Evaluating Competition between Verbal and Implicit Systems with Functional Near-Infrared Spectroscopy

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EVALUATING COMPETITION BETWEEN VERBAL AND IMPLICIT SYSTEMS WITH FUNCTIONAL NEAR-INFRARED SPECTROSCOPY

by

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ABSTRACT

In category learning, explicit processes function through the prefrontal cortex (PFC) and implicit processes function through the basal ganglia. Research suggested that these two systems compete with each other. The goal of this study was to shed light on this theory. 15 undergraduate subjects took part in an event-related experiment that required them to categorize computer-generated line-stimuli, which varied in length and/or angle depending on condition. Subjects participated in an explicit "rule-based" (RB) condition and an implicit "information-integration" (II) condition while connected to a functional near-infrared spectroscopy (fNIRS) apparatus, which measured the hemodynamic response (HR) in their PFC. Each condition contained 2 blocks. We hypothesized that the competition between explicit and implicit systems (COVIS) would be demonstrated if, by block 2, task-accuracy was approximately equal across conditions with PFC activity being comparatively higher in the II condition. This would indicate that subjects could learn the categorization task in both conditions but were only able to decipher an explicit rule in the RB condition; their PFC would struggle to do so in the II condition, resulting in perpetually high activation. In accordance with predictions, results revealed no difference in accuracy across conditions with significant difference in channel activation. There were channel trends ($p<.1$) which showed PFC activation decrease in the RB condition and increase in the II condition by block 2. While these results support our predictions, they are largely nonsignificant, which could be attributed to the event-related design. Future research should utilize a larger samples size for improved statistical power.

DEDICATION

For the Categorization and Decision Lab
for four years of opportunity

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INTRODUCTION

Categorization is fundamental to learning. As we take in raw information from stimuli around us, category learning serves as the scaffolding upon which we build the mental constructs that define our reality. Due to past efforts in behavioral and neurological research, the idea that there are multiple systems responsible for different types of category learning is now widely accepted. The evaluation of this multiple systems approach can be broken down into two generations of research (Ashby & Maddox, 2005).

Behavioral Background

The first generation of research focused on distinguishing between category learning processes that have been theorized to function through separate systems. While there are a variety of proposed systems, we focused on two of the most prominently studied ones, the explicit and implicit systems (Lee & Vanpaemel, 2008).

During category learning, the explicit system generally involves rule-based processes, relying on logic and hypothesis-testing to interpret stimulus properties. Explicit category criteria are very one-dimensional in nature so the optimal strategy is declarative; it can be verbally described with simple semantic labels (Ashby & Maddox, 2005).

However, when the complexity of criteria increases because more stimulus dimensions are added to the pre-decisional stages of categorization, semantic salience decreases as a result, and it becomes far more difficult to describe an optimal strategy verbally. When a rule becomes too non-declarative in this sense, the implicit learning system activates. This system works through information-integration processes, which rely on repetitive procedure and reinforcing feedback to associate stimulus properties with appropriate response (i.e. category). The research of Ashby and Maddox (2010) suggested that this implicit learning process is capable of taking many forms, from treating the stimulus as a Gestalt to combining stimulus dimensions almost algorithmically. Implicit learning occurs most optimally when reinforcing feedback immediately follows response to the stimulus. Feedback delays tend to slow or disrupt the integrative process (Ashby & Maddox, 2010).

Neuroimaging Background

The neural-network for explicit category learning primarily takes place in the prefrontal cortex (PFC), specifically, the dorsolateral PFC. This is the region most directly related to cognitive processes such as working memory and decision-making (Maddox & Ashby, 2004). The explicit system also shares connections to the anterior cingulate, the head of the caudate nucleus, the hippocampus and the temporal lobe. To elaborate, the PFC and the anterior cingulate collaborate as working memory in the process of executively identifying and selecting for a new rule. The head of the caudate nucleus functions in switching from an old rule to a new rule in the trial-and-error process that generally accompanies category learning. Lastly, the hippocampus and the temporal lobe are involved in the subsequent retentive learning process that occurs after the optimal rule has been selected (Ashby & Maddox, 2010).

