Taxing Working Memory: The Effects on Category Learning

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TAXING WORKING MEMORY:
THE EFFECTS ON CATEGORY LEARNING

by

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ABSTRACT

In the past decade, the COVIS model (Ashby, Alfonso-Reese, Turken, & Waldron, 1998) has emerged as the only neuropsychological theory for the existence of multiple brain systems for category learning. COVIS postulates that there are two systems, explicit and implicit, which compete against one another. These two systems reply on two discrete networks: explicit, or rule based categorization relies on executive function and working memory while implicit, or information integration categorization is mediated by dopaminergic pathways. The purpose of this pilot study was to further provide evidence for the existence of multiple systems of category learning. In all three experiments, we interrupted feedback processing using a modified Sternberg task. In Experiment 1 and 2, participants were separated into four conditions, rule based (RB) categorization with a short delay between feedback and the modified Sternberg task, RB categorization with a long delay, information integration (II) categorization with a short delay, and II categorization with a long delay. Participants in the RB conditions performed worse than those in the II conditions in Experiment 1 and 2. After determining there was no significant difference between the short and long delay manipulations, only the short delay was used for Experiment 3. Consistent with Experiment 1 and 2, participants in the RB condition performed worse than those in the II condition. Functional near-infrared spectroscopy (fNIRS) technology was also used in Experiment 3 to determine the difference in prefrontal activation between RB and II conditions. Although statistically not significant, across blocks, the difference in prefrontal activation increased.

DEDICATION

I dedicate this work to my Lord and Savior, Jesus Christ.
“Therefore let no man glory in men. For all things are yours.” – 1 Corinthians 3:21

ACKNOWLEDGEMENTS

I would first like to state my greatest appreciation for the members of my thesis committee. First and foremost, Thesis Chair, Dr. Corey Bohil for taking a chance on me and guiding me through completely unknown territory. Also, committee member from the major, Dr. Mark Neider, and committee member from outside the major, Susan Schott for all their additional support with proofreading and helping me through the defense. I would also like to express my upmost gratitude for all of the help and guidance given to me by the graduate and undergraduate students in the Categorization and Decision Making Lab, specifically, Sarah Williams and Andrew Wismer. Their dedication to my success has been truly humbling. I am also grateful to Kyle Butler and Doeby Ercolino for being patient and loving through all of the long, stressful days completing this thesis. And lastly, to my parents, the sacrifices I made in order to complete this thesis pale in comparison to the sacrifices you have made so that I may have better opportunities in life and for that, I will forever be thankful. Without each and every one of these people, I would have accomplished nothing.

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CHAPTER ONE: INTRODUCTION

Categorization is one of the most ubiquitous cognitive processes utilized by humans to interact with the world around them. Categorization is the mechanism an individual uses to group stimuli in his or her environment. This process allows an individual to identify familiar and novel stimuli and choose an appropriate response. This can apply to simple situations such as determining what a fork or a spoon is or to complex situations such as choosing the appropriate response in geopolitical situations.

Due to the pervasive nature of categorization, it has been a topic of much debate in recent years. Current research has identified two main strategies individuals use to categorize: rule- based and information integration. Rule-based (RB) categorization occurs when category membership can be determined by one or more easily verbalized rules. Information integration (II) categorization requires perceptual information be integrated before category membership can be specified. It was previously thought that these two strategies were mediated by the same brain system. However, a new theory, COVIS (competition between verbal and implicit systems), has emerged (Ashby, Alfonso-Reese, Turken, & Waldron, 1998). COVIS theory asserts RB categorization is mediated by an explicit system whereas II categorization is mediated by an implicit system.

LITERATURE REVIEW

COVIS

In the past decade, the COVIS model (Ashby, Alfonso-Reese, Turken, & Waldron, 1998) has been the only neuropsychological theory for the existence of multiple brain systems for categorical learning. COVIS postulates that there are two systems, verbal (or explicit) and implicit (or procedural), which compete against one another. The verbal system uses working memory and executive functioning to employ the best strategy to choose category membership whereas the implicit system incrementally learns through reinforcement involving the brain's dopamine reward system (Ashby & Maddox, 2011).

Rule-based tasks Rule-based (RB) categorization is mediated by the explicit system. In RB tasks, categories are defined by explicit, and often, one-dimensional rules (Ashby, Paul, & Maddox, 2011). It requires that an individual create, test, and retest a hypothesis to maximize response accuracy (Ashby & Maddox, 2005). This process relies on working memory to hold on to successful hypotheses or discard unsuccessful hypotheses, and executive functioning to switch attention between them (Ashby & Maddox, 2011). Evidence of the importance of working memory was found by Waldron and Ashby (2001), when they found that increasing the workload of working memory with a dual task (a numerical Stroop task, in this case) caused significant impairment in RB tasks. Zeithamova and Maddox (2006) also replicated these results. In both studies, the dual task did not have an impairing effect in the II condition. These findings provide excellent evidence of a dual system rather than a single system (Ashby & Ell, 2002).

