. One light source corresponds to four light sensors, therefore signals were collected from sixteen channels. These four light sources use near-infrared wavelength range which is between 650-900 nm. Near-infrared light is sent through the forehead, and cortex tissues are probed for about 1.5 cm. The infrared light can penetrate skin, skull, cerebrospinal fluid and brain tissue; but most likely to be absorbed by oxy- and deoxy-hemoglobin. The photodetectors monitor the change in infra-red light intensity by detecting the photons which weren't absorbed. The photons follow a banana shaped path between the detector and the light source. Since we can observe hemodynamic changes in the concentrations of oxy- and deoxy-hemoglobin values which result from cognitive activity in a specific region by the difference in the reflected signal, we can identify responses for a given task. Hemodynamic changes for a given task occur in a time span of 6 to 8 seconds, but the 16 sensors that collect the absorbed and non-absorbed fNIRS data measure the signal with a sampling rate of 500 milliseconds (2Hz).

While measuring activity using fNIRS several artifacts or noises such as head movement, facial movement, ambient light, ambient noise, respiration, heartbeat, muscle movement and slow hemodynamic response are observed. In order to reduce head and facial movement artifacts, each participant asked to refrain from moving their heads during the experiment. The experiment was conducted in artificial light, therefore ambient light was controlled. Ambient noise was controlled by conducting the experiment in a very quiet room. Other noises were analyzed with filtering

techniques and excluded from the data in the pre processing of data phase as explained below.

Block design technique was utilized in the experiment. Markers that indicate key events during the experimental protocol are synchronized in time with fNIR data. These markers were used to identify the beginning of 25 blocks in which each subject attempted 10 trials. First, linear phase, finite impulse (FIR) low pass filter with cut-off frequency of 0.14Hz was applied to the 16 channel raw fNIR data to eliminate high frequency noise due to physiologically irrelevant data (such as respiration, cardiac cycle and heart pulsation effects) and equipment noise. In order to eliminate noise due to motion artifact, sliding window motion artifact filter (Ayaz, 2010; Izzetoglu et al., 2005) was used. The analysis of blocks were compared to baseline recording which was recorded at the beginning of the experiment for 20 seconds, by asking the participants to rest with closed eyes.

For oxygenation calculations, modified Beer Lambert Law (Chance et al., 1998) was applied to the data to calculate oxy-hemoglobin and deoxy-hemoglobin concentration changes with “fnirSoft Software” (Ayaz, 2010). The analysis focused on the mean oxygenation value for each block. Oxygenation corresponded to the difference between oxy-hemoglobin and deoxy-hemoglobin concentrations. A positive increasing difference between oxy- and deoxy-hemoglobin values suggest that there is an increasing demand for oxygen at that period of time, hence there is increased activation under the corresponding voxel (Izzetoglu et al, 2005). Channels 1-2 and 15-16 correspond to Left and Right DLPFC respectively. For localizations of the channels see Figure 4. As explained in the literature survey earlier, DLPFC is the main area for the executive functions associated with working memory. Therefore, only channels related to the relationship between probability learning and working memory which are 1, 2, 15 and 16 were processed in the study. Other channels’s signals that are placed in the middle regions of the fNIRS device contained lots of

artifacts due to forehead shapes of some participants and ambient light leakage. Therefore channels occurring on the middle areas of the forehead are not processed in our study. Missing values occurred frequently; among 500 data points 228, 131, 170, 102 points were missing from channels 1, 2, 15, and 16 respectively. Therefore we had to average signals coming from channel 1 and 2 and signals coming from channels 15 and 16, resulting in a single left hemisphere DLPFC reading and a single right hemisphere DLPFC reading.

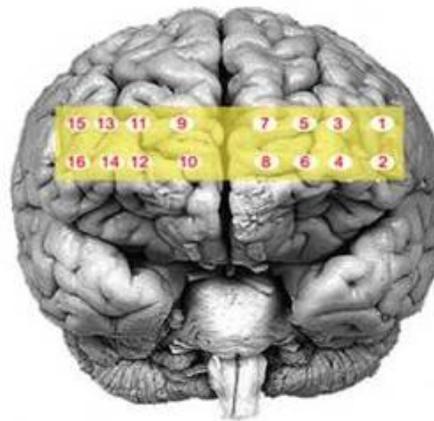


Figure 4. Channels and corresponding localizations: Channels 5-16: Right DLPFC, Channels 1-2: Left DLPFC

3. PROCEDURE

Ethical board submission for this experiment had been done on January 2011. Experiments were conducted at Informatics Insitute and Enocta Company in METU-TECH. After filling the demographics form and handedness inventory, participants were given informed consent (See Appendix B), then the experiment was re-explained and the questions raised were answered by the experimenter. Participants were told to make an assumption on which color was winning. In the keyboard there

were two color signs blue and red, and the participants were asked to press the color which they think is winning. Participants answered by using both of their hands, as left for blue and right for red. After these explanations fNIRS device was placed on their forehead. They were asked to start the experiment whenever they feel ready. First, 20 seconds of baseline recording was made and then the participants started the experiment. The probability learning experiment was presented to the participants in a 10.4 inch Acer laptop screen. Meanwhile, the experimenter was checking fNIRS signals in order to be sure that signals were in the recordable range. At the end of the experiment each participant was asked whether they noticed any pattern for the winning possibilities. Their answers were recorded, and then subjects were informed that there was not any specific pattern but blue boxes won 8 out of 10 times in each block of the experiment in a random way and the proportions of the boxes wasn't related to the winning property. Experiment lasted for approximately 25 minutes. Participants' choice of blue responses, response time, and correct responses were recorded and analyzed.

CHAPTER 4

RESULTS

After the experiment, a first-level behavioral analysis was made to find out whether the subjects performed the experiment as expected. Since the main aim of this study is to examine the involvement of prefrontal cortex in probability learning, participants who could not learn the task are excluded from the analysis. Participants are expected to exhibit learning behavior characterized by the number of Blue choices- after 10 blocks. When a participant chooses blue less than 5 times during the one block (5 blue choices indicate chance level), and if the participant does this more than once during the last 10 blocks, she/he is classified as not learners. According to these criteria, 4 of the participants were classified as non-learners. Last 10 block choices of these participants are given Figure 5 below, and average blue scores are given in Table 1. It is concluded that these four subjects could not learn that the probability of blue is higher for winning so they are excluded from further analysis. Their overall learning performance was approximately at the chance level within the last 10 blocks.

All analyses are conducted with 20 participants (11 F, 9 M) whose age range was between 21 to 36 ($M= 26.05$, $SD= 3.83$). 15 of them were students, rest of them were employees.