In contrast to the explicit system, the implicit system takes place primarily in the subcortical structures of the basal ganglia; it does not rely on the PFC. Research suggested that visual information regarding implicit stimuli projects directly from the visual cortex to the tail of the caudate nucleus where there is a massive convergence of inputs (Filoteo et al., 2004). The tail of the caudate nucleus is theorized to be involved in the process of associating stimuli properties with appropriate responses (i.e. categories). Additionally, it receives reinforcement learning through dopamine-mediated, cortical-striatal synapse strengthening via the substantia nigra. This is widely thought to be the mechanism for reward-mediated feedback recall. Lastly, the implicit system connects to the prefrontal and premotor cortices via inputs to Globus pallidus and thalamus (Ashby & Maddox, 2010).

COVIS Background

By behaviorally and neurologically comparing explicit and implicit category learning systems, it is seen that they function almost completely separate from each other. Today, with this multiple systems approach to category learning mapped out, a second generation of research is under way in which we question how these two systems influence each other. COVIS describes category learning as a competition between verbal (explicit) and implicit systems (Milton and Pothos, 2011).

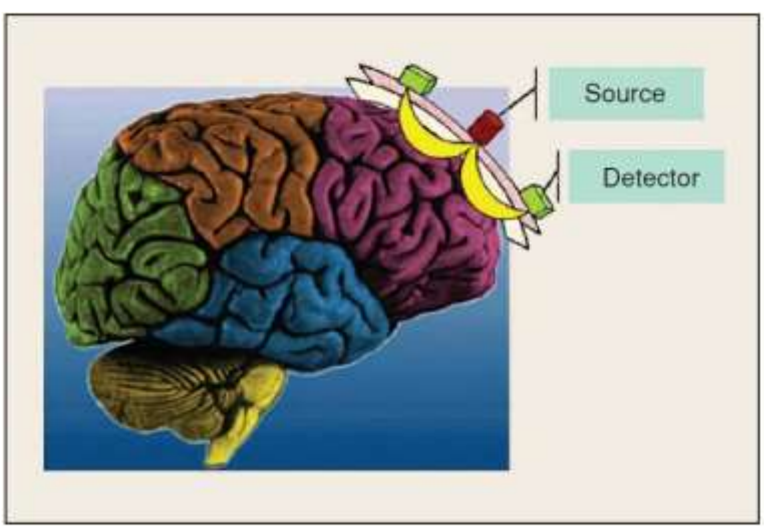
To start, COVIS suggests that the PFC-mediated explicit system controls initial stimuli analysis. If the category is able to be successfully learned with this initial response, there is no implicit subcortical activity. However, upon difficulty with learning a task explicitly, the implicit system activates, procedurally integrating the information. Despite subcortical activity, PFC activity will remain high as long as the observer continues trying to consciously decipher a rule (Ashby & Maddox, 2005).

Cooperative switching between the explicit and implicit systems does not occur automatically. It is in this sense that the research of Ashby and Maddox (2010) suggested that these two systems can actually interfere with each other. They propose that, when both systems are active, the explicit processes either inhibit implicit processes or deny them response control (Ashby & Maddox, 2010). Behavioral studies have demonstrated this by showing how incorrect observational training can trick the brain into prioritizing suboptimal explicit strategy over optimal implicit feedback (Ashby et al., 2002). In a study conducted by Ashby, Maddox and Bohil (2002), subjects tried to decipher and employ an explicit rule for a categorization task after having already learned the categories implicitly through prior procedural training, and they became worse at the task as a result because their implicit processing was overridden by this new explicit task. It is theorized that this interference specifically occurs in medial temporal lobe activation and striatal activation, which regulate retentive learning in the explicit system and implicit system respectively (Ashby & Maddox, 2010). The bottom line is that research illustrated how information processed by the explicit system and information processed by the implicit system are not ultimately pooled together in the brain; they are held separate, having been learned through exclusive pathways. It is for this reason that these systems can interfere with each other, which is what the "competition" in COVIS is referring to.

Neuroimaging

Figure 1

Channels Created between a Source and Two Detectors in FNIRS ("FNIR FAQ," 2016)



In this study we evaluated COVIS by measuring the differences in PFC activity between explicit and implicit categorization tasks using functional near-infrared spectroscopy (fNIRS). FNIRS is a non-invasive neuroimaging technology that functions through light-emitting optodes placed at the scalp. There are two types of optodes: sources and detectors. Sources emit near-infrared light while detectors collect the light that is scattered and reflected back by the cortical structures. As figure 1 illustrates, between every source and detector a channel is formed ("FNIR FAQ," 2016), which is used to measure the intensity of the reflected light via the Beer-Lambert law. This law relates the attenuation of light to the properties of the source (Izzetoglu et al., 2007). In this sense, reflected light can be analyzed to derive information regarding cortical activity.