Information-Integration tasks II categorization weighs information from multiple dimensions and the criteria for membership in each category cannot easily be verbalized. An optimal strategy depends heavily on learning from feedback. It is believed that learning occurs because of dopaminergic reinforcement from the substania nigra when the individual receives immediate feedback (Ashby & Maddox, 2011). Feedback is so critical to II learning that delaying feedback even two and a half seconds can result in significant impairment (Ashby, Maddox, & Bohil, 2003). Unlike RB category learning this type of learning occurs in the absence of conscious control.

Neuroimaging and Category Learning

Many studies in recent years have used neuroimaging techniques to discover which structures of the brain mediate category learning (Filoteo, Maddox, Simmons, Ing, Cagigas, Matthew, & Paulus, 2005; Normura, Maddox, Filoteo, Ing, Gitelman, Parrish, Mesulam, & Reber, 2007; Seger & Cincotta, 2005; Seger & Cincotta, 2006; Schnyer, Maddox, Ell, Davis, Pacheco, & Verfaellie, 2009). Schnyer et al. (2009) examined category learning in patients with damage to the prefrontal cortex (PFC) and in patients with PFC and basal ganglia damage. Against the controls, most PFC damaged patients showed significant impairment in both the RB and II tasks. Interestingly, most of those (2 out of 3) with damage to both the basal ganglia and the PFC showed significant impairment only in RB tasks.

In another study using fMRI, Seger and Cincotta (2005) focused on the role of the caudate nucleus. During the II tasks, both sides of the body and the tail of the caudate were activated. During the RB tasks, the greatest activation was found in the left superior frontal gyrus. When looking at just RB tasks using fMRI, Filoteo et al. (2005) found higher activation in the dorsolateral prefrontal cortex and posterior parietal cortex in participants that were able to learn the rule distinguishing category membership. Along with finding activation in the tail of the caudate during II tasks, Nomura et al. (2007) found activation in the medial temporal lobe activation during RB tasks. These studies have shown that RB categorization is mainly mediated by cortical structures while II categorization mostly relies on subcortical structures.

In 2006, Seger and Cincotta focused their attention on the frontal, striatal and hippocampal activation during rule-based learning using MRI. They found the greatest activation in the head of the caudate in the beginning of the task whereas the PFC was most active at the end of the task. Hippocampal activation was low when activation in the head of the caudate was high.

fNIRS and Category Learning

The vast majority of neuroimaging research, as it relates to category learning, has utilized fMRI. Recently, however, a new, more cost effective neuroimaging technique has emerged. Functional near-infrared spectroscopy (fNIRS) is light- weight, portable device that measures the change in blood flow in the top two to three millimeters of the cortex using near-infrared light (Bunce, Izzetoglu, Izzetoglu, Onaral, & Pourrezaei, 2006; Izzetoglu, Bunce, Izzetoglu, Onaral, & Pourrezaei, 2007). Changes in the concentration of oxygenated (oxy-Hb) and deoxygenated hemoglobin (Hb) are indicative of neural activity.

In an fNIRS system, light sources emit near infrared light into the scalp and through the skull. The corresponding light detectors reabsorb the light that was not lost due to the varying concentrations of oxy- and deoxy-Hb. That information is then converted to an estimate of the blood oxygen level dependent (BOLD) response providing the researcher with spatial information about brain activity.

Current Study

The purpose of this pilot study is to further provide evidence for the existence of multiple systems of category learning by taxing working memory during RB and II tasks. Because RB learning is so heavily dependent on working memory, we predict that this disruption will inhibit a person's ability to identify the appropriate explicit rule during RB tasks. Because II learning is not reliant on working memory, this disruption should have not have a detrimental effect during II tasks. This study also aims to replicate the neuroimaging findings from the current literature using the fNIRS.

EXPERIMENT ONE

In Experiment, 1 participants completed a categorization task using RB or II strategies. After each categorization trial, feedback was presented to indicate whether their categorization response was correct or incorrect. Following the feedback on each trial, participants completed a secondary working memory task (described below).

Experiment 1 was designed to test two hypotheses. First, participants in the II conditions should have higher accuracy rates than those in the RB conditions as a result of disrupting feedback processing. Because RB categorization employs executive functions and working memory to create and test hypotheses to determine the explicit rule, adding a secondary task that relies on the same system, will disrupt this process. II categorization, which is mediated by dopaminergic pathways, should remain unaffected. Second, a shorter delay between the categorization feedback and the start of the working memory task should cause a decrease in accuracy rates relative to a longer delay. We suspected that those in the RB conditions who immediately see the working memory task after feedback will have lower accuracy rates than those who have a two second delay before the working memory task is presented. Without any time to process feedback, it should be difficult for participants to figure out the rule necessary to establish category membership and thus have a negative effect on performance. In the longer delay, we presume that two seconds should be sufficient to process the feedback. Because previous studies have shown that an interruption of working memory does not affect II categorization, the length of the delay should not have an effect on accuracy. Prior research indicates that RB learning involves working memory so this should be disrupted by the working memory task the RB conditions.

