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Neuroimaging in Human Category Learning: A Comparison Between Functional Near-Infrared Spectroscopy (fNIR) and Functional Magnetic Resonance Imaging (fMRI)

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NEUROIMAGING IN HUMAN CATEGORY LEARNING:
A COMPARISON BETWEEN
FUNCTIONAL NEAR-INFRARED SPECTROSCOPY (fNIR) AND
FUNCTIONAL MAGNETIC RESONANCE IMAGING (fMRI)

by

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ABSTRACT

The objective of this thesis is to examine the validity of functional near-infrared spectroscopy (fNIR) to examine brain regions involved in rule based (RB) and information integration (II) category learning. We predicted similar patterns of activation found by past studies that used fMRI scans. Our goal was to test if fNIR would be able to detect changes in blood oxygenation levels of participants who learned to categorize (learners) vs. those that did not (non learners).

The stimulus set comprised of lines that differed in length and orientation. Participants had to learn to categorize by trial and error based on the feedback provided. Behavioral and neuroimaging data was recorded for both RB and II conditions. Results showed an upward trend in response accuracy over trials for participants identified as learners. Furthermore, blood oxygenation levels reported by fNIR indicated a systematic increase in oxygen consumption for learners as compared to non learners. These areas of increased prefrontal cortex activity recorded by fNIR correspond to the same areas found to be involved in categorization by fMRI. This paper reviews the background of category learning, explores various neuroimaging techniques in categorization research, and investigates the efficacy of fNIR as a relatively new neuroimaging modality by comparing it to fMRI.

ACKNOWLEDGMENTS

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INTRODUCTION

Categorization is an important cognitive skill we use to learn and understand the world around us. Assigning categories to objects or concepts not only helps us mentally sort things, but it also enables us to generate an effective response to a particular stimulus. For example, if you encounter a snake that is categorized as poisonous, your response would be very different than if you encountered a harmless garden snake. Similarly, a doctor would react differently to a malignant tumor than to a benign one. These examples show the importance of categorization in our daily lives and explain why a lot of cognitive psychology and neuroscience research has focused on examining human category learning involving various tasks.

Category learning research is dominated by three competing theories of categorization. Based on prototype theory, as we get more familiarized with a particular category (e.g., parrots) we form an abstract mental representation of the average (or prototypical) bird. Exemplar theory assumes that we categorize based on our experiences with each individual category member rather than a prototype (e.g., instead of using an average representation of the category parrot, all the memories for parrots encountered are used for categorizing). And decision bound theory suggests that we categorize based on rules or boundaries between categories rather than category exemplars (e.g., ripe vs. unripe fruit). In recent research on decision bound theory, two types of tasks have been particularly important, rule based (RB) and information integration (II) tasks.

Background

These above mentioned learning tasks were used in experiments during the second half of the 1990s when pioneer research on category learning focused on proving the existence of multiple category learning systems. Once the existence of multiple category learning systems was shown, researchers shifted their focus to understanding the interactions between the various systems when evidence for a competitive relationship was found. One theory known as COVIS (competition between verbal and implicit systems) provided an explanation for this competition based system (Ashby, Alfonso-Reese, Turken, & Waldron, 1998). As per the COVIS model, an explicit and a procedural learning based categorization system compete to determine the participant's response while learning a new category (Ashby & Maddox, 2005). Evidence has been found for the competition between the two systems, but it is unclear if the competition exists at the learning or output stage of categorization. Ashby and Crossley (2010) found that the use of an explicit system by a participant might inhibit the procedural system from contributing to their learning process. However, Erickson (2008) argued that this can be prevented by providing clues to participants about the specific system to be used for learning. Cognitive neuroscience studies have found a similar competition based system, namely between the medial temporal lobe and the striatum (Ashby & Maddox, 2011).

NEUROIMAGING IN CATEGORIZATION RESEARCH

Currently, cognitive scientists are further researching the working mechanisms of this competitive system and how information is mediated between the systems for categorization, learning and automaticity. They employ various neuroimaging techniques to study the neural correlates of the multiple systems that operate during human category representation and learning (Bunce, M. Izzetoglu, K. Izzetoglu, Onaral, & Pourrezaei, 2006). These imaging methods have proven to be very important for studying the brain-behavior relationships involved in category learning. Though each system has its advantages and disadvantages based on various spatial, temporal and quality standards, fMRI has been established as the current “gold standard” for measuring brain activity (Bunce et al., 2006).

fMRI as the gold standard for neuroimaging

There are several reasons for why fMRI is a preferred benchmark in clinical and research settings. It is a non invasive, radiation free method with high spatial resolution. It functions by measuring metabolism and changes in cerebral blood oxygenation levels during brain activation. Specifically, fMRI measures the blood oxygen level dependent (BOLD) signal which provides a measure of the relative changes of oxygenated and deoxygenated blood in the surrounding tissue of activity (Bunce et al., 2006). fMRI is commonly used by clinicians to study the anatomical bases of behavior in humans in order to aid their practice and research (Bunce et al., 2006). However, despite its prevalence fMRI has a few limitations. Bunce et al. (2006) identify some of these shortcomings of the system. To begin with, participants in an fMRI study have to lie down in a confined space for long periods of time and stay still as the machine is very sensitive to movement. The cooling system used for the magnets is loud and can interfere with the study. Also, trained staff are required to administer an fMRI. Moreover, large amounts of space are required to store the machine, making it an unattractive option for academic or field research settings. The system is also very expensive, costing millions of dollars in initial investment (Bunce et al., 2006). So, though fMRI is an effective and dominant neuroimaging method, it is not free from limitations.