FNIRS functions through an "optical window" of 700-900nm, which is where the skin, tissue and bone above the cortex are transparent to near-infrared light. FNIRS directs light at hemoglobin within the cerebral blood vessels. The chromophores of oxygenated-hemoglobin (oxy-Hb) and deoxygenated-hemoglobin (deoxy-Hb) absorb and reflect this light differently (Bunce et al., 2006). By measuring changes in the optical density between two wavelengths of near-infrared light immediately above and below 810 nm (i.e. the isosbestic point), where oxy-Hb and deoxy-Hb display identical light absorption, the modified Beer-Lambert law (mBLL) is used to calculate oxy-Hb concentration as a function of total photon path length (Izzetoglu et al., 2007). In simpler terms, the fNIRS can track localized changes in oxy-HB concentration to measure oxygen levels in a chosen region of the cortex (Bunce et al., 2006).

In this study, fNIRS specifically measured the hemodynamic response (HR), which is the phenomenon of relative increase in cerebral blood flow and volume (i.e. neurovascular coupling) that occurs as the body rapidly fuels activated neural tissue with additional nutrients, which includes oxygen. Thus, HR is indicative of functional activity in the brain (Bhogal et al., 2015; Cui et al., 2011).

Experiment

By using fNIRS to measure HR in the prefrontal cortex (PFC), we sought to gain insight into the competitive relationship between explicit and implicit learning processes that is described by COVIS. While connected to the fNIRS apparatus, subjects were given the task of assigning computer-generated line-stimuli lines to category “A” or category “B” based on length and/or angle. Depending upon the condition, subjects were to accomplish this task through either explicit or implicit categorization processes. There were two conditions: the explicit “rule-based” (RB) condition and the implicit “information-integration” (II) condition. Each condition contained 2 blocks. As subjects performed the task, task accuracy and channel activation were recorded across condition and block.

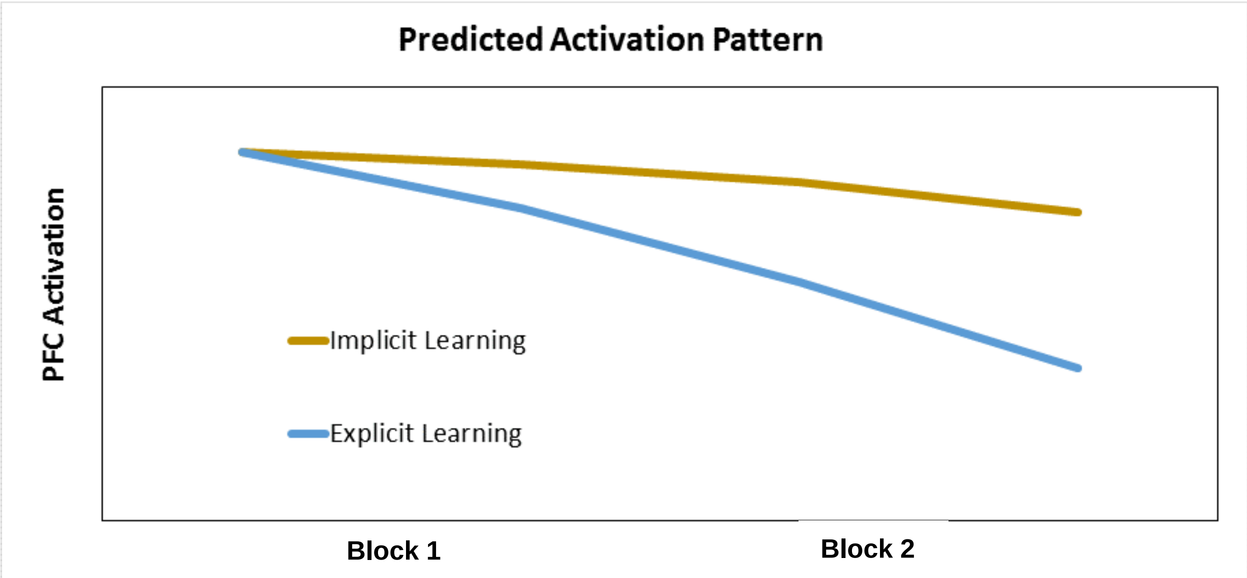
A major contribution of this study was that it employed a rapid event-related design instead of the block design that is traditionally used in category learning research. While in block design, stimuli are presented in an alternating sequence of baseline and categorization trials; in event-related design, stimuli are presented in a randomized sequence and are purely categorization trials. From a behavioral perspective, this lack of baseline trials serves to shorten the task and make room for additional categorization trials, which increases overall task efficiency. From a neuroimaging perspective, the event-related design allows for channel activation to be measured per individual trial rather than as an average across blocks, as is the case in block design. This served to increase estimation efficiency, creating a finer-grained representation of HR in the PFC (Schaeffer et al., 2014).