Method

Participants A total of 25 participants were recruited from the University of Central Florida’s Psychology Research Participant System. Participants were randomly assigned to each condition: short (zero seconds) delay with RB categorization, long (two seconds) delay with RB categorization, short delay with II categorization, and long delay with II categorization. In exchange for participation, students received extra credit, which was applied to a general psychology course

Stimuli The stimuli in all conditions were lines varying in length and orientation. In RB conditions, only the length of the stimulus was necessary to determine category membership whereas length and orientation were necessary to determine category membership in the II conditions. **Figure 1** and **Figure 2** are scatterplots for the RB and II stimuli. Each point in the scatterplot represents a specific stimulus with its respective length and angle value presented during the experiment. In all four conditions, participants completed a variant of the Sternberg task. In the Sternberg task, a row of four single-digit numbers were presented for 500 milliseconds then removed, followed by a single digit number that may or may not have been from the original set of numbers. Subjects had to respond whether the second number was part of the first set.

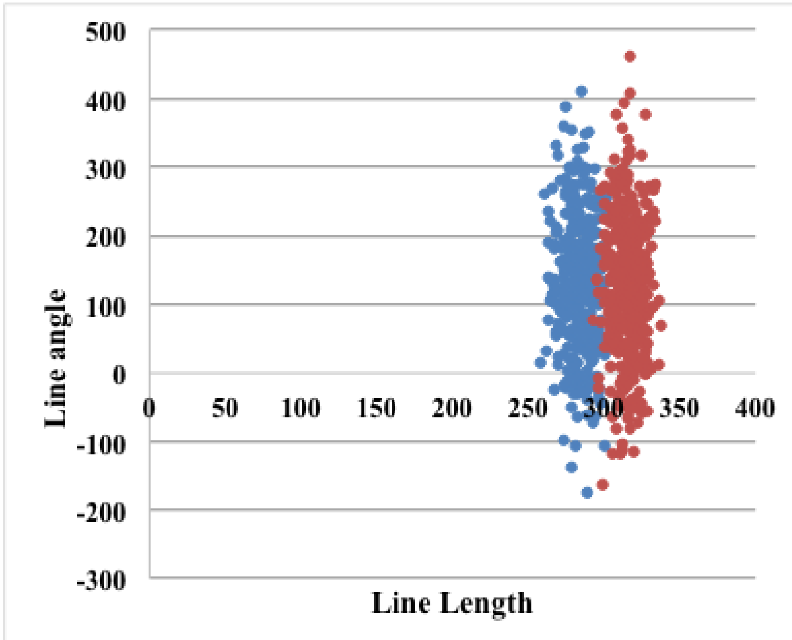


Figure 1. *Stimulus space values in RB category rule conditions*

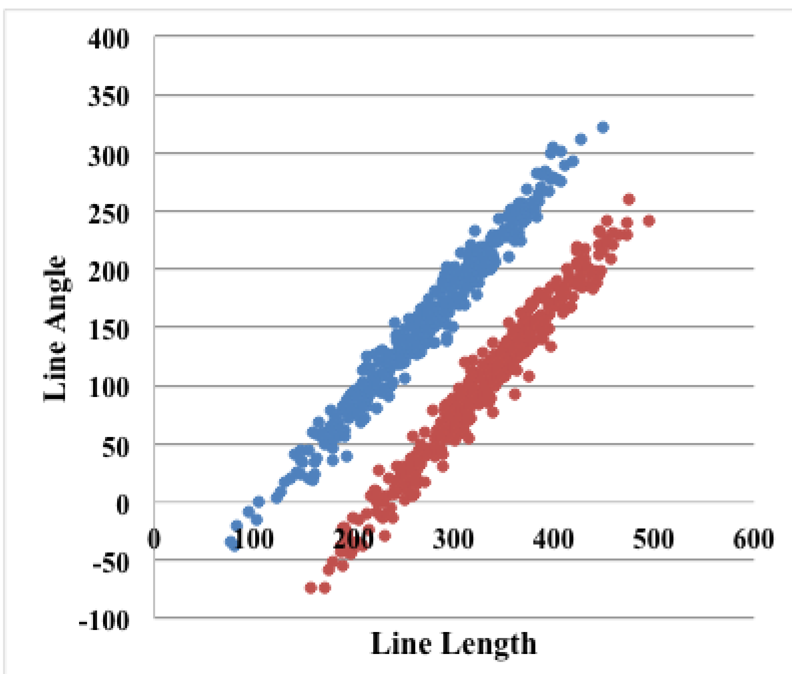


Figure 2. *Stimulus space values in II category rule conditions*

Procedure The task was comprised two difference phases, baseline trials and categorization trials (the category task followed by the working memory task). Participants completed six baseline trials followed by six categorization trials. This sequence was repeated in 25 blocks for a total of 150 baseline trials and 150 categorization trials. On each baseline trial, there was a blue or yellow line, varying in length and orientation. Participants were instructed to categorize the line based on just the color. Participants responded by hitting the corresponding color key on the keyboard. The stimulus was present for no more than five seconds. If a participant took longer than five seconds to respond, the trial was considered invalid and was repeated. Although accuracy on these trials were expected to be 100%, the purpose of adding baseline trials was to have a task that was similar to the categorization task but allowed participants to ignore the length and orientation dimensions. On each categorization trial, participants categorized a white line as being “A” or “B”. They did this by pressing the corresponding key on the keyboard. The stimulus was present for no more than five seconds. If a participant took longer than five seconds to respond, the trial was considered invalid and was repeated. Following the category response, feedback was given, and then, either immediately or two seconds after (depending on the experimental condition), the Sternberg task was presented. Participants then responded “Yes” or “No” as to whether the last number presented was from the original set of four. They did this by pressing the corresponding key on the keyboard. The entire categorization trial lasted nine and a half seconds. This design was chosen to determine the effects of secondary task on category learning for a later experiment examining cortical activity.