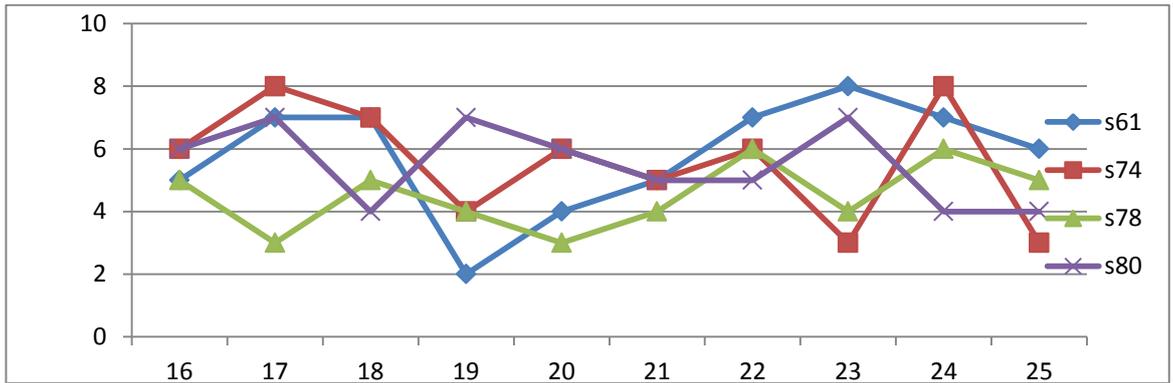


Figure 5. Non-learner participants' blue responses for the last 10 blocks (x axis: One block trials, y axis: Blocks)

Table 1. Non-learner participants' blue average scores for the last 10 blocks

Subject	Blue Score
s61	5.8
s74	5.6
s78	4.5
s80	5.5

1. DESCRIPTIVE RESULTS

As specified earlier, all subjects who could not learn the task and have drug history were excluded from the analysis. Therefore the analysis was conducted with 20 subjects. Descriptive information regarding the variables in the entire experiment are

presented in Table 2. Descriptive information consists of 20 subjects' averaged response in each of 25 blocks (20*25= 500 points). Blue scores is given out of 10, response time is in msec, Mean Ch. 1&2 and 15&16 are given as micro molar.

Table 2. Descriptive information of the variables

Variables	N	Mean	SD
Blue Selection	498	7.39	0.80
Response Time	500	1086.44	306.12
Mean Ch. 1&2	483	.0013	.2300
MeanCh. 15&16	462	.0021	.2538

2. BEHAVIORAL RESULTS

Behavioral analyses include selection of blue, correct answer rate and response time. In Figure 6 below, the averages of number of blue choices and the average number of correct responses of all participants are shown throughout the course of the experiment. As seen from this figure, choices of blue increase as the subjects learn probabilities. Participants' first 12 blocks and last 13 blocks of blue scores are compared with a dependent t-test. They chose blue significantly more in the last 13 blocks ($M = 8.23$; $SD = 1.55$) than in the first 12 blocks ($M = 6.48$; $SD = 1.91$); $t(6.18) = -11.46$, $p < .01$.

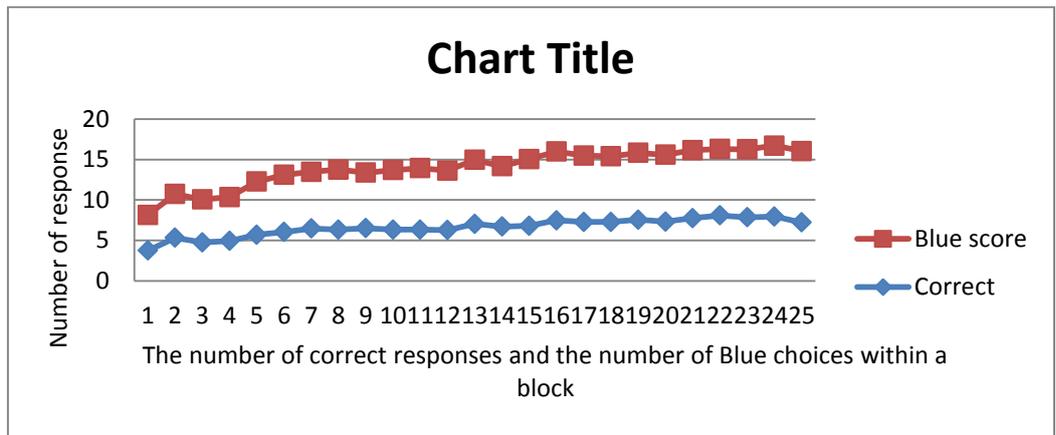


Figure 6. Performance of all participants in the experiment.

In Figure 7 below, average reaction times of all participants for each block throughout the experiment are shown. As seen from this figure the reaction times get faster as the subjects learn the task. However, response time comparison for the first 12 blocks and the last 13 blocks was not found significant. Participants gave responses in nearly the same amount of time in the first 12 blocks ($M = 1153.05$; $SD = 288.37$) as compared to the last 13 blocks ($M = 1023.98$; $SD = 309.64$); $t(498) = 4.815$, $p > .05$; ns.

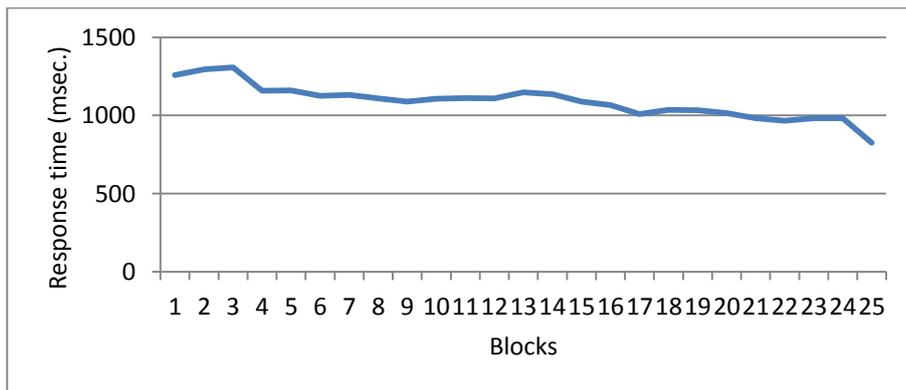


Figure 7. Response time scores of all participants for all blocks.

Response time comparison made with first 5 and last 5 blocks in order to see the effect of learning during the first and last trials of the experiment. Independent t-test

was conducted in order to see the proposed difference. Participants responded significantly faster in the last 5 blocks ($M = 966.79$; $SD = 286.98$) of the experiment compared to first 5 blocks. ($M = 1205.80$; $SD = 306.74$); $t(199) = 5.70$, $p < .00$. Graph for this analysis is given in Figure 8.

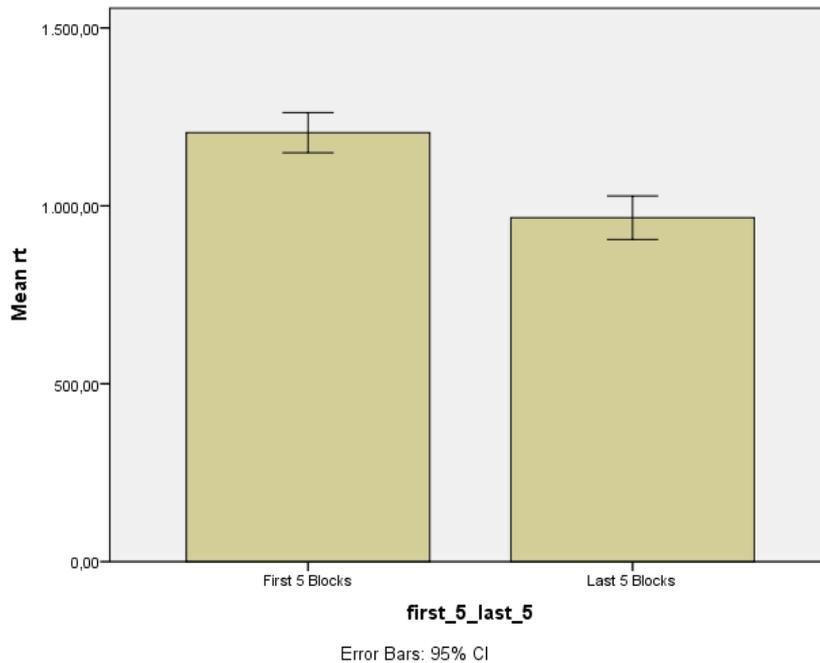


Figure 8. Response time scores for the first 5 and last 5 blocks. Error bars indicate 95% confidence intervals (y axis: Response time in msec.)