Predictions

The behavioral outcome of this study should rear higher accuracy for block 1 in the RB condition than in the II condition. We predicted this because the implicit learning process of the II condition should take relatively longer than the explicit process of the RB condition. This claim took into account initial PFC interference; we understood subjects would likely try to employ suboptimal RB strategy before relying on II feedback. By block 2, we predicted that accuracy should be higher across conditions because this would indicate that learning took place. Furthermore, by block 2, accuracy should also be about equal across conditions because no one condition was intended to be more efficient than the other; we were only trying to show that they functioned through two separate category learning systems.

Figure 2

Predicted Activation Pattern per Condition across Block



Using fNIRS to evaluate HR in subjects, channel activation should start out equal across conditions because, as previously stated, the initial response to a novel stimulus dimension is always explicit; however, by the end of the experiment, channel activation should be comparatively higher for the II condition than for the RB condition. This pattern is depicted in figure 2. We predicted this because channel activation should quickly diminish in the RB condition because, as subjects learn the verbal rule, the task should become automatic, requiring less cortical activation as a result. While, on the other hand, channel activation should remain high in the II condition across blocks because, in theory, the PFC remains active, despite subcortical activity, as long as subjects are still consciously seeking an explicit rule for implicit categories. Since they should never be able to do this optimally, the PFC remains perpetually active. Neuroimaging results of this nature, combined with equivalent behavioral accuracy across conditions, would adequately reflect COVIS theory.

METHOD

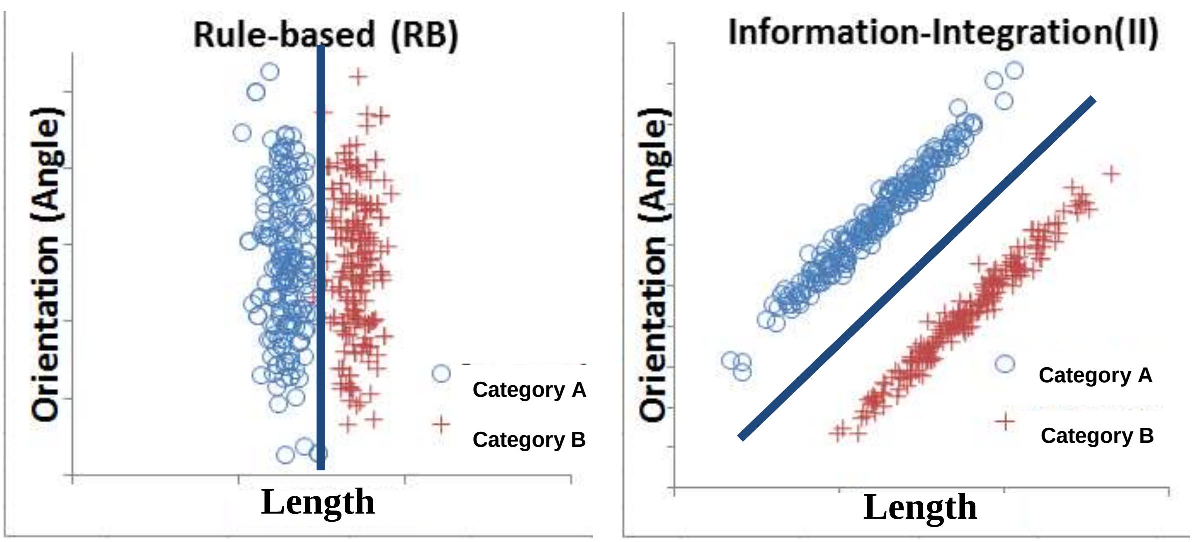
Participants

Participants were undergraduates from the University of Central Florida and received course credit for their participation. As validated by UCF's Psychology Research Participation System, they were male or female, over the age of 18 and healthy. A total of 15 subjects participated in this study. Each subject participated in both conditions, comprising one session of approximately 2-hour duration.