In the present study, we aimed to investigate a new neuroimaging technique called functional near-infrared spectroscopy (fNIR). Our goal was to establish the validity of this new and emerging modality by comparing it to the current benchmark for measuring neural activity, namely fMRI. We achieved this goal by replicating a study done by Filoteo, Maddox, Simmons, Ing, Cagigas, Matthews and Paulus (2005) and partially replicating the Cincotta and Seger (2007) experiment. In this study, we examined the acquisition of rule based (RB) and information integration (II) categories by using fNIR and behavioral data as participants performed categorization tasks. The rule based task employed in our experiment is adapted from the perceptual categorization task used in the study conducted by Filoteo et al. (2005). The information integration task is based on the Cincotta and Seger study (2007) study. Both these experiments used fMRI scans to pinpoint increased oxygen consumption in active brain areas involved in the categorization tasks. We predicted that we would find similar patterns of brain activation using the fNIR system. With our study, we aimed to establish the efficacy and importance of this new and emerging neuroimaging technique for categorization research. fNIR is a considerably cheaper and more flexible neuroimaging system compared to fMRI. Our study will pave the way for future researchers to both investigate this new system and utilize it in experiments where the use of fMRI is not feasible.

fNIR in cognitive research

Several studies have examined the efficacy of fNIR for studying cognitive performance. For example, a cognitive performance measurement study in which the participants played a video game where they had to categorize between known vs. unknown planes with or without a secondary verbal task (M. Izzetoglu, Bunce, K. Izzetoglu, Onaral & Pourrezaei, 2007). Participants were each provided with 4 sets of 3 repetitions which included 6, 12, 18 and 24 plane scenarios. The participants' performance and blood oxygenation levels in the dorsolateral prefrontal cortex were measured using fNIR. The researchers predicted that blood oxygenation levels would rise in the prefrontal cortex with increasing task load and performance measures. This hypothesis was supported by the data recorded by fNIR while participants completed the task. Another study conducted by the same group of researchers comprised of a working memory assessment study (Izzetoglu et al., 2007). This study was designed to replicate the results of an fMRI study involving the same task. The commonly used N-back task was used where single consonants were displayed for 500 ms with an interval of 2,500 ms to 9 participants. Four conditions called 0-back, 1-back, 2-back and 3-back were used. Participants in the 0-back condition had to respond to a prespecified letter by pressing a key. In the 1-back condition, the target letter was like the one displayed right before it. In the 2-back condition, the target represented the letter from 2 trials ago. The resulting conclusions using fNIR were in congruence with the results from the fMRI study. So, fNIR was able to replicate the same results obtained by fMRI studies indicating a positive relationship between increasing task load and blood oxygenation levels.

Another study involving fNIR was a problem solving study using anagrams (Izzetoglu et al., 2007). Participants were shown blocks of three letters 3L, 4L and 5L anagrams serially to test for time required to solve the anagram and the associated hemodynamic changes. A strong positive correlation, R= 0.94 was established between the behavioral response (actual response time) and rise time (time needed for hemodynamic changes to peak). As the anagrams got harder, the participants took longer to respond. This implied that as task difficulty increased, participants took more time and oxygen to solve the anagram. In another study, 15 participants were chosen to measure their attention using a combination of EEG and fNIR imaging while they performed a visual target categorization task (Izzetoglu et al., 2007). Participants had to press one of two buttons for target (XXXXX) and context (OOOOO) stimuli. The results indicated that target stimuli generated higher oxygenation levels compared to context stimuli. This study also proved that fNIR can be readily combined with other neuroimaging techniques like EEG to assess cognitive activity such as attention. These four studies show that fNIR technology can be successfully used in cognitive psychology research to measure problem solving, working memory, attention etc. Also, the data from these studies is in harmony with the data from other neuroimaging techniques like EEG and fMRI.

Comparing fNIR with fMRI

Functional near-infrared spectroscopy (fNIR) is a relatively new brain imaging approach that uses near-infrared light and receptors to record brain activity (Bunce et al., 2006; Izzetoglu et al., 2007). Like fMRI, fNIR measures the BOLD signal to scan neural activity involved in a behavioral task. fNIR measures the ratio of oxygenated and deoxygenated blood in the activated area using near-infrared light between 700-900nm. The fNIR system used in the current research was able to record brain activity in Brodman areas (Figure 1) BA9, BA10, BA46, BA45, BA47, and BA44 (Izzetoglu et al., 2007). Past research using PET and fMRI scans has indicated the importance of these dorsolateral and anterior frontal cortex areas in working and episodic memory, solving problems, inhibiting response and perceiving smell (Izzetoglu et al., 2007). Specifically, the areas involved in working memory and selective attention are important for rule based learning and as these are accessible using fNIR, it can be an effective neuroimaging technique to study neural mechanisms underlying categorization.

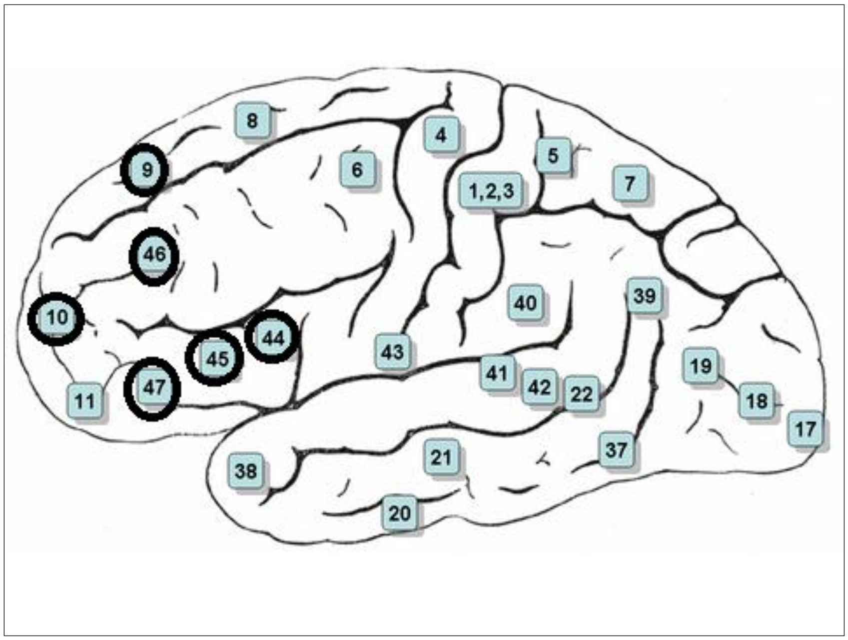

Figure 1: Lateral image of the brain with circled Brodmann areas accessible by fNIR
Source: Wikipedia
http://en.wikipedia.org/wiki/Brodmann_area