Results

Average accuracy across blocks for all four conditions can be found in **Figure 3**. A mixed factor ANOVA was conducted to determine if there was a main effect for the type of categorization task, length of the delay between the category feedback and the Sternberg working memory task, and an interaction between the two. Results indicated there was a main effect for the type of categorization task, F (1, 21) = 8.80, p = .01. On average, participants in the RB conditions had lower accuracy (M = 51%, SD = 2%) across blocks than participants in the II conditions (M = 57%, SD = 2%). Participants, regardless of categorization task, had lower accuracy (M = 54%, SD = 2%) when there was no delay between category feedback and the Sternberg task as opposed to those in the conditions with the two second delay (M = 57%, SD = 2%). However, this difference was not significant, F (1, 21) = .286, p = .60. Interaction between category rule condition and delay condition was not significant, F (1, 21) = .02, p = .89. There was a significant interaction between block and category rule type, F (2, 40) = 3.49, p = .04. Those in the RB conditions showed a significant increase in accuracy across blocks whereas those in the II conditions did not. No other interactions were found to be significant.

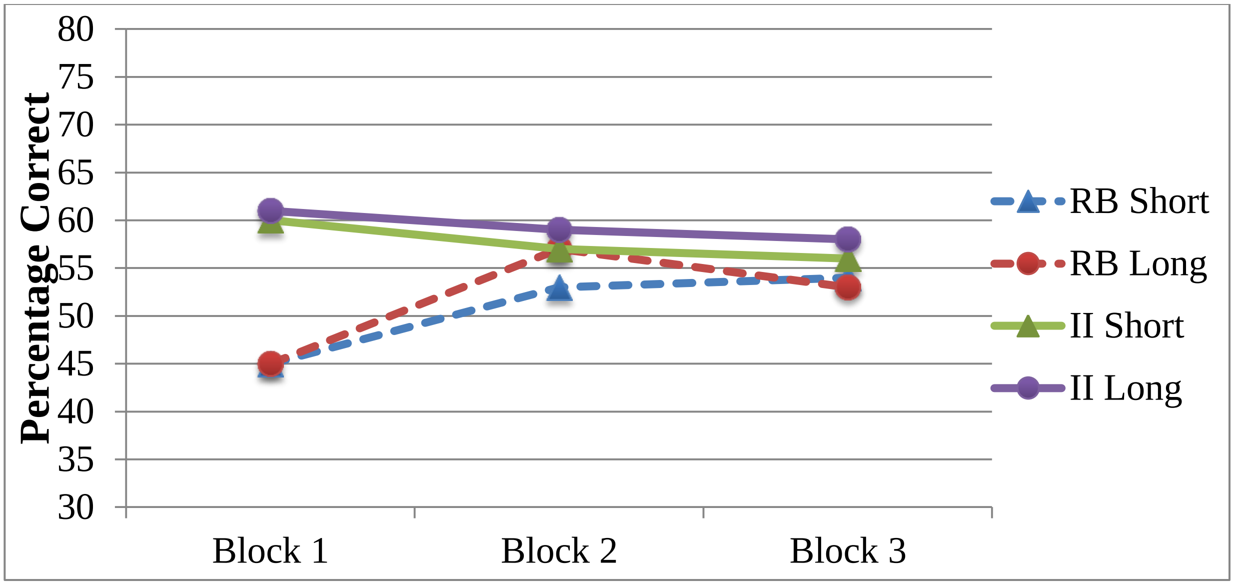


Figure 3. *Accuracy rates by block for each category learning condition in Experiment 1*

Discussion

In terms of the hypotheses, the results were mixed. As expected, the working memory task seemed to have a greater effect on rule based categorization. Although we predicted the length of the delay would not affect performance in II conditions, the length of the delay did not have the intended effect on performance in RB conditions. The interaction between block and category task showed a large increase in accuracy from block one and block two and then a tapering off between block two and three in RB conditions. In II conditions, accuracy started off high and did not change much over the three blocks.

These results are generally consistent with the current literature in showing detriment in rule based categorization and no apparent detriment in information integration categorization as a result of a disruption in feedback processing. Based on the results, it seems that the short and long delay had an equally negative impact on learning in RB conditions. Further experimentation would be needed to see if a longer delay between the categorization task and the working memory task would have less of an effect on learning.

EXPERIMENT TWO

Because of the low accuracy rates found in all conditions in Experiment 1, we decided to try a different task design to see if that would improve accuracy rates. We theorized that the rapid alternating between baseline and categorization trials, itself, was disrupting learning. In experiment two, we allowed participants to practice the task before completing baseline and test trials. Again, this design was created to potentially use in the later experiment measuring PFC activation. We also decided to increase the sample size. Despite these changes, our hypotheses remained the same. The secondary task should have an adverse effect on RB performance and no effect on II performance. The length of the delay between feedback and the secondary task should also effect RB performance and have no effect on II performance. Participants in the RB short condition should also performance worse than participants in the RB long condition.

