What is Implicit About Implicit Category Learning?

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WHAT IS IMPLICIT ABOUT IMPLICIT CATEGORY LEARNING?

by

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ABSTRACT

The conscious or unconscious acquirement of knowledge in implicit category learning was examined in accordance with predictions made by the COVIS theory of categorization (Ashby & Maddox, 2011). COVIS assumes separate category learning systems. The explicit system relies on easily verbalized rules while the implicit system requires integration of more than one stimulus dimension. Participants in this experiment categorized lines varying in length and orientation as belonging to one of two categories; in the rule-based (RB) condition only length was relevant, while participants in the information integration (II) condition needed to integrate both dimensions. Corrective feedback was provided during training. In test phases, participants were asked to attribute their responses to one of four criteria (guess, intuition, memory, or rule), a measure adapted from Dienes and Scott (2005). Neural activity in dorsolateral prefrontal cortex (DLPFC) was recorded with a 20-optode fNIRS system. We found that in the implicit (II) learning condition, participants who reported guessing less than half the time were learning but were unconscious to the structures driving that learning, reflected by accuracy, attribution self-report and neural activation. Our results substantiate the claim that implicit category learning is mediated unconsciously and evidence the dual-system model of categorization postulated by COVIS, furthering our understanding of category learning and thus, the ways in which to improve it.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

INTRODUCTION

Medical doctors review highly variable breast scans to determine whether an individual's breast tissue does or does not contain cancer cells, with each of the two decisions affecting how they proceed. Similarly, you may decide not to bring an umbrella to work by noting that the sky is clear on a given morning. Both scenarios are examples of categorization, a fundamental cognitive process that underlies our ability to differentiate and understand objects, concepts, and events. Distinct yet related items can be arranged into infinite numbers of category groups. These delineations allow us to predict patterns in our surroundings and prove effective as schemas for mental organization and stimulus-response behavior.

The process by which humans learn to categorize has been contested and explained by three opposing theories. Prototype theory suggests that a category group can be represented in the mind by an abstract prototype or average of the members of that group, which serves as the standard for category membership (Minda & Smith, 2011). Conversely, the exemplar model assumes that membership in a category is determined by individual memories for multiple entities (i.e, exemplars) in a category, rather than a single prototype (Nosofsky, 2011). Decision bound theory argues for categorization based on rules or boundaries between categories (Maddox & Ashby, 1993). Although multiple theories of categorization exist, few accurately represent category learning in light of the evidenced existence of multiple category learning systems in the latter half of the 1990s, at which point research shifted to understanding each system individually and as they interact (Ashby & Maddox, 2011).

One prominent theory, known as COVIS (for Competition between Verbal and Implicit Systems), assumes separate category learning systems, one implicit and one explicit, that are always active. The two systems compete to produce a categorization response dependent upon the nature of a given stimulus (Ashby, Alfonso-Reese, Turken & Waldron, 1998; Ashby & Maddox, 2005). COVIS maintains that explicit or rule-based (RB) learning relies on easily verbalized rules. The implicit, nonverbalizable system requires consideration of two or more stimulus dimensions, otherwise known as information-integration (II).

Neuroimaging in Categorization Research

Functional magnetic resonance imaging (fMRI) data suggest that explicit learning is mediated by a neural network including the dorsolateral prefrontal cortex (DLPFC), while the key structure implicated in the implicit system is the striatum, a subcortical input center of the basal ganglia. Activity in both areas can be further dissected by whether a given participant successfully learns or fails to learn the appropriate rule in a categorization study (Ashby & Maddox, 2011).

Two studies using fMRI technology evidenced increased activation in Brodmann Areas (BA) 9 and BA46 (Filoteo et al., 2005) and BA9, BA44 and BA47 (Cincotta & Seger, 2007) during rule-based and information-integration category learning tasks, respectively.

Filoteo et al. (2005) conducted a perceptual categorization task (i.e., explicit) using simple lines varying in length and orientation. Optimum accuracy required that participants only attend to line length and ignore line orientation, which they were to learn independently trial-by-trial. Filoteo et al. (2005) also used a comparator task in which participants categorized lines colored blue or yellow. Conversely, Cincotta and Seger (2007) employed feedback and observational learning tasks (i.e., implicit) using two stimuli sets, both varying spatially and by angle. One set included two lines, one varied in length and the other in angle. The second set featured circles varying in diameter, with center-to-edge lines varying in angle. Participants in this experiment needed to integrate both stimulus dimensions in both sets.