Participants used their left hand for the blue choice, and their right hand for their red choice. In order to examine a possible response time difference of using two hands a dependent t-test was conducted for all response time averaged for all participants on all blocks. There wasn't a significant difference between response time for using right ($M = 1105.91$; $SD = 184.57$) and left hand ($M = 1066.43$; $SD = 105.60$); $t(38.19) = .928$, $p > .05$, ns. Response time comparison graphs are given in Figure 9.

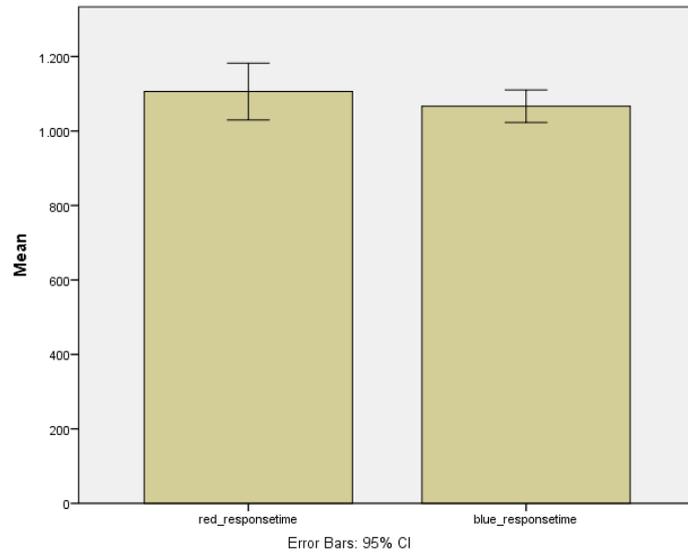


Figure 9. Mean response time comparison for red (right) and blue (left) choices. Error bars indicate 95% confidence intervals. (y-axis: ms.)

In order to categorize participants into frequency matching and maximization groups based on their behavioral responses, last 5 blocks are considered. We assumed that within the first 20 blocks, the subjects learned the probabilities so the last 5 blocks revealed their winning behaviour. Blue scores of the last five blocks are averaged to show every participants' score of blue (Table 3). In the experiment, blue boxes win in 8 of the 10 trials in one block, thus for maximization, the subject has to choose blue approximately 10 times, and for frequency matching the subject has to choose blue approximately 8 times. Since the average of last 5 blocks are taken into analysis, the cut off point is determined as 9. Subjects choosing blue more than 9 times in the last 5 blocks are put into the maximization strategy group, others are put into the frequency matching group. In the frequency matching strategy group, 12 participants had a mean blue score of 7.88 (SD = 0.82), and in the maximization strategy group 8 participants had a mean blue score of 9.4 (SD = 0.37). Distribution plots of two strategy groups' blue scores are given in Figure 10.

Table 3. Average Blue Scores within the last 5 blocks and corresponding learning categorizations.

Subject	Blue Score	Group
51	8.8	Frequency Matching
53	7.8	Frequency Matching
54	8	Frequency Matching
64	8	Frequency Matching
67	8.6	Frequency Matching
75	8.4	Frequency Matching
76	8.4	Frequency Matching
79	7.8	Frequency Matching
101	6.6	Frequency Matching
103	7	Frequency Matching
106	8.4	Frequency Matching
107	6.4	Frequency Matching
52	9.4	Maximization
55	9.6	Maximization
66	9	Maximization
70	9	Maximization
72	9.6	Maximization
102	9.6	Maximization
104	10	Maximization
105	9	Maximization

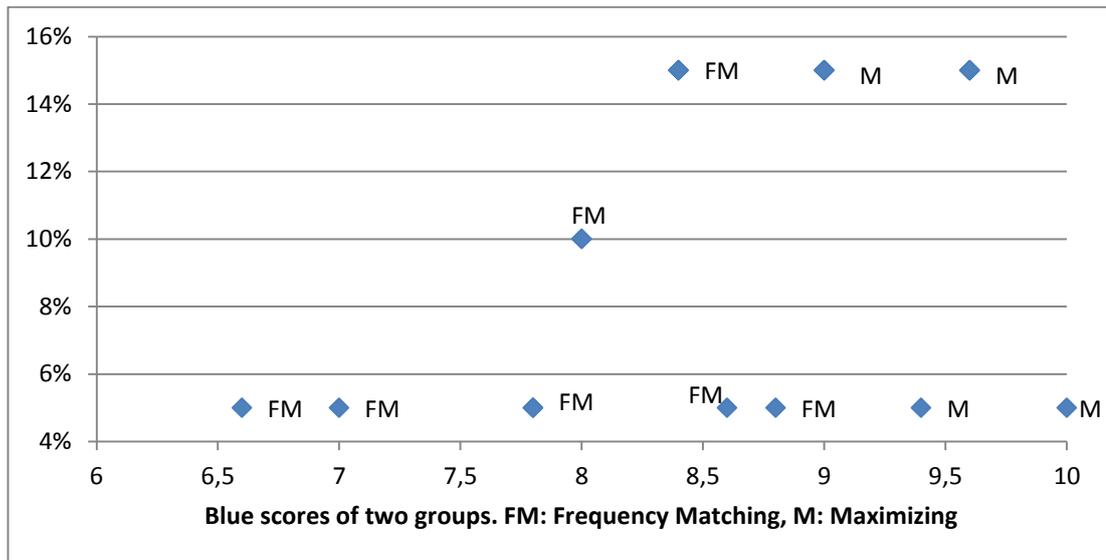


Figure 10. Distribution plot of strategy groups in terms of the blue score.

An independent t-test is conducted within the last 5 blocks to examine whether there is response time difference between 12 frequency matching strategy users and 8 maximization strategy users. In terms of response time, results indicate that there was not a significant difference between frequency matching and maximization groups. Mean scores can be seen in Table 4, and Figure 11. Frequency matchers spent nearly as same time with maximizers in the last 5 blocks of the experiment. $t(97) = -1.052, p = .148$ (one tailed), *ns*.

Table 4. Mean scores of response time for two groups

	Frequency Matching	Maximization	t	df
Response Time	992.90	926.63	-1.051	97

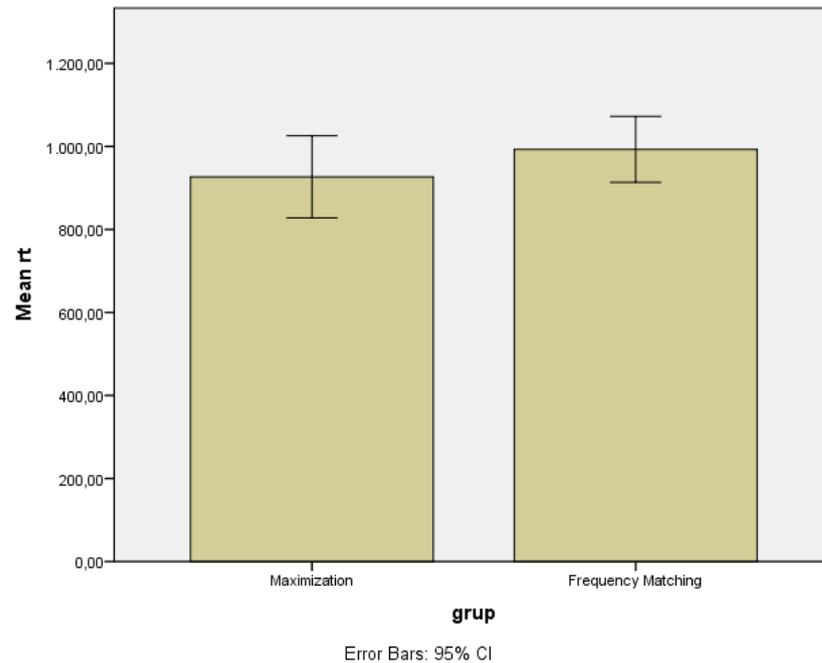


Figure 11. Response time differences in the last 5 block for two different behavioral groups. Error bars indicate 95% confidence intervals (y-axis: ms.)