Method

Participants A total of 64 participants were recruited from the University of Central Florida's Psychology Research Participant System. Participants were randomly assigned to each condition: short delay with RB categorization, long delay with RB categorization, short delay with II categorization, and long delay with II categorization. In exchange for participation, students received extra credit, which was applied to a general psychology course.

Stimuli The stimuli used in Experiment 2 were identical to the ones used in the Experiment 1.

Procedure This task was divided into three different phases: training, baseline, and test. The task began with a set of 30 training trials, followed by 10 baseline trials and 10 test trials. Participants completed this sequence eight times for a total of 400 trials. In the training trials, participants categorized a white line (sampled from 2 categories as described in Experiment 1) as a member of category "A" or "B", feedback (the correct category label) was displayed, and then, either immediately or two seconds after (depending on the experimental condition), the Sternberg task was presented as in Experiment 1. On each baseline trial, either a blue or yellow line was presented. The participant's task was to press the corresponding key on the keyboard to indicate its color, followed by feedback. On test trials, participants categorized the whites lines as "A" or "B" but feedback was not given. Altogether, there were 240 training trials, 80 baseline trials, and 80 test trials.

Results

Training phases Average accuracy across blocks for the four conditions can be found in **Figure 4**. A mixed factor ANOVA was performed comparing category task and delay. Consistent with the first experiment, there was a main effect for the type of categorization task, F (1,60) = 4.74, p = .03. During the training phases, accuracy rates in the RB conditions were lower (M = 46%, SD = 1%) than those in the II conditions (M = 60%, SD = 2%). The short delay conditions had higher accuracy (M = 59%, SD = 2%) than long delay conditions (M = 57%, SD = 2%). This finding was not significant, F (1, 60) = .08, p = .24. There was no interaction between category task and delay condition, F (1, 60) =.03, p = .49. There was a main effect of block, F (7, 420) = 4.565, p < .01 and an interaction between block and category, F (7, 420) = 5.27, p<.01. RB conditions showed the greatest increase in accuracy across blocks but in the II conditions, accuracy rates actually decreased across blocks.

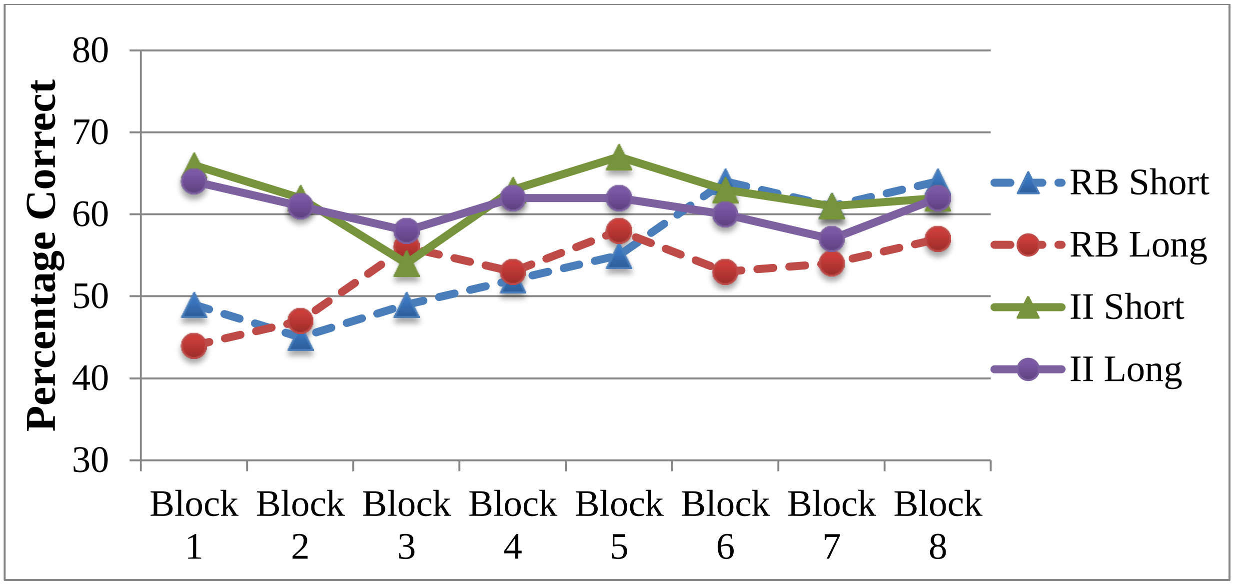


Figure 4. *Training phase accuracy rates by block for each category learning condition in Experiment 2*

Test phases Average accuracy across blocks for all four conditions can be found in **Figure 5**. A mixed factor ANOVA was performed comparing category task and delay. Results indicated there was a main effect for the type of categorization task, F (1, 60) = 5.42, p = .02. Participants' accuracy rates in the RB conditions were worse (M = 55%, SD = 2%) than those of the participants in the II conditions (M = 61%, SD = 2%). Comparing the delay factor, F (1, 22) = .481, p = .96, accuracy from the short conditions were the same (M = 58%, SD = 2%) as the long delay conditions (M = 58%, SD = 2%). Again, no interaction was found between both factors, F (1, 22) = .133, p = .61. A main effect for block was found, F (7, 420) = 3.27, p < .01 and also an interaction between block and category, F (7, 420) = 4.57, p<.01.