THE FNIR SYSTEM

The operating principles of fNIR are based on a mechanism called neurovascular coupling (Izzetoglu et al., 2007). Increased neural activity in a brain region results in decrease in oxygenated blood in the surrounding area. As per neurovascular coupling, the brain sends more oxygenated blood to the site of activity leading to an increase in oxygenated blood. fNIR measures the ratio of oxygenated (oxy-Hb) and deoxygenated blood (deoxy- Hb) following activity in a specific brain region with the help of near-infrared light. In this manner, researchers can view oxygenation levels in real time as participants perform a cognitive task (Izzetoglu et al., 2007).

fNIR Components

The current study used an fNIR system designed by fNIR Devices, LLC. The chief components of the fNIR system include an fNIR sensor pad (Figure 2) that is for the participant’s forehead and the fNIR control box (Figure 3). The fNIR sensor pad includes four light sources consisting LEDs to emit light and ten detectors to record brain activity in the dorsolateral and anterior frontal cortex areas of the brain. There are a total of 16 signal channels or optodes (Figure 2) with a distance of 2.5cm between the source and detector on the sensor pad.

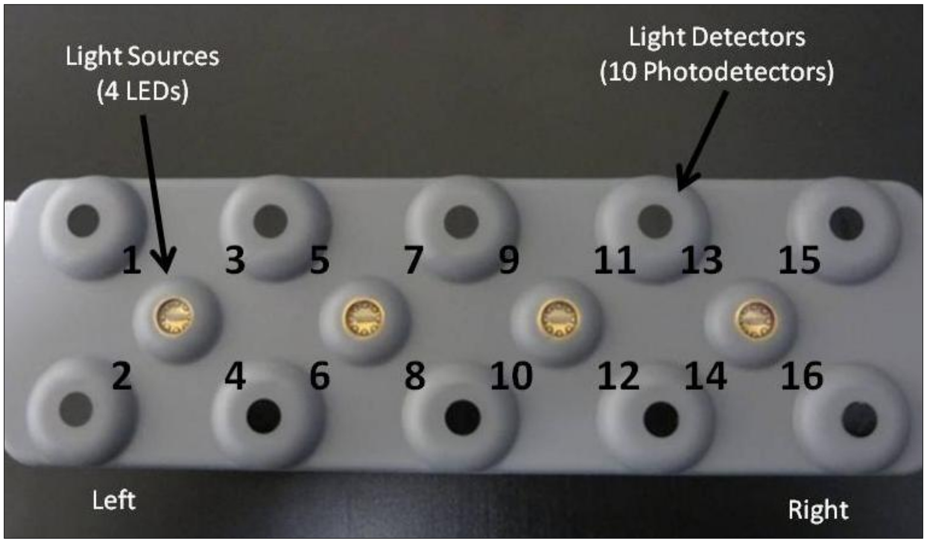

Figure 2: fNIR sensor pad to be applied to the forehead
Image shows 4 LED light sources to emit light, 10 photodetectors to detect light with a total of 16 channels to record blood oxygenation levels.

Figure 3: fNIR control box for data acquisition

METHODS

Our study aimed to compare the results of two fMRI category learning studies to the data we obtained using the fNIR system. We expected to find similar activation in frontal brain regions accessible by the fNIR. For this purpose, we replicated the study conducted by Filoteo et al. (2005) which involved a perceptual categorization task to study rule based (RB) category learning using fMRI. Another study by Cincotta and Seger (2007) used fMRI scans in order to examine the effect of feedback on category learning and consequent brain activity using an information integration task (II). These two fMRI studies recorded blood oxygenation level dependent (BOLD) signals while participants learned to categorize. Increased brain activation was found in Brodmann areas BA9, BA40 and BA6 by Filoteo et al. (2005) and in areas BA9, BA44 and BA47 by Cincotta and Seger (2007) among other areas (see circled areas in Figure 4 & 5).

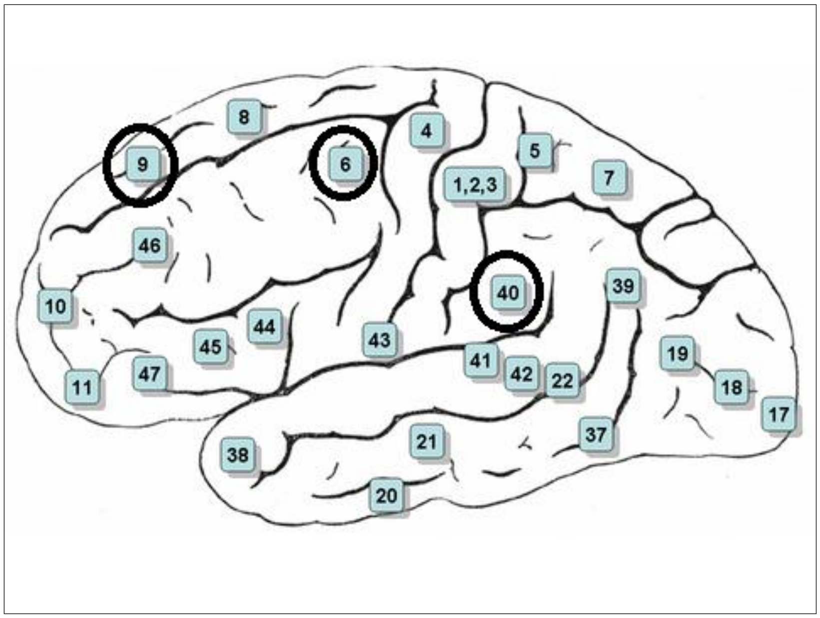

Figure 4: Areas of increased brain activation (circled Brodmann areas) found by Filoteo et al. 2005
Source: Wikipedia
http://en.wikipedia.org/wiki/Brodmann_area