3. fNIRS RESULTS

As stated before, fNIRS device has 16 channels. In data collection all channels were active, however fNIRS signal analysis showed that signals from all channels were not useable due to excessive noise. Since data from the 1st, 2nd, 15th, 16th channels reflected activity in the DLPFC, only signals collected from these channels are considered for analysis. 1st and 2nd channels measures activity from the left DLPFC; whereas 15th and 16th measures from the right DLPFC. For analysis, two channels in each hemisphere are averaged to circumvent the problem of missing data. Throughout the rest of this chapter, fNIRS variables will be mentioned as Mean Ch 1&2 and Mean Ch 15&16. fNIRS oxygeneation signals from channel averages of 15&16 and 1&2 for all 25 blocks (averaged for all participants) can be seen in figure

12 below. Oxgenation levels for the both hemisphere decreased as the task had been learned.

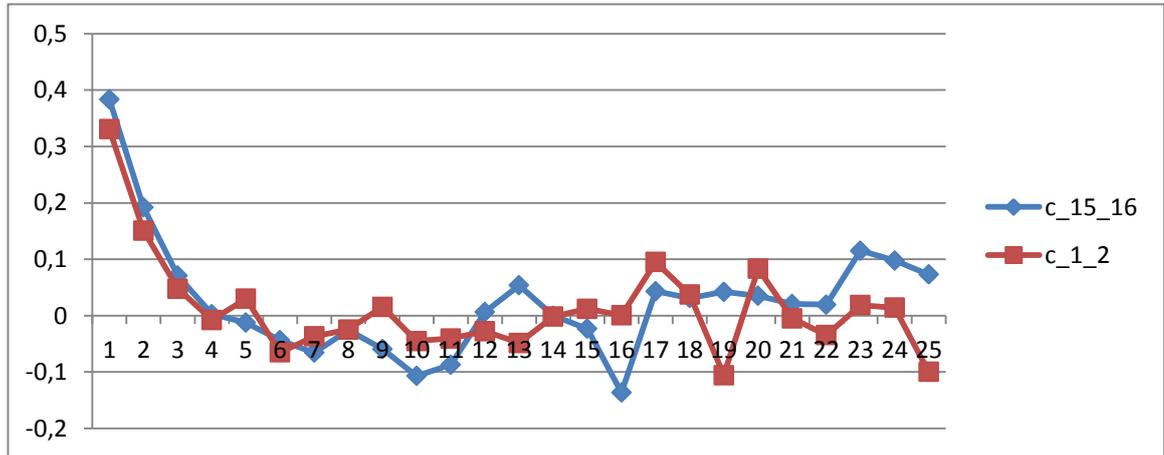


Figure 12. Mean fNIRS Oxygenation signals from channels 15&16 (Right DLPFC) and 1&2 (Left DLPFC) (y-axis: Blocks, x-axis: Oxygenation change)

In order to show the relationship between fNIRS signals taken from 1st, 2nd, 15th,16th channels, response time, and blue scores binary correlations are conducted. In this analysis, variables are averaged for all subjects, and correlations were made across all 25 block points. Results are presented in Table 5.

Table 5. Correlations between variables

Variables	Mean Ch. 1&2	Mean Ch. 15&16	Response Time
Blue Selection	-.593**	-.408*	-.864 **
Mean Ch. 1&2		.716**	.506**
Mean Ch. 15&16			.265

Note. ** $p < .01$; * $p < .05$ (one-tailed)

There is a significant negative relationship between blue score and average ch 1&2 ($r = - .59, p < 0.01$), and average ch 15&16 ($r = - .40, p < .05$) . Correlation between blue score and response time is also negative and significant ($r = - .86, p < 0.01$). Average of channels 1&2 and 15&16 are also significantly correlated with each other ($r = .71$), $p < .01$. But response time is only significantly correlated to average channels 1&2 ($r = .50$), $p < .00$ but not channels 15&16. These statistics indicate that as learning occurs, the fNIRS signal reduces in correlation with reaction times as hypothesized before. The correlations between the blue score and Mean Ch 1&2, and the blue score and Mean Ch 15&16 are given in Figure 13 and Figure 14.

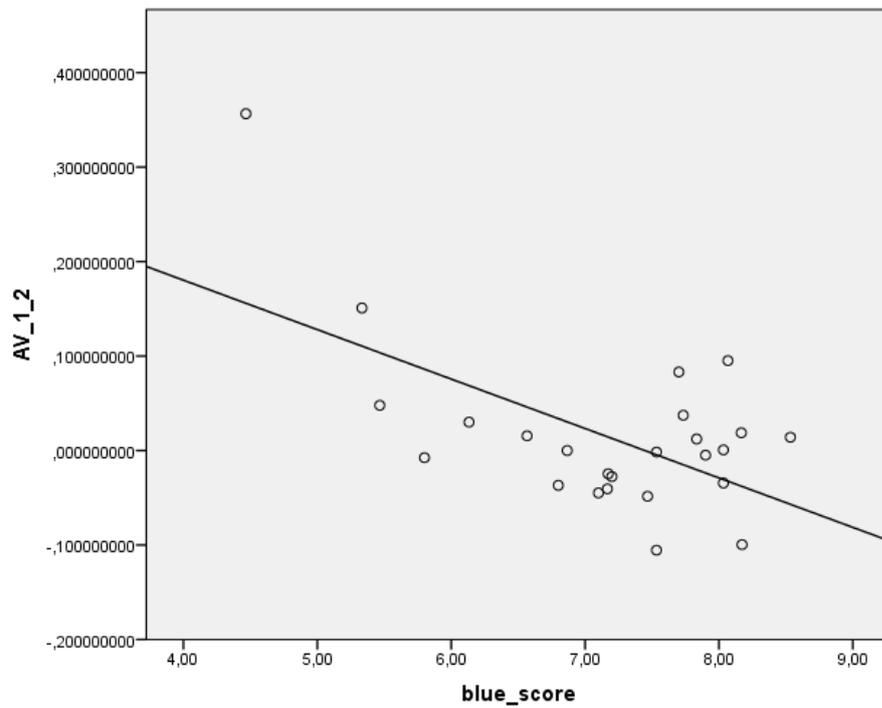


Figure 13. Correlation between blue score and Mean Ch. 1&2

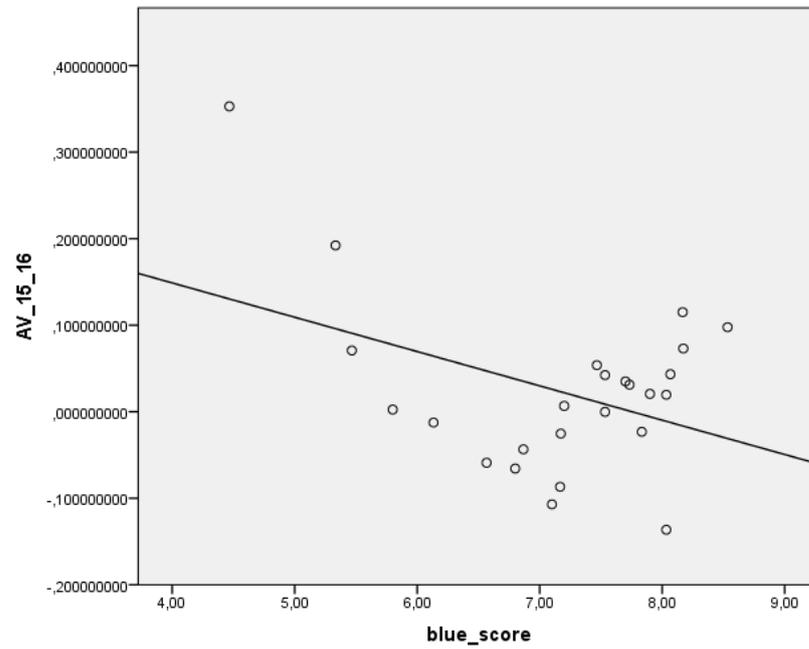


Figure 14. Correlation between blue score and Mean Ch. 15&16

fNIRS signals of the frequency matching and the maximization groups are given in Figure 15 and 16 for Mean Ch. 1&2 and Mean Ch. 15&16 respectively.