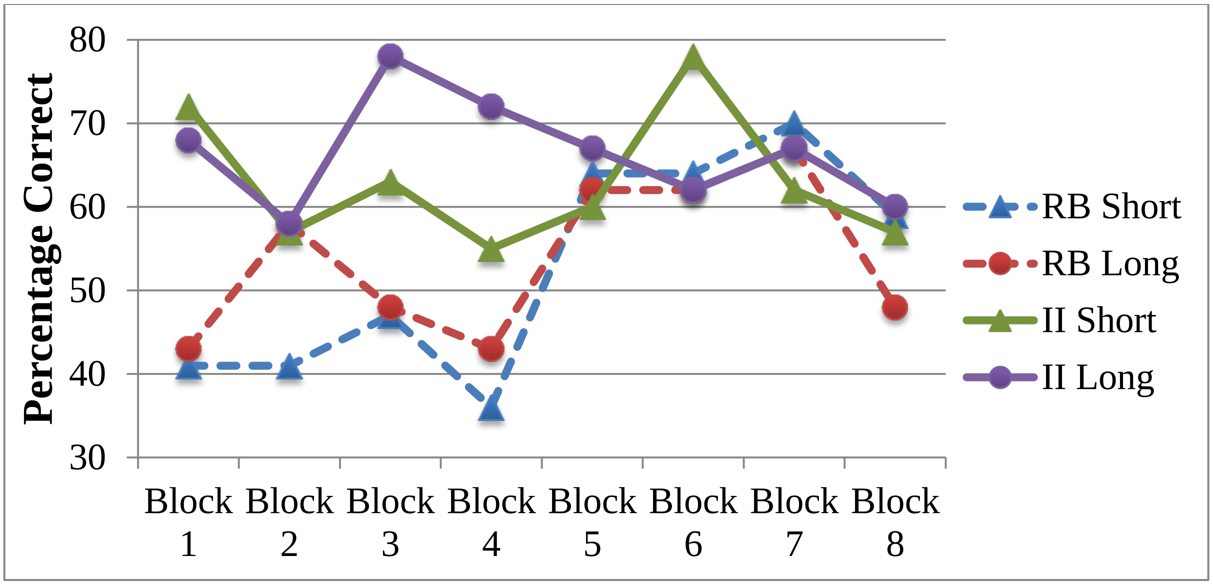


Figure 5. *Test phase accuracy rates by block for each category learning condition in Experiment 2*

Discussion

The results of Experiment 2 did not deviate much from the results of Experiment 1. The main effect of category was still observed along with a lack of evidence to support a main effect for delay and an interaction between both factors in the training and test phases. Again, there was an interaction between block and category task in both phases. In the training phase, individuals in the RB conditions showed a steady increase in accuracy while individuals in the II conditions had more fluctuation but generally showed a decrease in accuracy across blocks. The accuracy rates in the test phase also showed the same trend. The only exceptional finding between Experiment 1 and 2 was the main effect for block. In Experiment 2, there was an overall increase in accuracy across blocks seen in the training and test phase.

EXPERIMENT THREE

In the third experiment, along with the behavioral task, we added the use of the fNIRS to measure hemodynamic changes in prefrontal cortex. After the first two experiments showed the length of the delay had no effect on accuracy rates, we decided to only use the RB and II conditions with no delay between feedback and the working memory task. Our hypothesis regarding the behavioral data was still that participants in the II condition would perform better than those in RB condition. In terms of the neuroimaging data, we expected to see higher levels of brain activity in the prefrontal cortex for participants in the RB condition compared to those in the II condition. Based on the current literature, RB category learning utilizes structures in the prefrontal cortex while II category learning utilizes subcortical structures.

Method

Participants A total of 10 participants were recruited from the University of Central Florida's Psychology Research Participant System. Participants were randomly assigned to one of two conditions: short delay with RB categorization or short delay with II categorization. In exchange for participation, students were given extra credit, which was applied to a general psychology course.

Stimuli The stimuli used in Experiment 3 were identical to the ones use in Experiment 1 and 2.

Procedure The task used for this experiment was identical to the first experiment with two exceptions. First, in addition to collecting behavioral data, neuroimaging data was also collected. Second, the number of instruction screens participants saw in between blocks was reduced. In Experiment 1, the instructions were shown to participants in between every 12 trials (six baseline and six categorization trials). For this experiment, the instruction screen was only displayed every 60 trials (five sets of six baseline and five sets of six categorization trials). The task design from Experiment 1 was chosen because there was not enough evidence to suggest the changes made to the task in Experiment 2 improved accuracy rates. Also, because Experiment 2 provided only 80 test phase categorization trials verses 150 categorization trials in Experiment 1, the first design would provide more data for neuroimaging analysis.