Materials

Figure 3

Rule-based vs Information-Integration Stimuli



This experiment was written and presented in Matlab, using the Psychophysics Toolbox extensions (Brainard, 1997; Pelli, 1997; Kleiner et al., 2007). In both the RB and II conditions, there were 320 computer-generated lines employed as stimuli, with 160 from category 1 and 160 from category 2. In total, 640 stimuli were employed in this experiment. Each line was of varying length and/or angle, depending on condition.

Figure 3 displays examples (not the actual stimuli) of stimulus values for RB and II categories, with the solid black lines acting as thresholds between category criteria. Each point in the scatterplot corresponds to a length and angle value of a single stimulus. RB stimuli adhered to one-dimensional category rules. The first panel in Figure 3 provides an example in which short stimuli are category A and long stimuli are category B. This one-dimensional rule could also be related to angle instead (e.g. steep stimuli are category A; flat stimuli are category B). On the other hand, II stimuli contained abstract variations of both dimensions. Looking at figure 3 again, at first glance it may seem like the II stimuli adhere to a simple rule combining length and angle, such as that category A stimuli are always steeper and shorter than the Category B stimuli; however, upon further scrutiny, it can be seen how that is not the case. At the top of the threshold (the black line), many of the category A stimuli are longer than the category B stimuli at the bottom of the threshold. Thus, optimal categorization of such stimuli required an implicit combination of length and angle that is impossible to describe verbally.

Apparatus

Figure 4

FNIRS Cap and Optodes

The fNIRS apparatus included a cap that held 16 light-emitting optodes that covered at the front of the scalp, a tablet to record data, and a computer to run the data collection program. These items were set up in a room separate from the us because subjects were to be isolated for the duration of the task. As figure 4 shows, the optodes were only placed in proximity to the PFC. The sources and detectors (optodes) were usually fashioned ipsilateral on the subjects' scalp for the clearest measurements. Additionally, the optodes were stabilized with an over-cap and the subjects were asked to use the available chin-rest to minimize any unnecessary movements. Between the 8 sources and 8 detectors used, there were a total of 20 channels formed. The data that emerged from them was recorded by a tablet. To ensure undisturbed data recording, the tablet was placed somewhere out of the way of the rest of the apparatus. The computer running the data collection program was positioned in respect to the chinrest so that the screen could be clearly seen. Additionally, the A and B keys used in the categorization task were made more salient with colored stickers so subjects did not have to strain themselves to see while they used the chinrest. Lastly, next to the computer there was a red button that signaled a door-bell sound from a portable speaker in another room, which served to inform us when subjects had finished the experimental task.

Design

This study was of a 2 x 2 factorial design. There were two independent variables, the explicit “rule-based” (RB) condition and implicit “information-integration” (II) condition. The study was also a within-subjects design; subjects took part in both the RB and the II conditions. In each condition, subjects were tasked with categorizing line-stimuli to either category A or category B. Category criteria varied by length and/or angle depending on condition. Trials were presented in order of stimulus, response and then feedback. Dependent variables were evaluated across 2 blocks. From the behavioral perspective, accuracy was recorded. From the neuroimaging perspective, channel activation was recorded.

The primary contribution of this study was that it presented stimuli through an event-related design rather than the generally used block design. Thus, instead of alternating sequences of categorization trials and baseline trials, stimuli were presented in a randomized sequence of categorization trials only. In addition to decreasing task duration, this change served to increase task efficiency by allotting more time for categorization trials and minimizing confounding variables, such as habituation and anticipation. This effect was furthered with a jitter inter-trial interval of 2.5 to 3 seconds between each trial, meaning the timing between each successive stimulus varied. Furthermore, the event-related design evaluated HR in the PFC for each individual trial instead of as an average across blocks, allowing for a more in-depth assessment of HR (i.e. increased estimation efficiency).

In addition to block, PFC activation was also measured across condition and channel. This study employed general linear analysis to refine neuroimaging data by truncating excess sequences, removing discontinuities and/or artifacts, filtering out noise, and accommodating any other extraneous variables that might have otherwise produced error. After this preparatory process, statistical parametric mapping was employed to interpret the neuroimaging data sequences.

Procedure

Subjects signed up for the study via UCF's Psychology Research Participation System, where they were assigned an anonymous ID number and directed to the lab on a specific day and time. When a subject arrived they were signed-in and given an informed consent to read while the researcher did preliminary setup of the study. This involved setting up the appropriate condition (RB of II) in Matlab as well as the fNIRS data acquisition program. The subject was then escorted to the room where the fNIRS was located. The subject was debriefed about the setup protocol, which required them to turn off their cell phone and part their hair (if they had any) down the middle before beginning. Once this was done, the subject was non-invasively situated into the fNIRS apparatus.