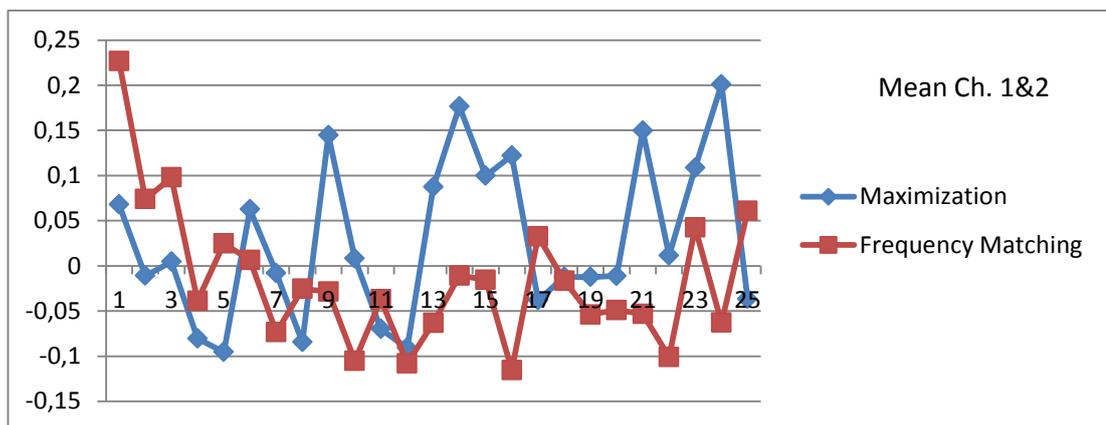


Figure 15. fNIRS signals for the two stragey groups in the left hemisphere.

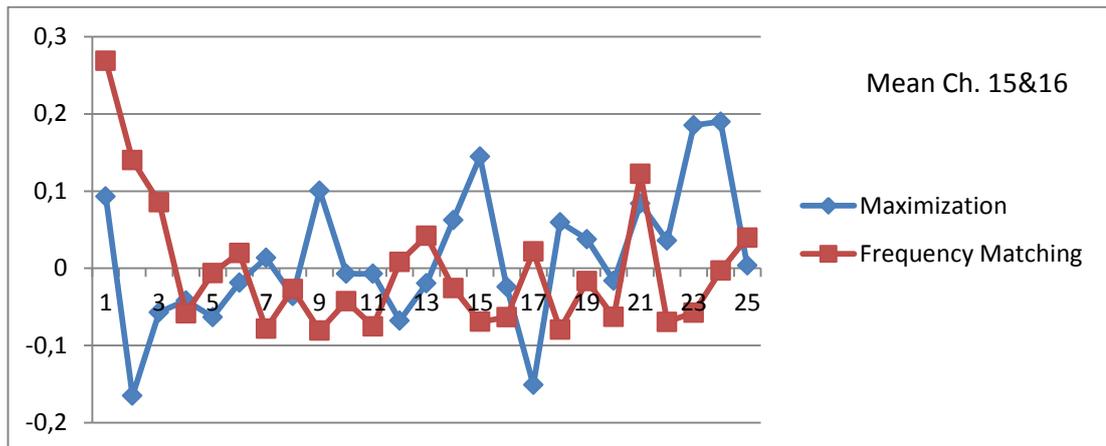


Figure 16. fNIRS signals for the two strategy groups in the right hemisphere.

Before the group analysis, fNIRS data was normalized by shifting the signal average to zero in order to get rid of signal differences between the two groups. Group differences in the fNIRS signal are expected not in the absolute magnitude of the signal, but in the difference (reduction) of the signal after learning occurs midway throughout the experiment. In order to normalize the data, first each participant's mean for 25 blocks was calculated. Then this mean was subtracted from each signal in the last 5 blocks, and new data were created for the last 5 blocks. Both for Mean Ch. 1&2 and Mean Ch. 15&16, minimum and maximum scores were obtained from these new data, and only these scores were taken for the analysis: T-tests were conducted in two strategy groups in normalized minimum and maximum fNIRS signals from Mean Ch. 1&2 and Mean Ch. 15&16 for the last 5 blocks.

Two groups did not differ for minimum Mean Ch. 1&2, $t(17) = 1.072$, *ns.* and for Mean Ch. 15&16, $t(18) = -.478$, *ns.* Also, two groups did not differ for maximum Mean Ch. 1&2, $t(17) = -.619$, *ns.* and for Mean Ch. 15&16, $t(18) = -1.067$, *ns.* Table 6 shows independent t-test results, and Figure 11 and 12 shows error bars for the fNIRS signals two groups for minimum and maximum values of different channels. Since t-test results weren't significant for group comparisons in two

hemispheres, further analysis for localizations of two strategies weren't conducted. However, for further studies Figure 19 and 20 shows scatter plots for the fNIRS signals two groups for minimum and maximum values of different channels.

Table 6. Strategy groups' differences in different channels on the last 5 blocks

	Frequency Matching	Maximization	t	df
Minimum signal in last 5 blocks				
Mean Ch. 1&2	-.2415	-.1606	-.619	17
Mean Ch. 15&16	-.2029	-.2401	-1.067	18
Maximum signal in last 5 blocks				
Mean Ch. 1&2	.2461	.2090	1.072	17
Mean Ch. 15&16	.2799	.1853	-.478	18

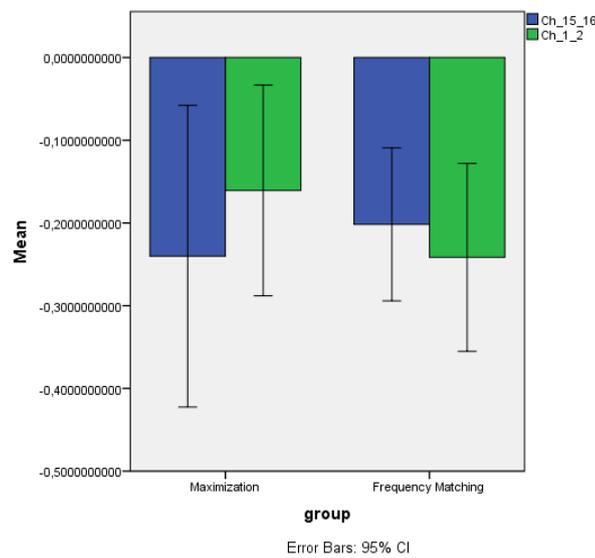


Figure 17. Minimum fnirs signal distribution attained at the L and R hemispheres for the last 5 blocks. Error bars indicate 95% confidence intervals (y axis: micromolar)