Instrumentation A NIRx NIRSport 88 fNIRS system with eight sources and eight detection sensors covering the prefrontal cortex was used in this experiment. See **Figure 6** for an example. Participants placed their chin in a chin rest where the head remained for the duration of the task, except during breaks between blocks that allowed them to move.

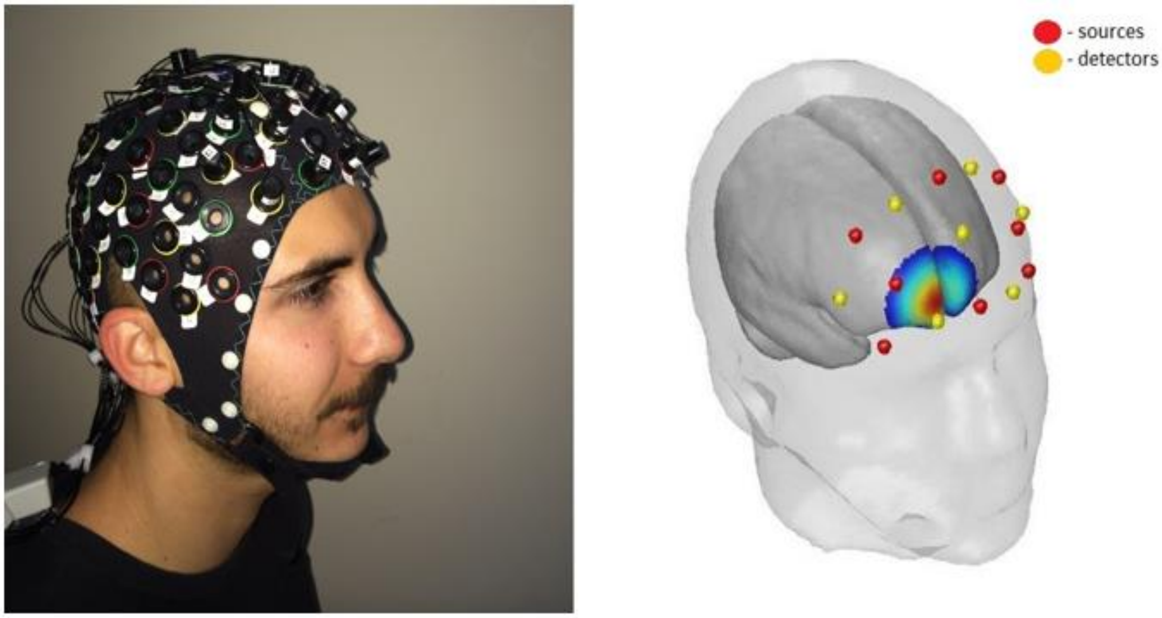


Figure 6. *Participant wearing fNIRS cap with source and detector placement*

Results

Behavioral Data Average accuracy across blocks for both conditions can be found in **Figure 7**. A one way repeated measures ANOVA was conducted and results indicated that there was a close to significant main effect for category task, F (1, 8) = 3.70, p = .09. Those in the RB condition had lower accuracy rates (M = 49%, SD = 3%) than those in the II condition (M = 56%. SD = 3%). There was also a main effect for block, F (4, 32) = 2.77, p = .04.

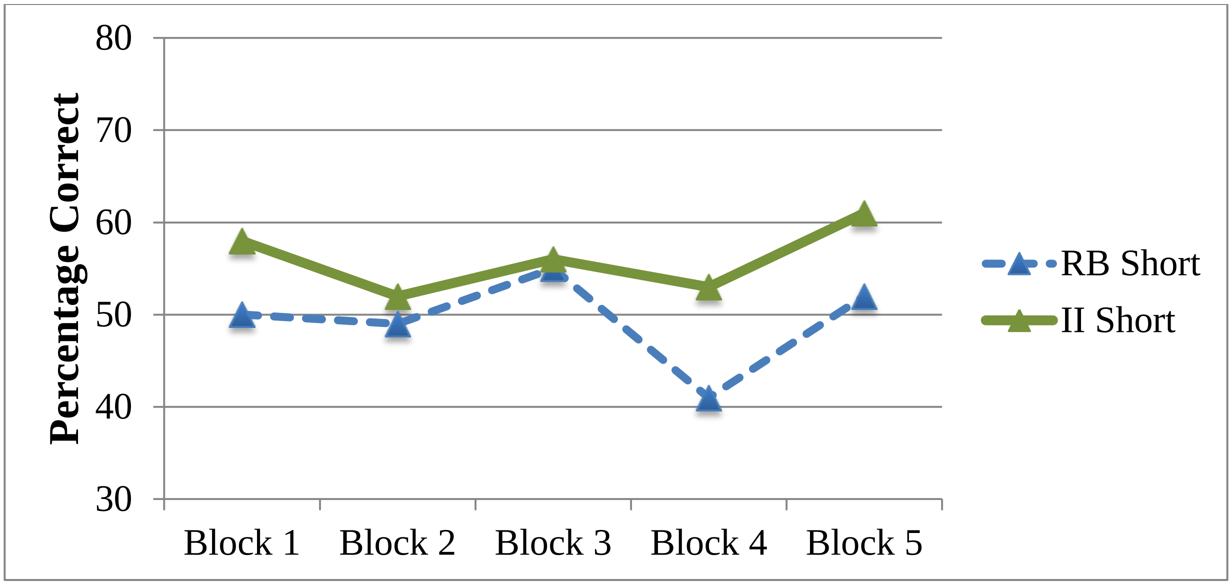


Figure 7. *Accuracy rates by block for each category learning condition in Experiment 3*