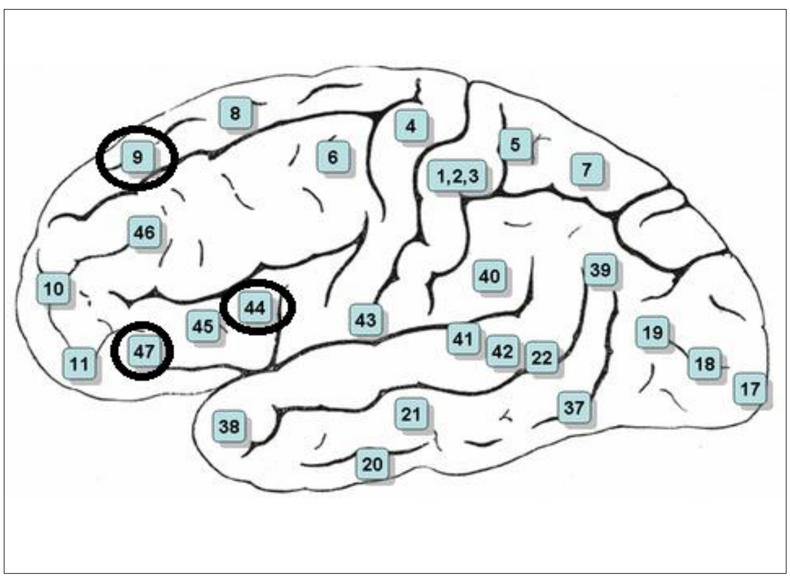

Figure 5: Areas of increased brain activation (circled Brodmann areas) found by Cincotta and Seger, 2007
Source: Wikipedia
http://en.wikipedia.org/wiki/Brodmann_area

The current study consisted of 2 experimental conditions for category learning namely, rule based (RB) condition and information integration (II) condition. We used a within subjects design where all participants completed both conditions of the study. The order of the experimental conditions was counterbalanced for all participants. The stimuli consisted of a series of lines with differing lengths and orientations. In the II condition, a correct response required participants to pay attention to both stimulus dimensions simultaneously. Alternatively, in the RB condition, participants had to attend only to a single stimulus dimension (length) and ignore the other dimension (orientation). After participants made their response, feedback appeared on the screen, "Correct, That was A," or "Incorrect, That was B." Each participant completed 24 blocks of 20 trials for both conditions. The 1st 10 trials in each block consisted of baseline tasks in which they were presented with the same stimuli (single lines of varying lengths and orientations), but as shown in Figure 6, the stimuli were either yellow or blue and participants had to decide what color the lines were. The next 10 trials were experimental trials (Figure 7) consisting of single white lines varying in length and orientation and participants had to assign them to either category A or B. These 20 trials (10 baseline + 10 experimental) were repeated 24 times for a total of 480 trials for both RB and II conditions.

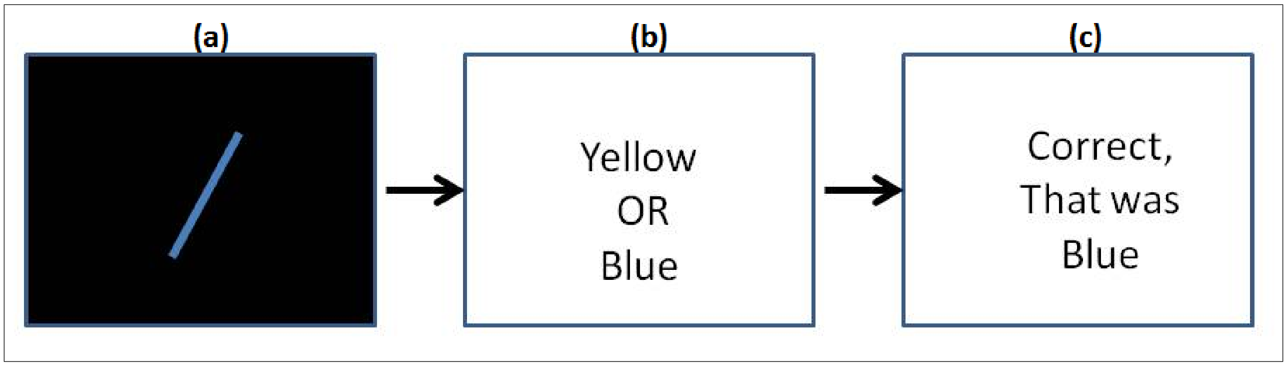

Figure 6: Baseline stimulus
(a) In a baseline trial, either a blue or yellow line of different length and orientation would appear on the screen. (b) Participants made a choice by hitting a blue or a yellow key on the keyboard to categorize lines based on color. (c) Feedback was provided after choice was made.

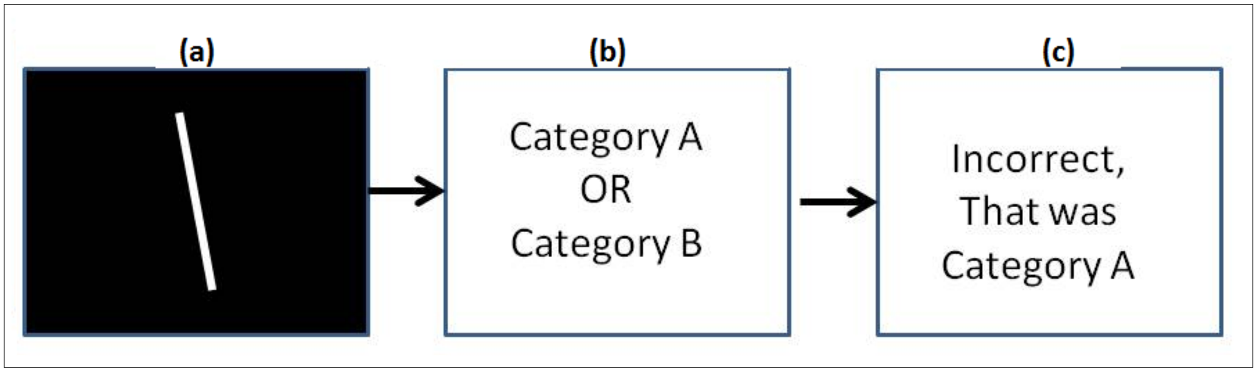

Figure 7: Experimental stimulus
(a) In experimental trials for both RB and II conditions, one at a time lines of varying lengths and orientations would appear on the screen. (b) Participants had to categorize lines into two categories, A and B based on their lengths and orientations (c) Feedback was provided after choice about categorization was made to enable participants to learn the categorization rules on a trial by trial basis. In RB condition, participants had to learn to ignore orientation of lines and categorize based on length only. For II condition, participants had to learn to pay attention to both dimensions to categorize.