Setup generally took about fifteen minutes to complete. This process involved the researcher measuring the subject's cap-size with a tape-measure and then carefully fashioning the appropriate cap on the subject's head. The subject could adjust the chin-strap to their liking. Caps and chin straps were chemically washed beforehand to ensure sanitary conditions. Before the optodes were inserted, the we used a blunt wooden pick to gently separate the subject's hair through the optode inserts and then subsequently applied water-soluble ultrasound gel to the exposed scalp via a blunt syringe. Beforehand, the subject was shown that both the pick and the syringe were blunt to help ensure their comfort and security. Next, the optodes were inserted appropriately and the over-cap was situated over the optodes. We then calibrated the fNIRS system to ensure the apparatus was functioning properly. Finally, if calibration appeared suitable, the subject was asked to situate themselves on the chinrest, which they could adjust to their liking.

At this point, the subject received any final debriefing that was necessary, such as instructions for the computer task and details regarding the keyboard layout. The subject was informed that there were two categories, denoted "A" and "B", and each were equally likely to occur. They chose category A by pressing the "z" key (labeled "A" with a sticker) and category B by pressing the "/" key (labeled "B" with a sticker). Once they were fully debriefed, the subject was free to begin the categorization task. It took approximately 30 minutes per condition with a five-minute break in between for a total of about 1 hour and 5 minutes to complete the study. The purpose of the was to give the subject time to forget any residual rules they had retained from the previous condition. We also informed them that there was no cross-over in rules between conditions.

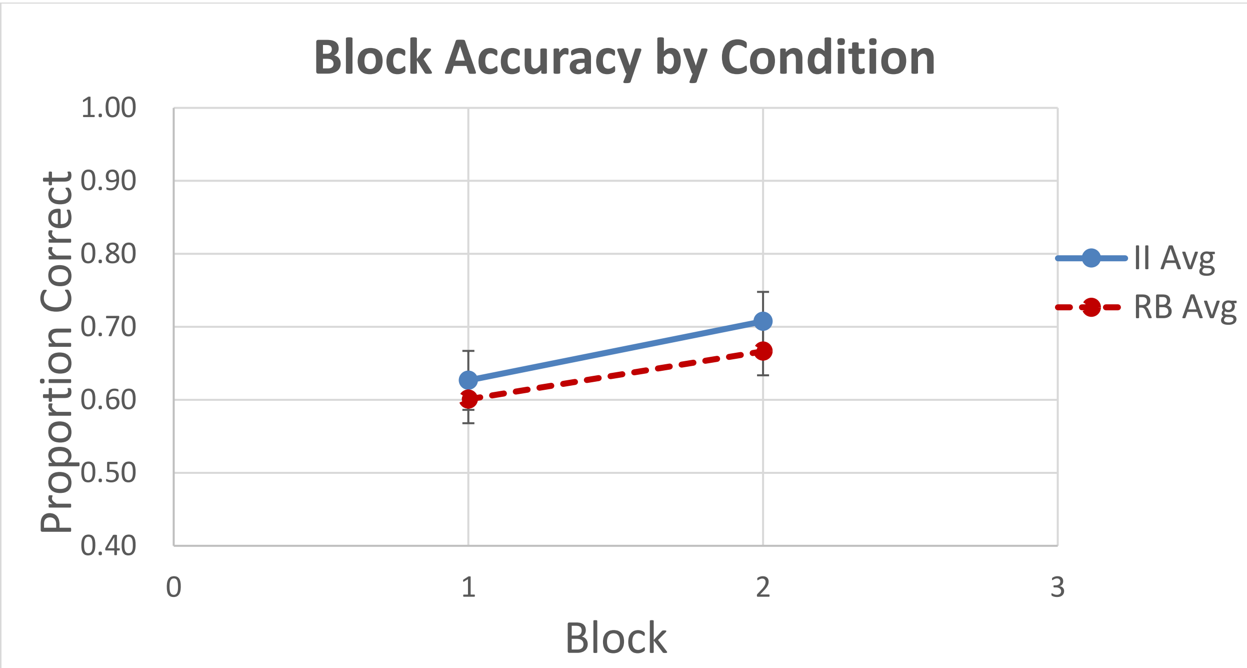
When the subject was finished they were presented with a black screen with salient red lettering that informed them that they had finished and were to contact the researcher. To do this, the subject was to press the red button next to the computer as previously instructed in the debriefing, which alerted the researcher in other room of their status. The subject was then released from the apparatus and awarded class credit as compensation. The researcher was responsible for sanitizing the cap and other materials afterward before the next subject arrived. Including setup and cleanup, the entire study took approximately 2 hours to conduct.