Neuroimaging Data Statistical parametric mapping (SPM) analyses were used to determine the difference in OxyHb levels in the prefrontal cortex between RB and II conditions. The data was broken up into three blocks and an F-test was conducted for each to compare conditions. In all three blocks, the difference in prefrontal activation was found to be not significant. However, F-test results approached significance across blocks: block one (p = .21), block two (p = .12), and block three (p = .08). Images from the SPM analysis can be found in **Figure 8**. Preliminary follow-up analyses (t-tests) indicated slightly higher activation in the II condition by block three, although this trend was not significant. Also, these F-tests results have not been corrected for multiple comparisons, which further weaken any conclusions based on the current pilot study results.

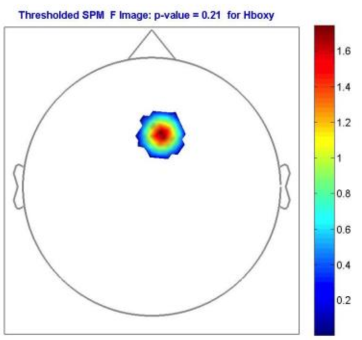
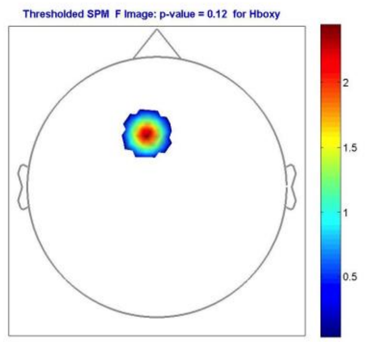
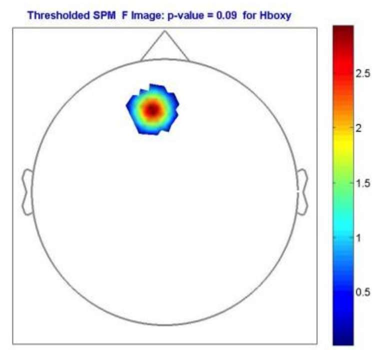
Block One	Block Two	Block Three
		

Figure 8. *Differences in OxyHb by block for each category learning condition in Experiment 3*

Discussion

Although the behavioral differences between conditions were not statistically significant, they do follow the same trend seen in Experiment 1 and Experiment 2 in terms of main effect for category task and a main effect for block. Performance in the II condition was better than performance in the RB condition but performance in both increased over time. It is also interesting that, across blocks, the difference in prefrontal activation increased.

GENERAL DISCUSSION

The purpose of this pilot study was to further provide evidence for the existence of multiple systems of category learning. COVIS theory predicts that because the explicit system relies on executive function and working memory, taxing working memory with a dual task will disrupt a person's ability to learn explicit categories while the implicit system, mediated by dopaminergic pathways, would remain unaffected.

In all three experiments, we tested these predictions by interrupting feedback processing using a modified Sternberg task. In Experiment 1 and 2, participants categorized stimuli and after feedback, they either had no time or two seconds to process the feedback before the Sternberg task was presented. After determining there was not a significant difference in the short and long delay manipulations, only the short delay conditions were used for Experiment 3, which consistently had a deleterious effect on learning in RB conditions.

The crucial role of executive function and working memory for RB category learning was supported in all three experiments. In each, participants in RB conditions consistently performed worse than those in II conditions – regardless of the timing of the feedback disruption. The delay manipulation in Experiment 1 and 2 did not have the intended effect but one could speculate that both the short and the long delay still had a detrimental effect on rule based categorization. The neuroimaging results in Experiment 3 (which did not include a long-delay condition) failed to show a significant difference between category tasks, although the difference was close to significant by the third block of training.

Limitations and Directions for Future Research

Although sample size is often noted as a limitation in many studies, it is worth noting that in this study, increasing the sample size in Experiment 2 had a negligible effect on the results. In this case, it is more likely that the main limitation was the abnormally low accuracy in all conditions. One explanation for the poor performance is the complexity of the task. Participants were required to utilize six different keys on the keyboard which could have been difficult to keep track of. It is also possible the differences in the stimulus set used in all three experiments were not salient enough. Specifically in the RB categorization condition, the differences in length of the lines between categories were very small and perhaps too small for effective learning. With the accuracy rates in this study, it was impossible to separate participant as learners and non-learners as was done in previous studies considering most participants learned poorly.

Because of the low accuracy, future research should choose a different stimulus set or make the differences in the stimuli more noticeable. This would increase the generalizability of the results found in this study. This problem will have to be addressed before we can learn about the brain's response to different feedback delay conditions in category rule learning.

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