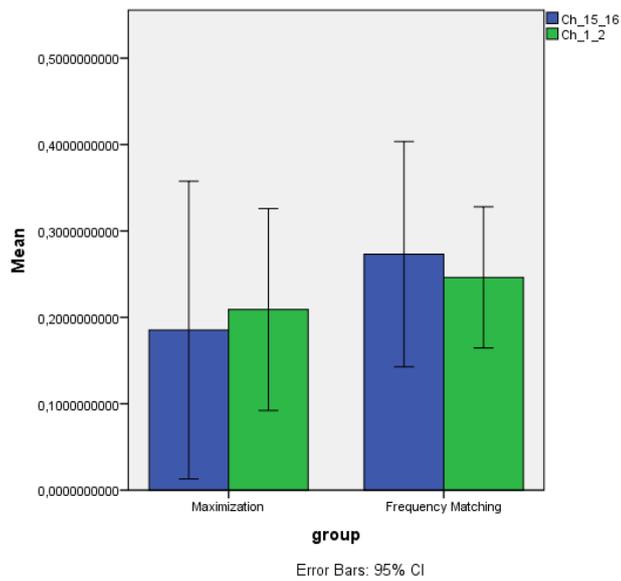


Figure 18. Maximum fnirs signal distribution attained at the L and R hemispheres for the last 5 blocks. Error bars indicate 95% confidence intervals. (y axis: micromolar)

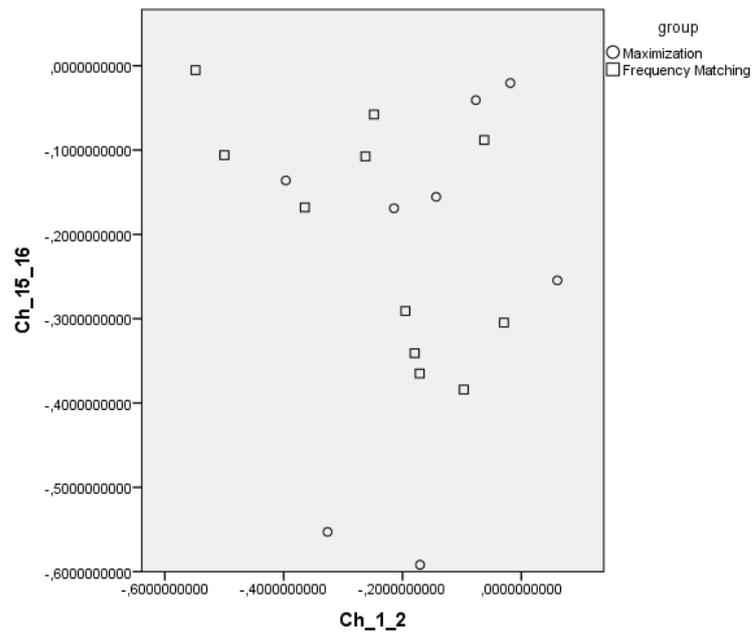


Figure 19. Minimum fnirs signal scatter plots distribution attained at the L and R hemispheres for the last 5 blocks

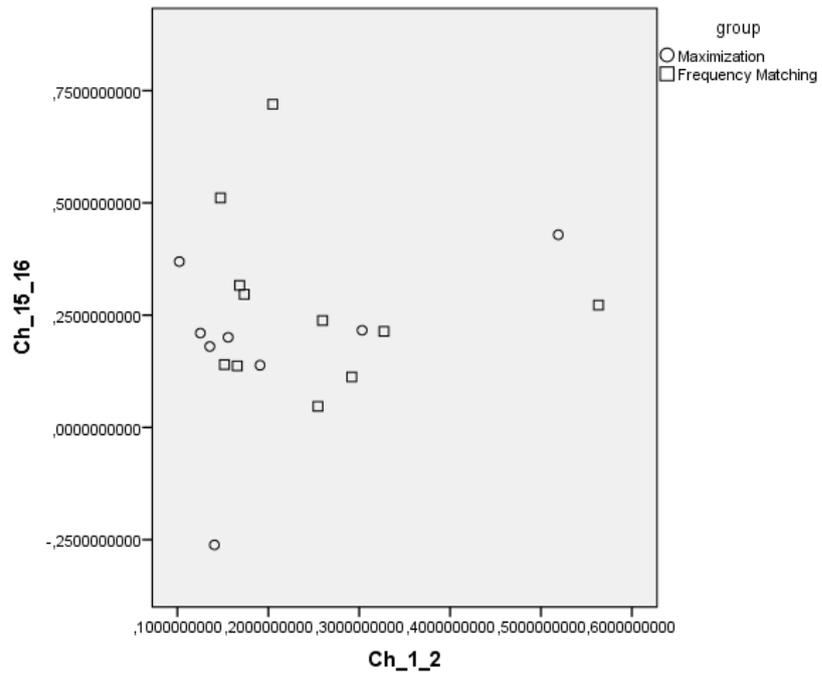


Figure 20. Maximum fnirs signal scatter plots distribution attained at the L and R hemispheres for the last 5 blocks.

CHAPTER 5

DISCUSSION

In this study the interaction of working memory with probability learning had been examined. 20 participants' responses, reaction times and fNIRS signals were compared and analyzed. It was found that working memory activity, as operationalized as fNIRS signals from right and left DLPFC, decreased through the experiment as the participants learned the task. Similarly, reaction time also decreased.

This study showed that, individuals gained the knowledge of probabilities of the stimuli presented in the experiment. The experiment presented a probability distribution of winning stimuli over the trials; these probabilities were unknown to the subjects at the beginning of the experiment. During the trials, participants learned the probabilities with the feedback given after each trial. That is; participants displayed their expectations as to which event will occur and then they were allowed to see the outcomes. The initial condition for probability learning is simply to observe the sequences of trials in which some recurring stimulus pattern and then understanding the probabilities of the stimuli.

When participants' blue selection responses are compared for the first 12 and last 13 blocks; there was a significant difference. Participants chose blue significantly more

than in the last set of blocks than in the first set of blocks. This result indicates a general pattern of learning of the most winning stimuli. However, significant response time difference was not found between first and last blocks of the experiment. When participants were asked about their strategy use for finding the winning options at the end of the experiment, most of them reported that although they thought the blue boxes win more, they continued to try to understand when blue boxes win and when red boxes win. Therefore, even when they understand blue was winning more, they still searched for patterns. That might be the reason for the insignificant difference in reaction times between first and last trials of the experiment.

Participants used their both hands while answering: They pressed for blue with their left hands and for red with their right hands. In order to look for possible differences might occur from this situation, response times were compared for right and left hand use. For each block red and blue choices were allocated and then averaged, therefore 25 left and right hand choice data were created. That was compared with t-test and no significant difference found. This insignificant result is consistent with the aims of the study, since no difference was expected from using both hands. Counterbalancing for the stimulus selecting options could have been made, however that would result in designing two experiments and randomization could be different in two experiments.

As explained in the literature chapter in detail; people have a tendency to search for patterns. Gal and Baron (1996) explained this situation as the failure of understanding independence of events, and Tversky and Edwards (1966) explained as the increased utility of correctly predicting rare event (correctly predicting red boxes in the current experiment). Another description is individuals do not understand the fact that the events in the series are random, so they use a problem-solving approach for the task; instead of using a statistical logic. As stated before in Woldorf's

experiment (2004) participants gave up searching for patterns when they understand that sequences were random. In our experiment, stimuli are presented randomly such that subjects would understand that sequences were random. However, the number of boxes was used as an irrelevant cue to the subject to make them believe as if there is some other dimension of the task to be figured out. Thus, it was expected that most of the participants will look for patterns, while others will maximize their responses.