Participants

Eleven participants (6 female and 5 male) consented to participate in the study. The ages of the participants ranged from 18 to 22 with the average age being 19. Participants were screened for being color blind and taking mind altering medication. Two hours were allotted for the study and all eleven participants received two research credit points for their participation.

Procedure

Upon arrival, participants were given an informed consent which explained the purpose of the study and the fNIR system. Thereafter, an oral questionnaire regarding the age, gender, handedness, color blindness and mind altering medication was administered to screen the participants. The fNIR sensor pad was then applied to participant's forehead and the participants were asked to keep their chin in a chinrest to minimize motion artifacts (Figure 8). Participants were instructed to read instructions on the screen about the upcoming tasks. Two keys were marked A and B on the keyboard to enable participants to make choices during the categorization tasks and two other keys were marked blue and yellow for the choices for the baseline task. Initial baseline signal was recorded by asking participants to stay still and relax their mind for 10 seconds. Once baseline was noted, the experiment began and behavioral and neuroimaging data was recorded.

The experiment consisted of baseline tasks and categorization tasks for each condition to compare brain activation areas relative to baseline. fNIR recorded data for the baseline and categorization tasks so participants wore the fNIR sensor pad during the entire study. For the baseline task, participants had to press the blue button when a blue line appeared on the screen and the yellow button for the yellow line. In the categorization task, they were asked to press the button marked “A” on the keyboard if the stimulus belonged to category A and press “B” if the stimulus belonged to category B. The stimulus consisted of lines of varying lengths and orientations. The orientation of the lines was not relevant for categorization in the RB condition, but it was in the II condition, so participants had to learn to ignore orientation and learn to categorize based on the length of the lines on a trial by trial basis based on the feedback provided.

Figure 8: Participant doing the categorization task on the computer while wearing an fNIR sensor pad

RESULTS

Behavioral and neuroimaging data was collected for each participant for both II and RB conditions. The behavioral data was collapsed from 480 trials to 6 blocks of 80 trials for each participant and averaged across participants for ease of analysis. With respect to the neuroimaging data, blood oxygenation levels for categorization tasks relative to baseline were recorded for 16 channels. Oxygenation levels were averaged for each channel for all participants to depict mean oxygenation levels across participants. Blood oxygenation levels of learners vs. non learners were compared to identify the relationship between increased brain activation and category learning.

Behavioral results

Our prediction for the behavioral results was that we should see learning over blocks measured by an increase in accuracy for the categorization task for both conditions. We hoped to see an upward trend in response accuracy over the 6 blocks thereby implying learning. As shown in Figure 9, there is an upward trend in the response accuracy for the categorization tasks in both conditions over the 6 blocks. This confirms our prediction that learning occurred during the trials. Additionally, we expected to see a more rapid increase in response accuracy in the RB condition compared to the II condition. However, the behavioral data for both conditions appears virtually identical across blocks except for block 2 where response accuracy drops for RB condition and spikes for II condition (Figure 9).

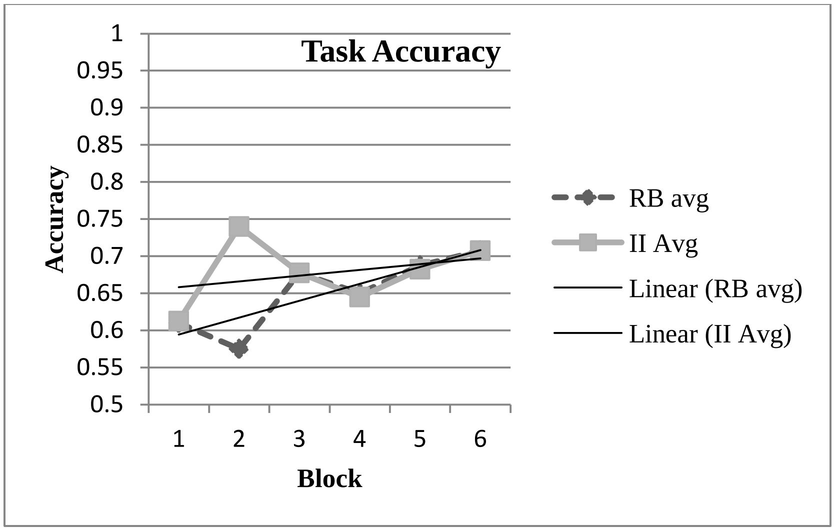

Figure 9: Average task accuracy for participants across blocks.
An upward trend is visible in participants' response accuracy from the start to the end of the experiment across the 6 blocks. 480 trials were collapsed to 6 blocks consisting of 80 trials each and task accuracy was averaged for each block for all participants. Accuracy in percentage is indicated on the y axis.

Based on an Analysis of Variance (ANOVA), block effect is not significant for either condition or for data collapsed across conditions II and RB. ANOVA showed that there was no significant difference between RB and II conditions for task accuracy. A single factor ANOVA showed that there was no significant difference between blocks in RB condition, $F(5,54)=1.249$, $p=.299$. Similarly, single factor ANOVA for the II condition also showed no significant difference between the blocks, $F(5,54)=1.762$, $p=0.136$. Additionally, a two factor with replication ANOVA design displayed no significant effect across the blocks. There was no significant difference both between RB and II conditions, $F(1,108)= 1.301$, $p=.256$ and between blocks $F(5,108)=1.413$, $p=.225$. On the other hand, when we used t-test to compare blocks1 and 6, significant difference was found confirming the evidence for learning. A paired two sample for means t-test was used to test for learning between blocks 1 and 6 for both conditions. For the RB condition, when average task accuracy was compared for block 1 ($M=0.61$, $SD= 0.009$) and block 6 (*M*=0.71, *SD*=0.029) for all participants, a significant difference in accuracy ($t[9]=-2.374$, $p<.05$) was observed verifying the evidence for learning across the blocks. Likewise, in II condition, on comparing block 1 (*M*=0.61, *SD*=0.014) and block 6 (*M*=0.71, *SD*=0.008) for average task accuracy for all participants, a significant difference ($t(9)= -2.229$, $p<.05$) was found which proves that learning occurred.