RESULTS

Behavioral Results

Figure 5

RB and II Accuracy Averaged across Blocks

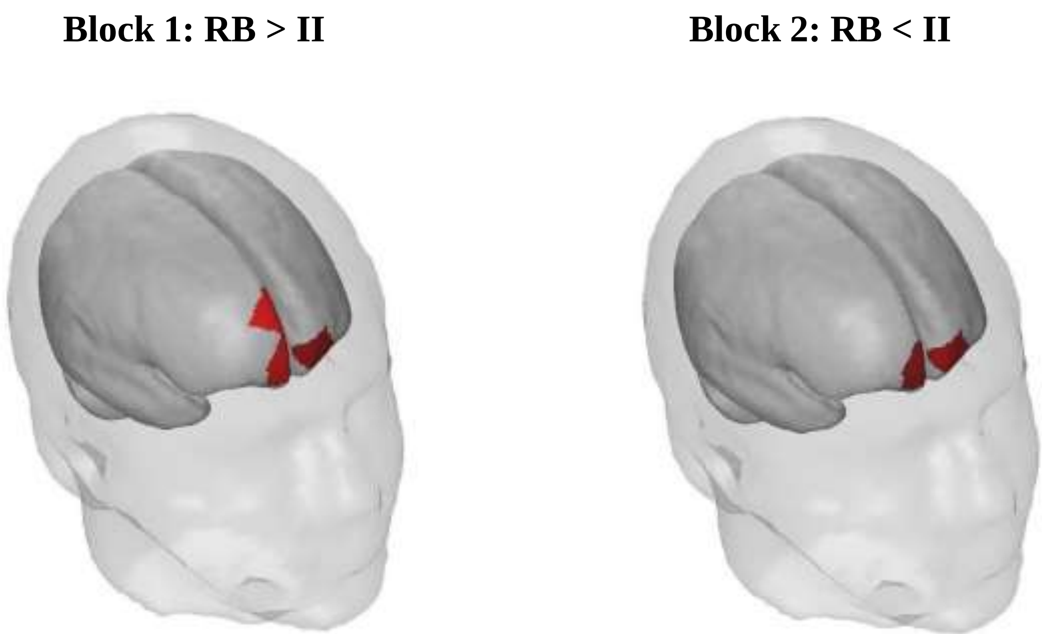


Behavioral data from this study was analyzed with a repeated-measures analysis of variance (ANOVA). Results revealed that there was no main effect for condition, which indicates that there was not a significant difference in accuracy across conditions. However, there was a main effect for block (F (1, 14) = 15.35, p = .002), which indicates that there was a significant difference in accuracy across blocks. As shown in Figure 5, accuracy was overall higher in Block 2 (M = .711, SD = .367) than in Block 1 (M = .635, SD = .296), meaning that learning took place in both conditions. Additionally, there was no significant interaction between condition and block, indicating that accuracy across blocks did not vary as function of condition; condition did not affect the outcome of block accuracy.

Neuroimaging Results

Figure 6

Topographs Showing Locations of Significant Difference between RB and II Conditions



A mixed effects ANOVA was conducted on the neuroimaging data for this study. Results for the neuroimaging data were largely nonsignificant; there was no main effect for either condition or block and there were no interactions. However, there was a main effect for channel (F (19, 266) = 4.78, $p < .05$), indicating a significant difference in activation between the 20 channels measured. While pairwise comparisons revealed no significant differences (at the α = .05 level) in channel activation related to condition or block, some channels showed trends ($p < .1$) that are worth noting. During block 1, there was a relatively higher F-value and, thus, greater activation for the RB condition than the II condition at channel 13 (F (1, 14) = 3.365, p = .088), channel 14 (F (1, 14) = 3.973, p = .066) and channel 15 (F (1, 14) = 3.447, p = .085). Additionally, during block 2, there was relatively higher activation for the II condition than in the RB condition at channel 19 (F (1, 14) = 3.223, p = .094). Figure 6 shows the cortical regions covered by these channels, illustrating how PFC activation decreases across blocks for the RB condition yet remains relatively high in the II condition. These trends match our predictions regarding changes in HR over time for the RB and II conditions.