Correlation results are consistent with the literature (Smith & Jonides's, 1997). Since probability learning task requires keeping track of the past winning options, clear activation was observed in DLPFC which is part of the working memory network. Activation in both left and right dorsolateral parts of the cortex negatively correlated with blue score. Since selecting blue means that the experimental contingencies are learned, consistent with the Koch et al. (2008)'s study, a decrease in prefrontal cortex activation was expected. In that study, activation in DLPFC had also decreased as the cue-outcome relation was learned. Probability learning task involves working memory, for which, the executive component is localized to DLPFC. The relationship of this type of tasks, working memory and prefrontal cortex had been largely examined and clarified in the literature so far (Goldman-Rakic, 1992; Owen, Evans & Petrides, 1996; Owen et al. 1999; Petrides, 1994; 1996; Smith & Jonides's, 1997).

Correlations between blue score and DLPFC in both hemispheres was significant, however correlation with left hemisphere channels ($r = -.59$) were higher than that of right hemisphere channels ($r = -.40$). Wolford et al. (2000) concluded that hypothesis formation in such a probability learning task was located in left hemisphere. However, in their study with split-brain patients, activation in the frequency matching group was observed in left hemisphere, while right hemisphere activation was more prominent for the maximization group. Thus, it can't be a clear conclusion that hypothesis formation could be in left hemisphere. Another study (Miller &

Valsangkar-Smyth, 2004) proposed that right hemisphere is the center for probability learning, and they showed significant activations in the right hemisphere for the frequency matching group. Since there are more participants who used frequency matching strategy in the current study and the general mean for choosing blue is closer to optimal level of frequency matching, our study is consistent with Woldorf et al. (2004) study. In the probability learning experiment, participants rely on counting in order to learn the probabilities. Also, since the task involved boxes and placement of the red/blue boxes were also considered visuo-spatial sketchpad is also active. Counting is located in left hemisphere, while visuo-spatial informations located in the right hemisphere (Smith & Jonides's, 1997; Rypma, Berger & D'Esposito's, 2002; Rypma et. al, 1999). Since this study showed that the activations were higher in the left hemisphere, it can be concluded that probability learning task relied on counting and left hemisphere more than visuo-spatial sketchpad and right hemisphere.

It is suggested that, the understanding of cue-outcome relationship becomes stable during the last blocks of the experiment (Knowlton, Squire & Gluck, 1994). Therefore, the analyses which were related to the phase of the experiment where learning is finalized were made with the last 5 blocks. In order to categorize participants into two behavioral groups, blue scores for the last 5 blocks were considered. Since the highest probability rate of the stimulus was 80%, the mean rate of blue presses as 8 was the optimal score. Therefore, the participants are categorized into the frequency matching group if their last 5 block of blue scores were below 9 and maximization group if their last 5 block of blue scores were 9 and higher. Among 20 participants, 12 of them used frequency matching strategy, and rest of them used maximization strategy. In the literature, most of the studies stated more frequency matching strategy use than maximization. Thus; current study's results are consistent with Shanks et al. (2002), Taylor et al. (2012), Derks and Paclisanu (1967) and many more.

After experiment, reporting of participants revealed the fact that most of them understood the correct probabilities of the winning option. However, they stuck to a sub-optimal strategy as frequency matching, which is a clear example of the urge to search for patterns similar to several other probability learning experiments. This tendency had been argued a lot, for instance: Gambler's Fallacy (Tversky & Kahneman; 1972), and Yellot's study (1969). Brackbill and Bravos's (1962) model explains this irrational behavior by suggesting that participants obtain a greater utility by correctly finding the less frequent option by chance. Therefore, they do not maximize their behavior, but try to match the frequencies of two stimuli. They believe they can achieve 100% correct rate in one block. However, since the cues occur probabilistically, this is unlikely. There had been other explanations: for instance, Koehler and James (2009)'s explanation of readily stored mechanism (Even though participants rated maximization strategy was a better strategy, they fail to implement it), Taylor et al.'s (2012) explanation for the clearance of the strategies (When the task was explained explicitly, subjects used maximization, whereas when explanation was not given they tend to use frequency matching), and effects of the type of stimuli (When compared with neutral outcome stimulus; participants who were fearful of these animals performed worse) (Thomas & LaBar, 2008), or number of trials (The longer the trials, the more participants use maximization strategy) (Shanks et al., 2002).

Response time comparison for the two strategy groups did not reveal significant difference. Both groups spend similar amount of time during the last 5 blocks of the experiment. Frequency matchers were expected to spend more time than maximizers, since maximizers select the most frequent option repeatedly while frequency matching strategy users spend time to match the frequencies of probabilities. Only one participant in the maximization group selected the most frequent option with a mean score of 10, other participants in the group scored between 9 and 10. Thus probably the maximizers also spend time such as frequency matchers to find the least frequent option. Another explanation for this result might be the boredom effect

(Keren & Wagenaar, 1985). Shanks's study (2002) showed the relation between the number of trials and results of the experiment. Due to situations like participants were wearing slightly uncomfortable device on their forehead and some participants' reported headaches at the last part of the experiment; last 5 blocks of the experiment might have had several uncontrolled factors. These factors might have affected response time on the last 5 blocks. As explained in the literature, participants who made blue scores between 9-9.9 could be classified as over matchers, not maximizers. However since there was only one participant who scored 10, it was hard to differentiate others from the true maximizer as group comparison would not be possible with only 1 maximization strategy user.

On another front, we investigated the brain activity of the two behavioral groups: The maximization and frequency matching strategy groups did not differ in terms of fNIRS signals. Also, these two groups did not show differentiation in left and right channels. Group comparisons were expected to differ in terms of activation level. Our main hypothesis was that as the task has been learned, activation would decrease. Similarly, lower levels of activation were expected in the maximization group than the frequency matching group because people in the frequency matching groups keep actively searching for patterns. Maximization strategy users give up for pattern search and choose the most frequent option almost always while the opposite is valid for the frequency matching strategy users. The frequency matching group try to match the frequencies of two stimuli so they need working memory and hence higher brain activation is expected. These hypothesized group comparisons were done with normalized data. The difference between the groups was not significant. That is, maximization and frequency matching groups did not yield a significant difference of fNIRS signals. Also, it was hypothesized that, there will be a localization difference between frequency matching and maximization strategy groups. Since the literature have conflicting findings, the hemisphere of the localization of the two groups was not clear. As the t-test didn't yield any significant

difference between the groups in both hemisphere, further analysis wasn't conducted to examine localization differences.

There can be several reasons for these insignificant group comparisons. The most important one is the categorization decision of the participants. Blue score range was 6.8-10, and although there was a cutoff point at 9, some scores of the several members of the two groups were very similar. Also, categorizing participants into groups were made according to the last 5 blocks. Different categorization techniques that we used -such as discriminating participants within the range of one or two standard deviations, using last 7 blocks, or crossing out last two blocks for boredom effect- did not reveal a consistent list of subjects in both groups. Even though there was a clear learning effect for the whole set of participants, this effect could not be differentiated into behaviorally distinct groups.

To sum up, our study investigated the relationship between probability learning mechanisms and prefrontal cortex. The central executive function of working memory's interaction was evident in DLPFC. However, we were not able to distinguish the subjects in the two behavioral groups in terms of their DLPFC activations. As a result only the first two hypotheses were confirmed:

- (1) Due to the utilization of WM resources, DLPFC activity is decreases as the task is learned. After the winning color and probability is learned, the activation in DLPFC is decreases since there is less need to use monitoring resources to win. If the occurrence of winning choice is increased, DLPFC activity is decreases as well.

- (2) Once the task has been learned, reaction time is decreases pattern searching is performed less. Negative correlation between reaction time and task performance is found

Limitations of the study:

During the experiment, DLPFC activity was measured from fNIRS. This activity was hypothesized as measured from working memory activations. However, since the task was a probability learning task and this task activates not only working memory but also activates decision making process we can't be %100 sure about the reasons of the activity. Therefore, it is wrong to conclude that all the activity was resulted from working memory. Different detailed techniques like fMRI scans would give more elaborate results on the reasons of the activity; however that was not possible in the scope of this study.