Neuroimaging results

For neuroimaging results, we expected to see an increase in brain activation relative to baseline tasks in both RB and II conditions. In other words, we expected to see a positive change from baseline across the 16 channels for categorization tasks. As shown in Figure 10 and 11, when averaged over 16 channels, a systematic increase can be seen in II condition over RB condition. More channels reported consistent increase in blood oxygenation levels in the II condition.

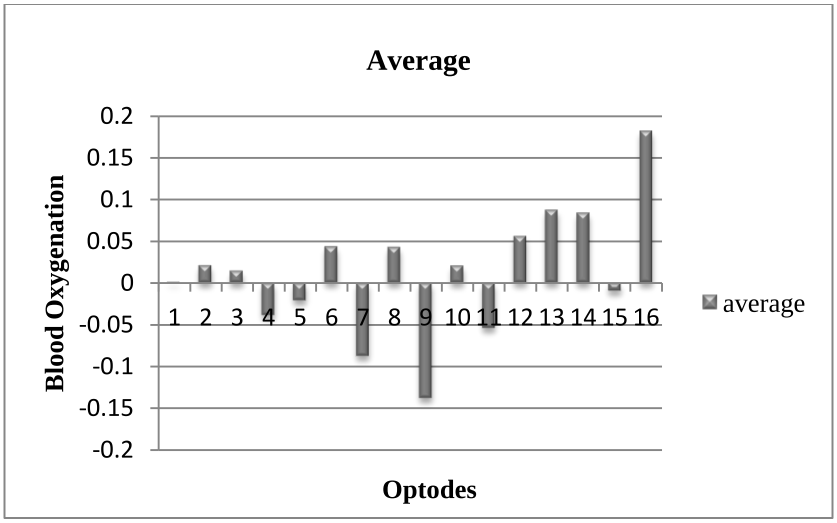

Figure 10. Average blood oxygenation levels for rule-based (RB) condition

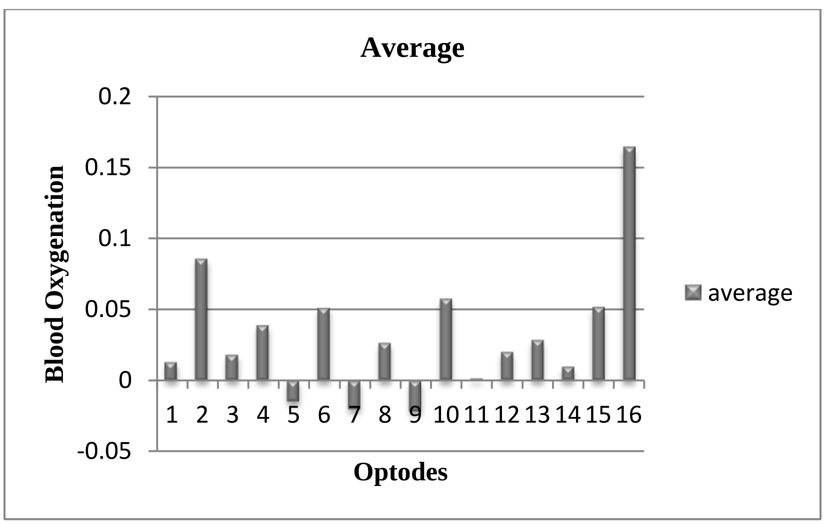

Figure 11. Average blood oxygenation levels for information integration (II) condition

Learners vs. Non-Learners

Participants were identified as learners and non learners by establishing an arbitrary standard at 70% response accuracy. So, participants with 70% accuracy and above were characterized as learners and participants with below 70 % accuracy on the categorization tasks were characterized as non learners.

Behavioral Data

As evidenced by the behavioral data, some participants were learners and some were not. Block 6 was isolated for both conditions as it was the last block and we expected to find the most difference between the learners and non learners in this block. In RB condition, we found that participants 5,8,9,10 and 11 were above 70% accuracy compared to the other participants (non learners) in the final block (see Figure 12). With reference to the II condition, participants 4,5,8, 9,10 and 11 were above 70% accuracy in block 6 compared to the others (Figure 13). Also, a trend in accuracy over blocks is visible for those identified as learners or non learners (Figure 14 & 15). It is clear that the learners improved from beginning to end of training, while the non learners did not.