Neuroimaging technology is a means by which to draw correlative conclusions between neural function and behavior in a category-learning paradigm. As it pertains to COVIS, discrepancies in neuroimaging data between RB and II categorization tasks support a dual-system model of categorization and can substantiate the theoretical claims that drive this research. Although fMRI has high spatial resolution, it is extremely costly. An emerging alternative is functional near-infrared spectroscopy (fNIRS). fNIRS operates via neurovascular coupling, by which cerebral blood flow and cerebral blood volume increase during neural activity. Oxygen floods the recruited area of the brain via oxygenated hemoglobin (oxy-Hb) to compensate for increased deoxygenated hemoglobin (deoxy-Hb), from which oxygen is withdrawn for use in metabolism (Izzetoglu, Bunce, Izzetoglu, Onaral, & Pourrezaei, 2007; Bunce, Izzetoglu, Izzetoglu, Onaral, & Pourrezaei 2006). Both oxy- and deoxy-Hb have optical properties in the near-infrared range, specifically 700-900nm. Thus, like fMRI, fNIRS measures the relative changes in concentration of these molecules (i.e., the BOLD response) (Bunce et al., 2006).

Whereas fMRI can access subcortical structures, fNIRS is limited to the cortical layer of DLPFC (BA9 & BA46), anterior PFC (BA 10), part of the inferior frontal gyrus (BA 45), and part of the ventral frontal cortex (BA47) (Izzetoglu et al., 2007), areas of the brain pertinent to executive function (Figure 1).

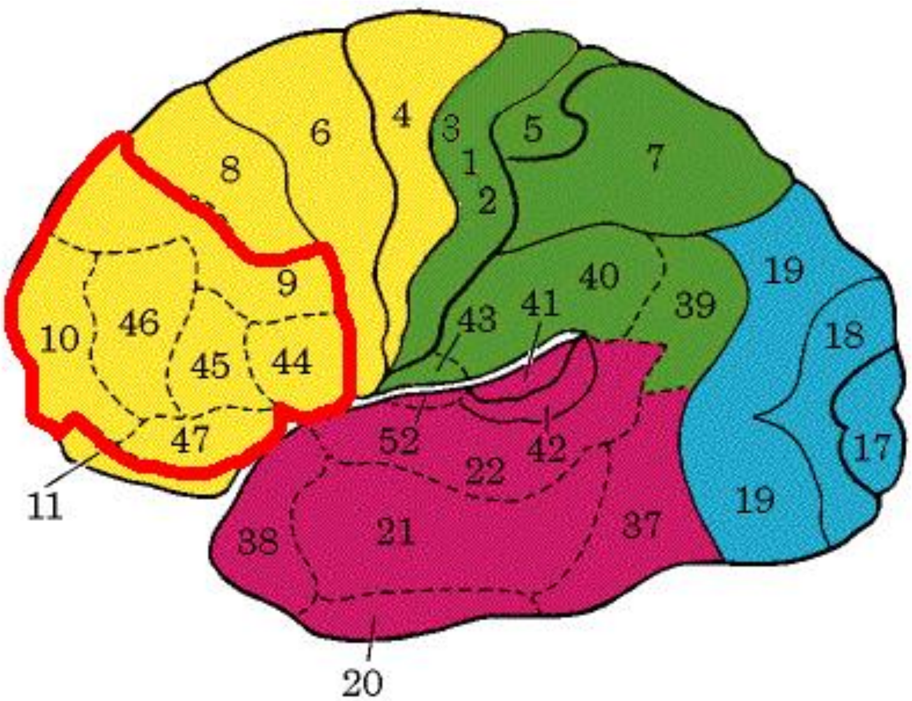

Figure 1: Sagittal view of the brain signifying relevant Brodmann areas in red
Source: University of Michigan
http://www.umich.edu/~cogneuro/jpg/Brodmann.html

Consciousness of Learning in an Implicit Categorization Task

Despite the growing body of neural and behavioral evidence supporting the dual-system model of category learning, the functional properties of the implicit system remain unclear. Categorization criteria acquired via the explicit system are determinably conscious to the individual because they are easily verbalized, but the consciousness of implicit learning is yet to be understood. In other words, it is unclear whether individuals are aware that they are acquiring knowledge in an implicit categorization task.

Dienes and Scott (2005) postulated that the implicit learning system could be dissociated into its conscious and unconscious components by means of subjective assessment including five criteria, namely guess, intuition, pre-existing knowledge, memory, and rule, representing a spectrum from unconscious to conscious. In an artificial grammar task, participants were trained in the structure of grammar strings before determining whether test strings fit the structure of the training material and attributing their decisions by the subjective measure. If participants were conscious of the grammar structure presented in training, Dienes and Scott (2005) contended that their reported attributions in the test phase should reflect that consciousness. Alternately, if the structural knowledge was unconsciously acquired, participants would likely believe they were guessing throughout the experiment. They concluded that their results validated this form of subjective measure in analyzing consciousness of acquired knowledge, noting that the guess and intuition criteria behaved similarly, as did the memory and rule criteria, while the pre-existing knowledge criterion was virtually unused.

In accordance with the results of Dienes and Scott (2005), we expected participants categorizing stimuli in an II task to report intuition more frequently than participants in an RB task. Alternately, we expected participants in an RB task to report rule as their source of knowledge more than participants in an II task. We postulated that neuroimaging data would corroborate these predictions, assuming that subjective measure reflects consciousness of knowledge when compared to categorization accuracy across RB and II tasks.