Dorsolateral and ventrolateral parts of the prefrontal cortex have different functioning of working memory. In general working memory is located on prefrontal cortex, but different parts of the cortex are active while executing tasks. For example rehearsal is localized to Broca's area in the ventral part, while central executive is localized to dorsal part (Jonides et al., 1996; Smith, E. & Jonides, J., 1997). By comparing dorsolateral and ventrolateral parts of the cortex, more accurate and diverse conclusions can be derived. fNIRS is suitable for such comparison, but the fNIRS device used in this study was not able to record from the middle parts of the cortex. Only DLPFC activity, which indicated the central executive component, was taken into consideration. Also, due to missing data 1st and 2nd, 15th and 16th channels signals were averaged, therefore possible differences between upper and lower channels could not be examined both for left and right sides. Miller et al. (2005) found activations for probability learning in ventrolateral-anterior-medial prefrontal cortex, right angular gyrus, and right inferior parietal lobe. Moreover, the frequency learning mechanism of probability learning is strongly associated with basal ganglia and dorsal striatum area. Brain activation patterns in these areas were not investigated in our study due to the limitations of the fNIRS device.

In this study 4 of the participants were classified as non-learners. Even though their data was not included in the analysis, further studies can compare response times or fNIRS signals with the learners. It was assumed and found that as participants learned the task their response time and DLPFC activations decreased. These results can be compared with non-learners response time and activation data and it can be expected that non-learner's response time won't be decreased as they are still trying to understand the task and also their DLPFC activity will not be decreased as well. This comparison was not available in this study, since there were only 4 non-learner participants.

Another limitation of our study is that the number of participants is low. Even though 29 participants were tested, 9 of them had to be eliminated due to drug history or because they could not learn the task. Also since there were only 20 participants, categorizing participants into strategy groups was an important limitation due to very close blue selection scores. Drug history should be questioned ahead of time and participants should be warned before the experiment in order to avoid such limitation. According to behavioral results some participants could not learn the task. Non-learner participants' post-experiment discussion revealed that they had no clue of the fact that blue boxes winning more, and they always tried different combinations for winning. When their last 10 blocks were examined, it was clear that they were not able to understand the task so learning was not evident.

Another limitation was the absence of counterbalancing winning color and changing the response buttons for the red and blue choices. Further studies should use more distributed and larger subject samples; so that larger strategy groups will be defined and analyzed.

CHAPTER 6

CONCLUSION

In our study we investigated how brain activity differed during probability learning. After the cue-outcome relation was learned, and probabilities of the stimuli are understood, working memory activity decreased. This decrease was measured by fNIRS signals from DLPFC which is the place for the executive function component of working memory.

The stimuli are presented randomly with certain probabilities, however people kept for searching a pattern between stimuli and could not understand the randomness of cues. While predicting outcomes, participants used two different strategies namely frequency matching and maximization. Although, maximization strategy is a more advantageous technique for winning more in the experiment, more participants used frequency matching strategy. These two groups did not differ in terms of response time, right and left DLPFC signals.

People believe that most of the sequences in the environment have a pattern. However, such a belief is wrong in some occasions like probability learning events. The urge for searching for patterns is a concern that has not only psychological but

also philosophical implications, so it must be investigated further. The need for searching for patterns and finding causal relationships have a variety of explanations and discussions. Yet, most of these discussions do not have a clear conclusion. When this situation is examined from an evolutionary perspective, it has been argued to have a survival value. Uncovering causal relationships has benefits in daily life. Thus, understanding the underlying logic of probability learning and decision-making is important and should be investigated further.

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APPENDICES

APPENDIX A

KATILIMCI BİLGİ FORMU

Cinsiyet: Kadın Erkek

Yaş:

Eğitim Durumu:

Lise Yüksekokul Üniversite Yüksek Lisans Doktora

Üniversite mezunuysanız/okuyorsanız bölümünüz?

Mesleğiniz?

Annenizin eğitim durumu:

İlköğretim Lise Yüksekokul Üniversit Yüksek Lisans/Doktora

Babanızın eğitim durumu:

İlköğretim Lise Yüksekokul Üniversit Yüksek Lisans/Doktora

Hayatınızın büyük kısmının geçtiği yer:

- Büyük şehir (nüfusu 1 milyondan fazla)
- Şehir (nüfusu 1 milyondan az)
- İlçe
- Kasaba
- Köy

Daha önce herhangi bir psikolojik ya da nörolojik ilaç aldınız mı?

- Evet Hayır

Aldıysanız hangi ilacı ne kadar süre ile kullandınız/ Hala kullanıyor musunuz?

APPENDIX B

Bu çalışma, Orta Doğu Teknik Üniversitesi Bilişsel Bilimler Yüksek Lisans Programı öğrencisi Filiz Gözenman tarafından Yrd. Doç. Dr. Didem Gökçay danışmanlığında yürütülen bir yüksek lisans tez çalışmasıdır. Çalışmanın amacı, katılımcıların bilgisayar ortamında yapacakları bir test sırasında functional Near-Infrared Spectroscopy (fNIRS) alın bölgelerinden beyindeki aktivasyonu ölçerek bilgi edinmektir. Çalışmaya katılım tamamen gönüllülük temelinde olmalıdır. Deneyde, sizden kimlik belirleyici hiçbir bilgi istenmemektedir. Cevaplarınız gizli tutulacak ve sadece araştırmacılar tarafından değerlendirilecektir; elde edilecek bilgiler bilimsel yayımlarda kullanılacaktır.

Çalışmamızda katılımcıların alın kısmına fNIRS sensörlerinden oluşan bir bant yerleştirilecek ve deneyle simultane olarak optik veriler toplanacaktır. Toplanan bu veriler, beyin aktivasyonlarını zamansal olarak izlememizi sağlayacaktır. Deney sırasında yaklaşık 20 dakika boyunca ekranda görülen renkli kutulardan hangisinin kazanacağı sorulacaktır. Toplam 250 uyarın gösterilecek ve her seferinde uyarılardan hangisinin kazanacağı denek tarafından tahmin edildikten sonra, aslında hangi uyarının kazanmış olduğu katılımcıya bildirilecektir.

Deney, genel olarak kişisel rahatsızlık vermemektedir. Ancak; katılım sırasında deneyden, ölçüm cihazından ya da herhangi başka bir nedenden ötürü kendinizi rahatsız hissederseniz cevaplama işini yarıda bırakıp çıkmakta serbestsiniz. Böyle bir durumda deney yürütücüsüne, deneyi tamamlamadığınızı söylemek yeterli olacaktır. Deney sonunda, bu çalışmayla ilgili sorularınız cevaplanacaktır. Bu çalışmaya katıldığınız için şimdiden teşekkür ederiz. Çalışma hakkında daha fazla bilgi almak için Enformatik Enstitüsü öğretim üyelerinden Yrd. Doç. Dr. Didem Gökçay (Oda: A216; Tel: 210 3750; E-posta: didem@ii.metu.edu.tr) ya da tez öğrencisi Filiz Gözenman (Tel: 536 6302885; E-posta: filizg@gmail.com) ile iletişim kurabilirsiniz.

Bu çalışmaya tamamen gönüllü olarak katılıyorum ve istediğim zaman yarıda kesip çıkabileceğimi biliyorum. Verdiğim bilgilerin bilimsel amaçlı yayımlarda kullanılmasını kabul ediyorum. (Formu doldurup imzaladıktan sonra uygulayıcıya geri veriniz).

İsim Soyad

Tarih

İmza