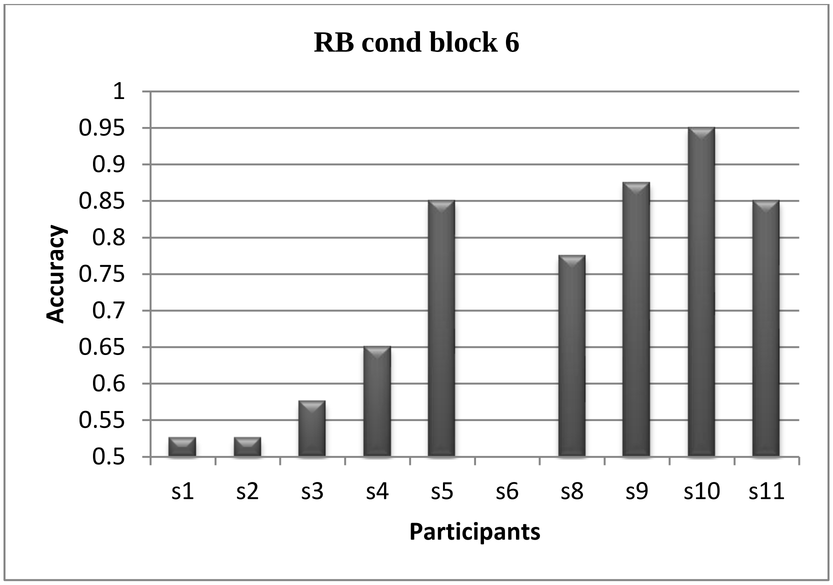

Figure 12: Task accuracy for participants in block 6 for RB condition

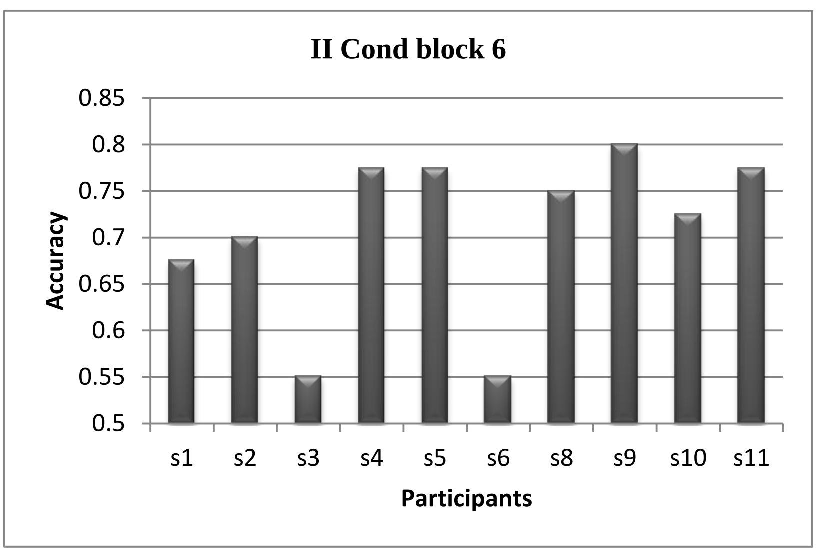

Figure 13: Task accuracy for participants in block 6 for II condition

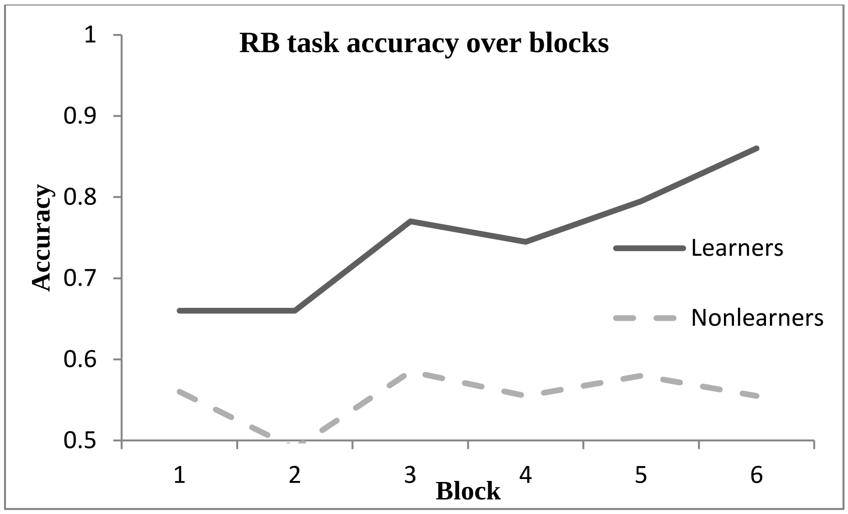

Figure 14: Average task accuracy over blocks between learners and non learners for RB

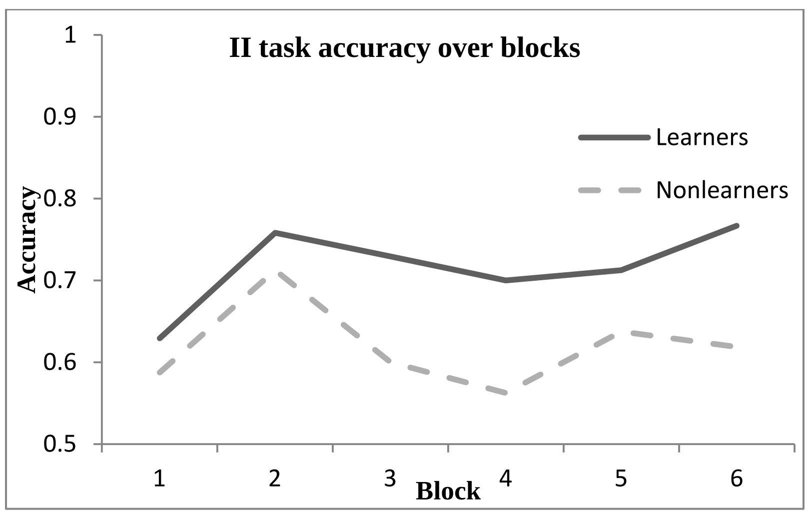

Figure 15: Average task accuracy over blocks between learners and non learners for II

Neuroimaging data

On comparing the blood oxygenation levels of the learners with the non learners, a noteworthy trend is noticed. The learners show increase in blood oxygen levels across the 16 channels implying that as learning occurred, increased blood flow and oxygen was required to compensate for the metabolic demands of the categorization task. We see almost a uniform increase in Oxy-Hb for both conditions for learners. On the other hand, there is wide fluctuation in the Oxy-Hb for the non learners for the 16 channels (Figures 16 and 17). So, in learners a clear increase in oxygenated blood is noticed across channels. However, with non learners the oxygenation levels appear to be random.