Linking BOLD Response to Implicit Knowledge

Based on present fMRI data, we expected hemodynamic activity to decrease over time as a product of the participant learning and continually applying the appropriate rule to the RB task. In the II task, we predicted DLPFC activity would decrease more slowly while participants continually applied a suboptimal (i.e. verbalizable) rule when a non-verbalizable rule was more optimal. If participant accuracy improved over the course of the II task, the elevated neural function and report of intuition would suggest that knowledge had been unconsciously acquired. Similarly, decreased neural activity during the RB task, in which participants would purportedly cite rule as the source of their knowledge, would evidence conscious acquirement of knowledge. In the present study, we used fNIRS to gain a more complete understanding of categorization knowledge by making explicit the relationship between brain and behavior.

The fNIRs System

In this experiment, we collected data with the NIRSport (Figure 2). This system, designed by NIRx, offers a flexible user-configured cap with 8 LED photoemitters and 8 active-detection receivers and operates on the principles of light absorption and dispersion. Once the light, in wavelengths of 760 nm and 850nm, is introduced into the cortex in continuous and slow pulses, it is either absorbed by chromophores oxy- and deoxy-Hb or scattered back the surface by intracellular bodies and collected by the photodetectors (NIRx, 2015; Izzetogulu et al., 2007).

The activation levels are determined by a modified-beer lambert law in which changes in absorption are a product of concentrative changes in oxy- and deoxy-HB, where scattered light remains constant despite cognitive activity (i.e., number of intracellular bodies do not change)(Izzetoglu et al., 2007).

Figure 2: NIRSport control systems and active-detection sensor cap
Source: NIRX
http://www.nirx.net/imagers/nirsport

METHODS

The present study aimed to assess for the conscious or unconscious acquisition of knowledge in the implicit category learning system via behavioral and neuroimaging data. Perceptual stimuli for the rule-based and information-integration tasks were adapted from the studies conducted by Filoteo et al. (2005) and Cincotta and Seger (2007), respectively, while the subjective measure is modeled after that of Dienes and Scott (2005).

One rule-based and one information-integration category structure was used in this experiment. Stimuli, sampled from a normal distribution, consisted of lines varying in length and orientation and are described in Figure 3. Symbols in Figure 3 represent features of each individual stimulus, with decision bounds denoting accuracy-maximizing criterion.

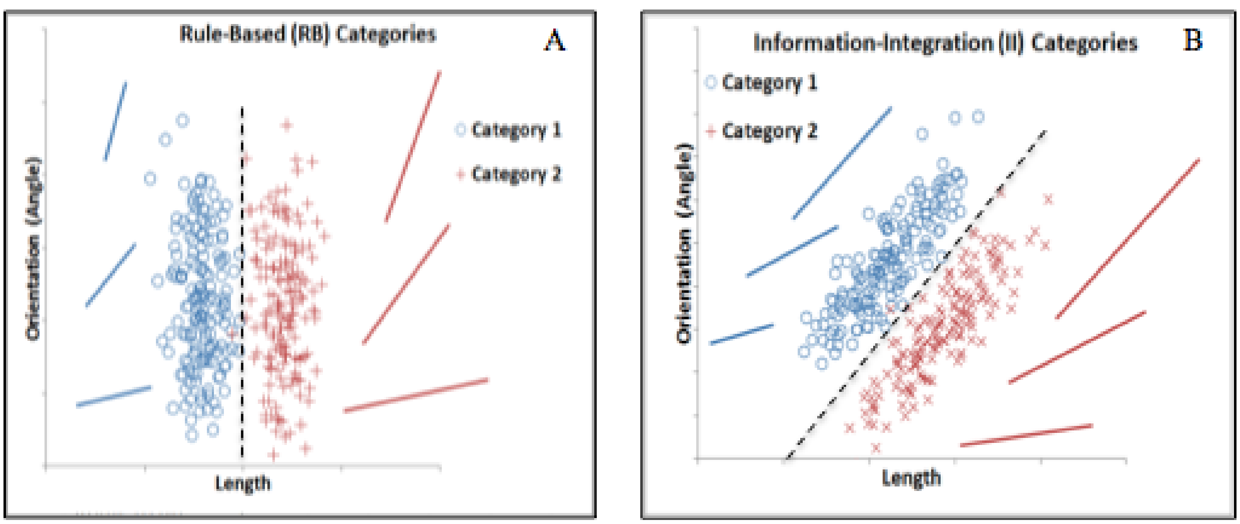

Figure 3: Stimuli distribution
On each trial, participants were presented with a line varying in length and orientation. (a) In the RB condition, only line length is relevant. (b) In the II category, participants needed consider length and orientation. Circles signify stimulus values for Category 1, while pluses signify values for Category 2, separated by the accuracy-maximizing decision rule, represented by the dotted line.