DISCUSSION

In this study 15 undergraduates participated in an experiment of a 2 x 2 within-subjects design, which compared an explicit, RB learning condition with an implicit, II learning condition across two blocks. Subjects performed the task of assigning lines to either category A or category B based on simple variations of length *or* angle in the RB condition and abstract variations of length *and* angle in the II condition. Stimuli were presented with an event-related design and a jitter inter-trial interval. Reinforcing feedback immediately followed the motor response to presented stimuli. Categorization accuracy was recorded across block and condition.

During the task, subjects were connected to an fNIRS apparatus, which employed the modified Beer-Lambert law to measure HR in the PFC through 20 channels (Izzetoglu et al., 2007). Neuroimaging data was processed using general linear analysis and interpreted using statistical parametric mapping (SPM). Localized differences in channel activation were recorded across condition, block and channel.

This study sought to shed light on the competition between explicit and implicit learning systems in accordance with COVIS theory. We hypothesized that accuracy would be higher after block 1 in the RB condition than in the II condition due to the inherently slower pace of the implicit processes, which takes into account PFC interference. However, we hypothesized that by block 2 accuracy would be about the same across conditions because equivalent learning should take place in both; we purely wanted to demonstrate how each condition functioned through a separate learning system.

Furthermore, we hypothesized that oxygen levels would indicate higher PFC activity in the II condition than in the RB condition by block 2. As subjects explicitly decipher the category rules of the RB stimuli, PFC activity should initially increase but then decrease when the optimal rule is learned because the task becomes more automatic. Whereas, in the II condition, explicit rules produced by the PFC are suboptimal; they are too one-dimensional. Thus, we predicted that PFC activity in the II condition would remain consistently high across the span of two blocks, as subjects perpetually sought but failed to decipher an explicit rule for these stimuli. It is important to stress that, even though subjects would never explicitly understand the II categories, they should still effectively learn them implicitly during this time.

A series of ANOVA were conducted on the data produced by this study. In the behavioral data, there were no significant results related to condition. In other words, the condition did not have an impact on accuracy. However, there were significant results related to block, indicating that accuracy was on average higher in block 2 than in block 1, which corresponds with our initial hypothesis, showing that learning took place.

In the neuroimaging data, there was a general significance for channels. As the first topograph in Figure 6 illustrates, individual comparisons of channels across conditions revealed trends ($p < .1$) that suggested a higher PFC activation during block 1 in the RB condition than the II condition for channel 13, channel 14 and channel 15. This result deviates from the part of our initial hypothesis that suggested channel activation should be equal across conditions in block 1. However, this result is in accordance with the part of our initial hypothesis that suggested RB processes should rear a higher degree of activation in block 1 but not in block 2. Additionally, as the second topograph in figure 6 illustrates, there was a trend that suggested a higher PFC activation during block 2 in the II condition than the RB condition for channel 19, which is in accordance with the part of our initial hypothesis that suggested II processes should maintain a high degree of activation across blocks.

To bring everything together, these results indicate that the RB condition employed explicit processes because, as subjects progressed in the task, PFC activity quickly lowered. These results also indicate that the II condition employed implicit processes because, as subjects progressed, PFC activity remained high. This shows that explicit learning is suboptimal here; the implicit cortical structures are better suited for the II task. Additionally, since there was no significant difference in accuracy across condition, it is shown that no one condition is more difficult than the other task-wise; they just function through separate systems. Overall, these results align with COVIS.

The major contribution of this study to category learning research was that it presented stimuli through a rapid event-related design. From the behavioral perspective, this meant that the task was shorter and more efficient due to a lack of baseline trials. From the neuroimaging perspective, this meant that HR was measured by trial, creating a more in-depth evaluation of HR. In other words, estimation efficiency was increased (Liu et al., 2001).

While there are many advantages to using an event-related design, it is not without weaknesses. For one, studies indicate that there tends to be a trade-off between higher estimation efficiency and lower detection power, making it more difficult to attain significant outcomes (Liu et al., 2001). The results of this study are a testament to this effect, in that the significance of our outcomes was far from ideal. Future endeavors might balance this trade-off by utilizing a larger sample size (N), which is a common way of raising statistical power.

Future research should also consider separating “learners” from “non-learners.” In our data pool, there were several subjects with accuracy below chance, indicating that they did not put much effort into the task. Such outliers diluted the data to an extent so factoring them out may also increase statistical power.

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