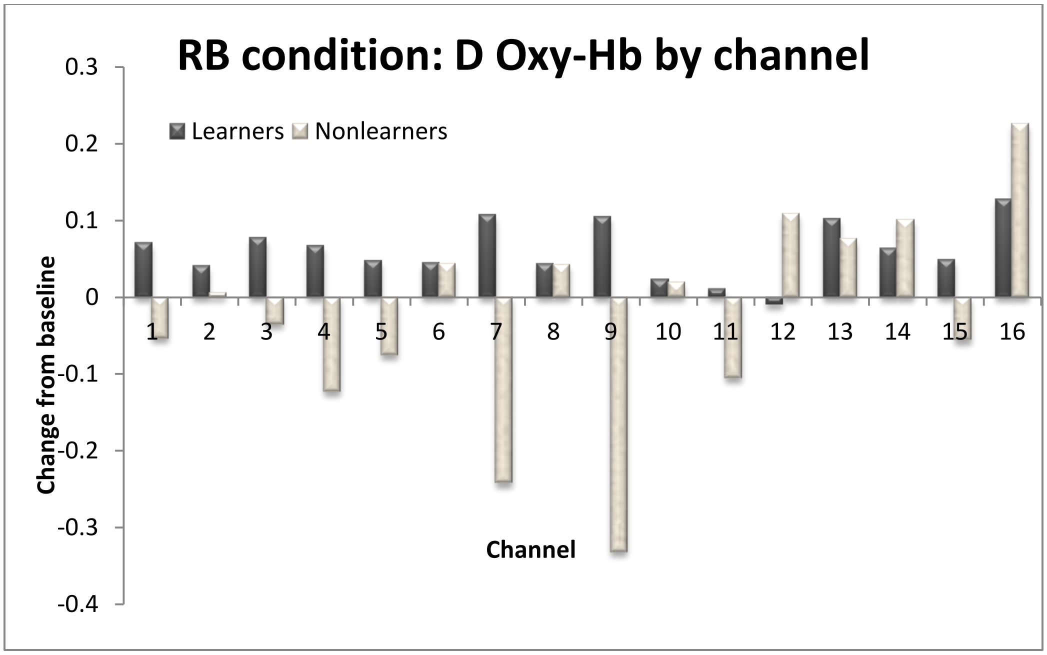

Figure 16: Oxygenation levels for learners vs. non learners across channels for RB condition

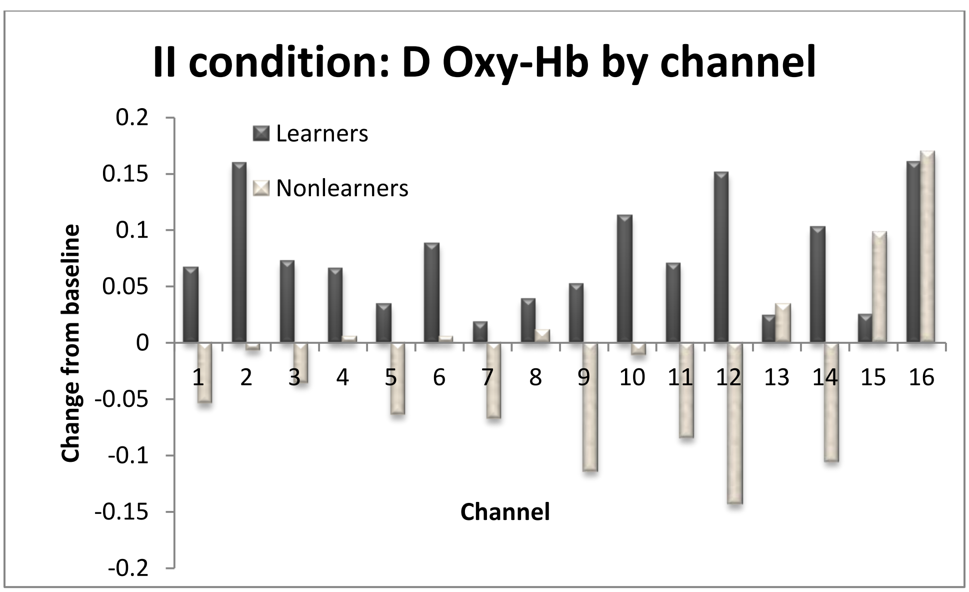

Figure 17: Oxygenation levels for learners vs. non learners across channels for II condition

DISCUSSION

This study investigated brain areas involved in category learning while participants completed rule based and information integration tasks. The baseline task consisted of participants identifying blue and yellow lines on the screen by hitting corresponding color buttons on the keyboard. The categorization task in RB condition required the participants to identify a one dimensional rule of categorization from provided feedback and assign stimuli to categories A or B. In the II condition, they were expected to integrate information about two or more features of the stimuli to make accurate decisions about category memberships. We recorded behavioral and neuroimaging data for all participants for both conditions.

We expected to find greater activation in brain regions involved in category learning in learners vs. non learners. Learning was defined as 70% or higher response accuracy for the categorization tasks for RB and II. The behavioral data showed evidence of learning across blocks for participants identified as learners. The study conducted by Filoteo et al. (2005) indicated different levels of activation in learners vs. non learners which was confirmed by our study as well.

Additionally, we also found activation in similar brain areas found by Filoteo et al. (2005) and Cincotta and Seger (2007). fNIR data revealed uniform increase in blood oxygenation levels in regions of interest in the brain in all 16 channels for learners relative to non learners. Compared to baseline tasks, blood oxygenation levels showed positive changes in the categorization tasks for the learners in contrast with the fluctuating negative and positive changes for the non learners.

Our goal was to verify that the fNIR system can detect changes in blood oxygenation levels of learners vs. non learners for category learning tasks. Past research has pinpointed specific brain regions like the dorsolateral prefrontal cortex in the brain for being involved in category learning tasks. fNIR was able to show activation in these areas making it a great tool for gathering neuroimaging data for categorization tasks. We know from prior work that we should expect increased oxygen consumption in Brodmann areas BA9, BA10, BA46, BA45, BA47, and BA44. Our neuroimaging data confirmed increased blood flow in these regions thereby establishing the efficacy of the fNIR system in comparison to fMRI.

CONCLUSION

The current study was able to establish the efficacy of the fNIR system by replicating the results of two fMRI studies. It is a newer neuroimaging modality that is non-invasive, portable and affordable compared to other systems. Our study was able to find results consistent with prior research in identifying the involvement of specific brain regions in categorization tasks. fMRI is the established gold standard for measuring brain activity. As our results are in line with results obtained by Filoteo et al. (2005) and Cincotta and Seger (2007) using fMRI scans, we have demonstrated the validity of fNIR in human category research.

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