For the RB task (Figure 3A), participants needed only consider line length, e.g., if the line is short, it belongs in category A and if the line is long, it belongs in category B; the II task (Figure 3B) required integration of both line length and orientation, for which there was no easily verbalizable rule.

Participants in this study, which was designed between subjects, completed 24 30-trial blocks of alternating 10-trial baseline, training, and test tasks, in that order. The baseline task is described in Figure 4 and employed the test stimuli, i.e. lines varying in length and orientation, colored blue or yellow, which participants identified by color. In the next 10 trials, corrective feedback shaped learning following categorical responses to test stimuli. The feedback, described in Figures 4 and 5, followed "Correct, that was A" for correct responses or "Incorrect, that was B" for incorrect responses. In the next 10 experimental trials, participants attributed their decisions to guess, intuition, memory or rule following their responses to the stimuli as belonging to either category A or B (Figure 6).

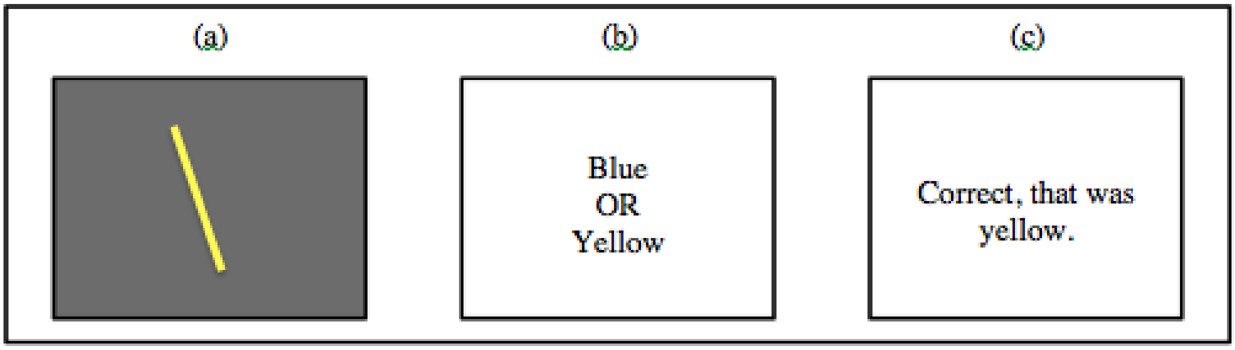

Figure 4: Baseline task
(a) Participants identified lines varying in length and orientation as either blue or yellow. (b) They recorded their responses by stroking a key marked blue or a key marked yellow based on the color of the line on the screen. (c) Corrective feedback was provided after recorded responses.

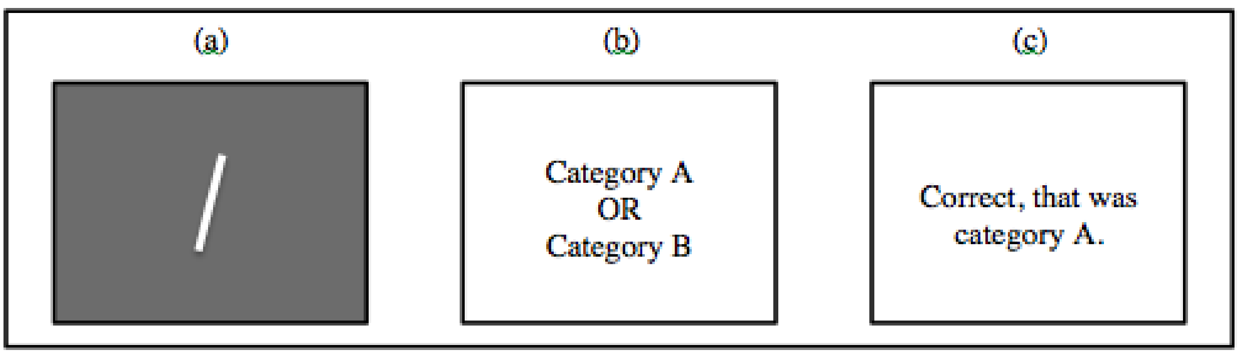

Figure 5: Training task
(a) During training trials, participants were presented with lines varying in length and orientation. (b) Participants categorized these lines as belonging to Category A or Category B based on each line's respective features. (c) Corrective feedback was provided to facilitate learning of accuracy-maximizing rule.

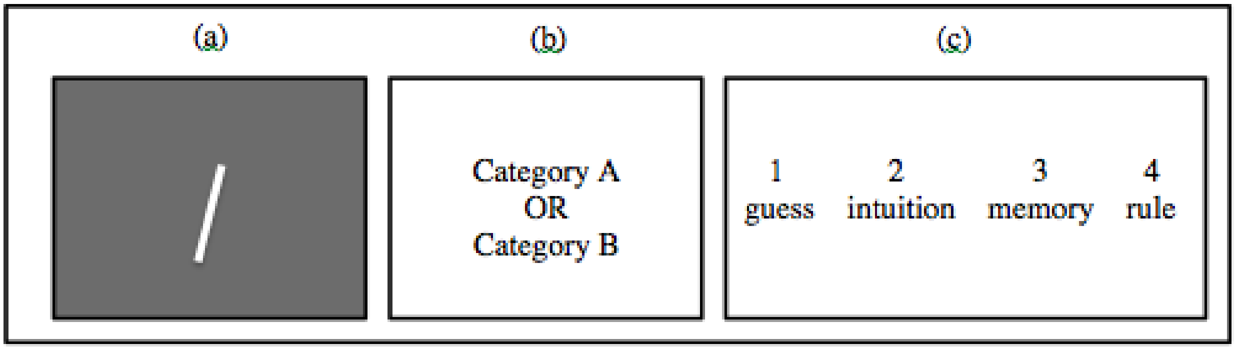

Figure 6: Attribution task
(a) During test trials, participants were presented with lines varying in length and orientation. (b) Participants categorized these lines as belonging to Category A or Category B based on each line's respective features. (c) Following responses, participants were asked to attribute their decision to one of the four criteria, i.e. guess, intuition, memory, or rule.

Participants

Eleven participants were recruited from the University of Central Florida undergraduate student population and received research credit for participation in this study. Demographic information, including skin and hair color, was collected from participants before experimentation, which lasted approximately 75 minutes, including an allotted 30 minutes for fNIRS setup.

Procedure

Informed consent was obtained from each participant before the experiment, which limitedly explained the purpose of the experiment and fNIRS device. In a room lit only by natural light, participants' heads were measured for circumference and relative centricity, denoting the size of the cap to be used. Cap size ranged from 54 to 60 inches in two-inch increments. Before applying the cap, participants were asked to part their hair down the center of the scalp as accurately as possible. Wooden spatulas were used to move hair away from the grommets in the cap and water soluble gel was applied to the scalp to facilitate the connection between the optodes and the skin. The fNIRS system was calibrated before and after applying an over cap to each participant's head to check for bad channels, which, if any were present, were corrected as best as possible before beginning the experiment.

Upon completing setup, participants were instructed to hold their head in a chinrest (for the duration of the experiment) to reduce motion interference and read the instructions appearing on the screen in front of them, at which point the fNIRS system began recording. The instructions informed participants that they would be using keyboard keys demarcated blue, yellow, A and B for the respective tasks. An additional instruction screen defined the four attribution criteria and their respective keyboard keys as follows: (1) guess: You have no basis whatsoever for your judgment. You might as well have flipped a coin to arrive at your choice, (2) intuition: You have some confidence in your judgment (anything from a small amount to complete certainty). You know, to some degree, that your judgment is right, but you have absolutely no idea why it is right, (3) memory: You based your judgment on memory for particular items from earlier trials and (4) rule: You based your judgment on some rule or rules acquired throughout training and that, if asked, you would be able to state your rule (Dienes & Scott, 2005). These definitions appeared at the beginning of each 30-trial block. An additional paper description of the attributions and their respective keys was placed on the desk to remind participants of the criteria. The pre-existing knowledge response was eliminated from this experiment.

RESULTS

Behavioral Results

Accuracy

Figure 7 displays average accuracy by block for the RB (n = 6) and II (n = 5) conditions. A two-way, mixed-factor ANOVA showed neither a significant effect of block, $F(2, 18) = 2.103$, $p = .151$, nor condition, $F(1, 9) = 0.90$, $p = .771$.

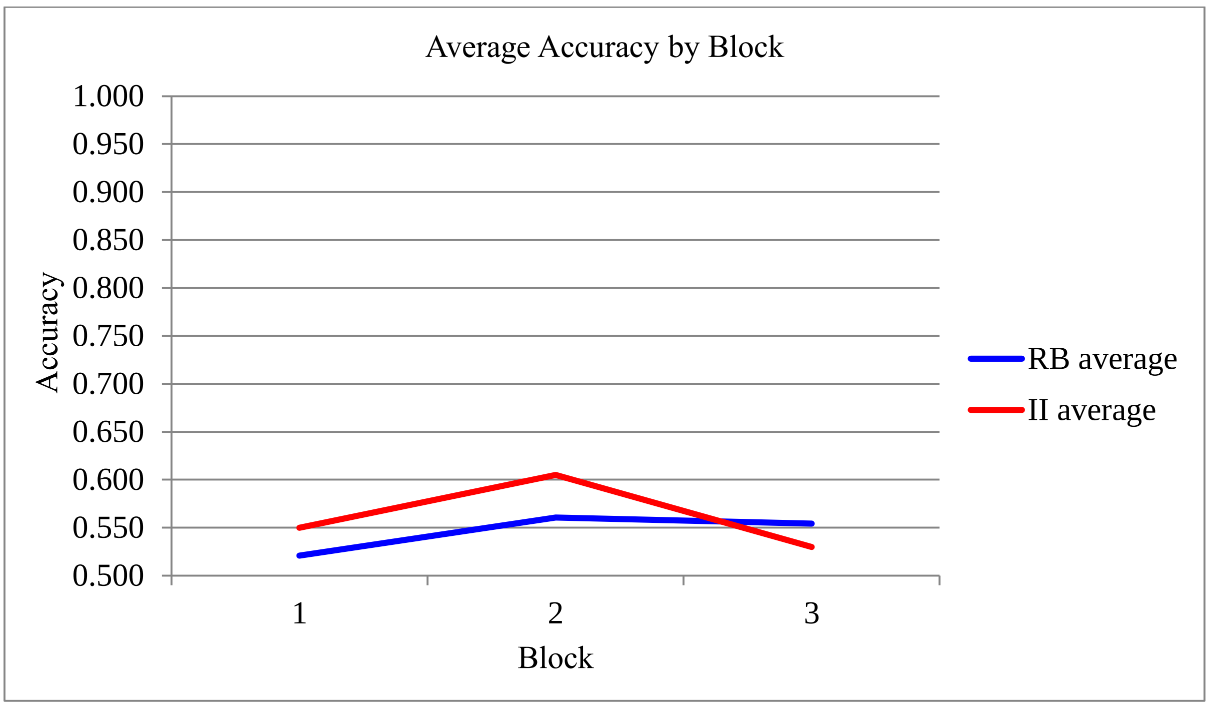

Figure 7: Average participant accuracy over blocks

Before analyzing attribution responses, we sorted participants into two categories ("guessers" and "non-guessers") to determine whether we could predict task accuracy by the extent to which participants reported the "guess" criterion. This designation was based on a median split using the proportion of guess responses. "Guessers" reported guess at a proportion of 0.5 or higher over blocks while “non-guessers” reported that they were guessing less than half the time, i.e., reported an average of the three other criteria (intuition, memory and rule) more than half of the time. In the RB condition (n = 6), there were three “guessers” and three “non-guessers. In the II condition (n = 5), there were two “guessers” and three “non-guessers.” In both conditions, we predicted that “non-guessers” would perform with higher accuracy than “guessers,” which is plotted in Figure 8.

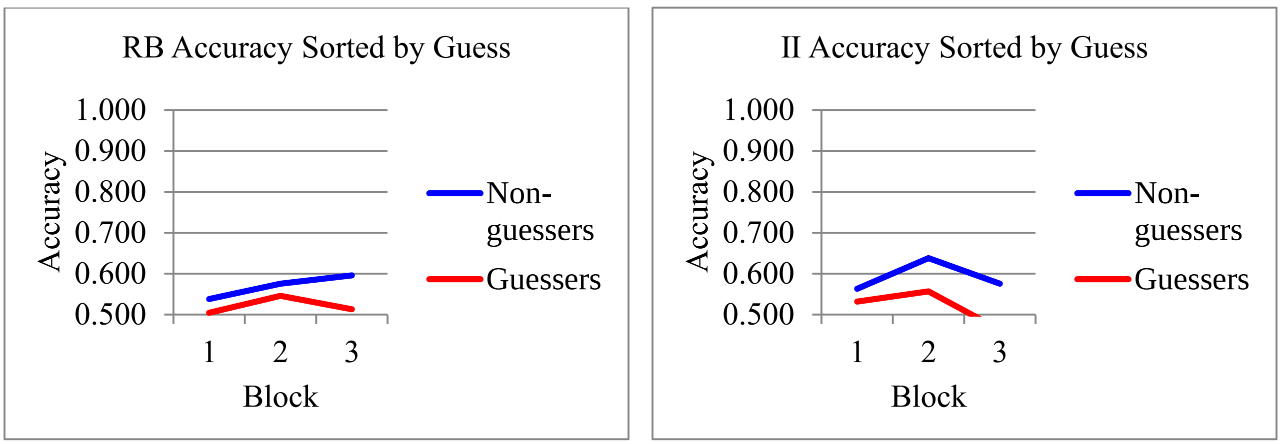

Figure 8: Accuracy for “guessers” and “non-guessers” by condition
“Non-guessers” performed with higher accuracy in both the RB and II conditions across blocks.

In block 3 of the II condition, we found a significant difference in accuracy between “guessers” and “non-guessers,” $t(1) = 2.887$, $p < .05$, and a near-significant effect in block 2 of the same condition, $t(1) = 1.347$, $p = .097$, evidencing learning across blocks for “non-guessers.”

Attributions

We compiled the average proportion of responses for each of the four attribution criteria by block, reported in Table 1.

Average Proportion of Reported Attributions				
RB	Guess	Intuition	Memory	Rule
Block 1	0.575	0.167	0.210	0.048
Block 2	0.625	0.160	0.146	0.069
Block 3	0.554	0.210	0.123	0.113
II	Guess	Intuition	Memory	Rule
Block 1	0.315	0.443	0.218	0.025
Block 2	0.280	0.415	0.245	0.060
Block 3	0.335	0.443	0.173	0.050

Table 1: Average proportion of responses for attribution criteria over blocks

We predicted that participants in the II condition would more often report intuition than those in the RB condition, whom we predicted would report rule more frequently than their II counterparts. The average proportion of responses for both criteria across condition and block are shown in Figure 9. We found a significant effect by condition for reporting of intuition, $F(1, 9) = 10.282$, $p < .05$, supporting our claim that participants in the II condition would report intuition more frequently. There was no significant effect of block, $F(2, 18) = 0.219$, $p = .651$. Participants in the RB condition attributed their responses to rule more often than participants in the II condition. This trend was largest by block 3, but not statistically significant.

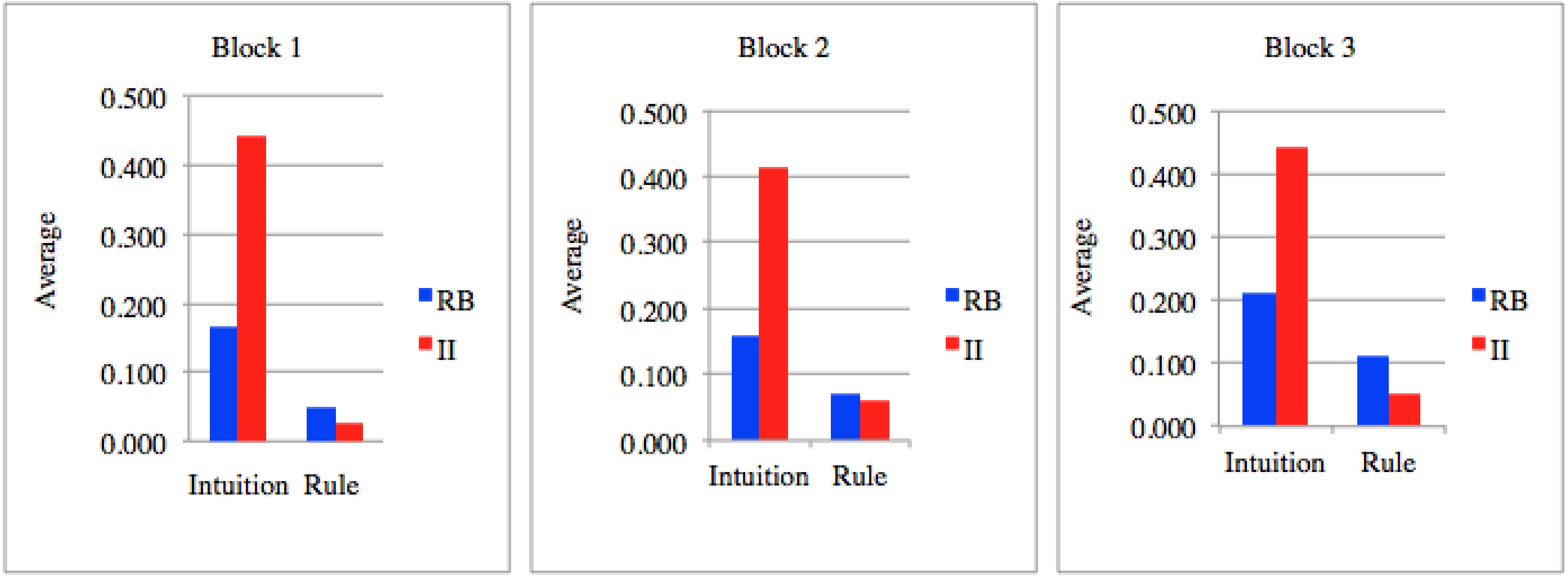

Figure 9: Average proportion of reported responses for intuition and rule
Participants in the II condition reported intuition more frequently than participants in the RB condition for all three blocks. Alternately, participants in the RB condition reported rule more frequently than those in the II condition for all three blocks.

Neuroimaging Results

We compared levels of BOLD activity across conditions for “non-guessers.” Figure 10 shows the average participant activation level per block, calculated by subtracting average levels in the RB condition from the II condition. The difference in activation was significant ($p < .05$) in block 3, supporting our hypothesis that hemodynamic response should decrease more rapidly in the RB condition than the II condition as participants learned and applied the appropriate rule. Given that the participants included in fNIRS analysis were selected on the basis of reporting that they were no longer guessing, these results also underscore the relationship between the behavioral results and attribution results. In the II condition, these same participants more frequently reported using intuition than using a rule.

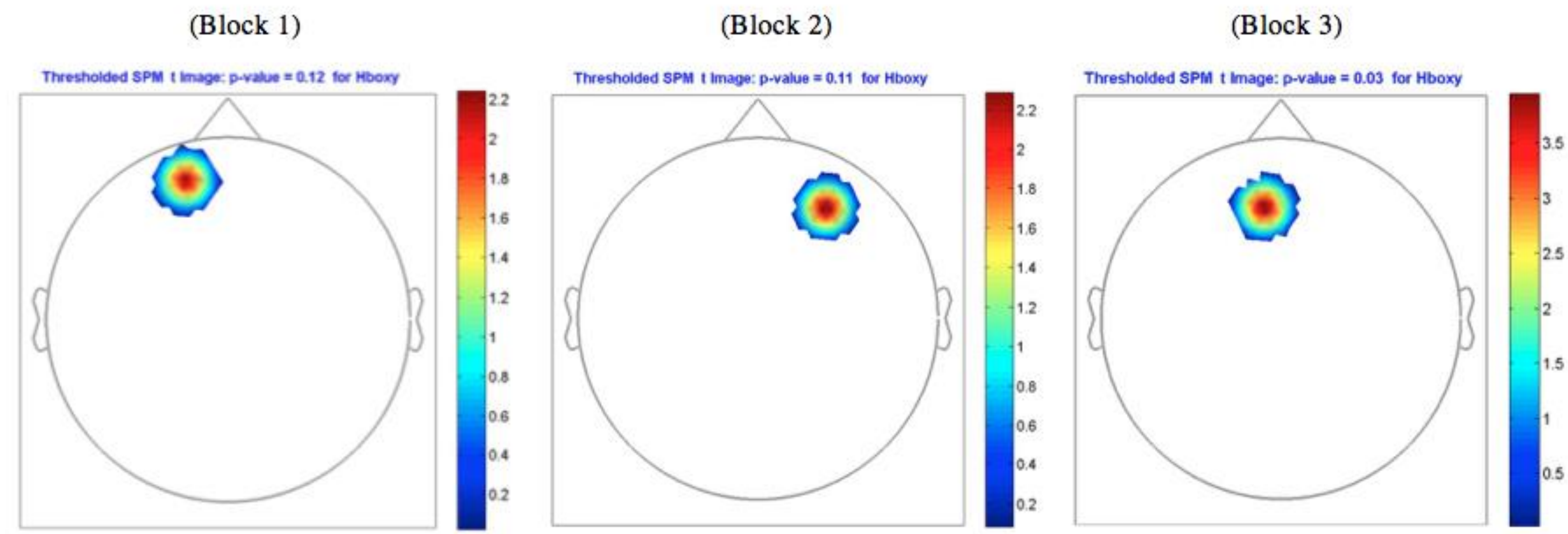

Figure 10: BOLD activity over blocks for "non-guessers"
The average level of activity in the II condition minus the average level of activity in the RB condition is reported here. For all three blocks, hemodynamic activity decreased at a slower rate in the II than RB condition. This effect was significant in block 3.

DISCUSSION

In this study, we examined the conscious or unconscious acquirement of knowledge during rule-based and information-integration category learning tasks. Each participant completed a baseline task by identifying blue and yellow lines with corresponding blue and yellow keyboard keys before completing two categorization tasks, one with corrective feedback (training) and one with subjective report after each category response. The attribution report consisted of four criteria: (1) guess: You have no basis whatsoever for your judgment. You might as well have flipped a coin to arrive at your choice, (2) intuition: You have some confidence in your judgment (anything from a small amount to complete certainty). You know, to some degree, that your judgment is right, but you have absolutely no idea why it is right, (3) memory: You based your judgment on memory for particular items from earlier trials and (4) rule: You based your judgment on some rule or rules acquired throughout training and that, if asked, you would be able to state your rule (Dienes & Scott, 2005). The stimuli sets for both conditions consisted of lines varying in length and orientation. Participants in the RB condition needed only concentrate on length while participants in the II condition needed to integrate both stimulus dimensions (length and orientation) to maximize accuracy.

By sorting participants as "guessers" and "non-guessers," we were able to establish via accuracy data that "non-guessers" did learn, i.e., acquire knowledge, over blocks at near-significance in the second block and significance in the third block. We hypothesized that participants in the II condition would report intuition more frequently than participants in the RB condition, for which we found a significant difference by condition. We also found evidence that participants in the RB condition reported rule more frequently, although these results were nonsignificant. Based on our findings, we can predict with some certainty that participants who do not believe they are guessing in an implicit task will improve in accuracy over time yet remain unsure of the basis for their category judgments, or at least feel they cannot quite verbalize the basis for responding. Thus, our results support that claim that in an implicit learning paradigm, category knowledge is acquired unconsciously for participants who learn to perform the task.

By analyzing fNIRS data from "non-guessers," we were further able to underscore the relationship between behavioral data and subjective measure. Hemodynamic response decreased more rapidly for participants in the RB condition, suggesting that participants in the II condition did not consciously acquire the appropriate rule for the II task. Our findings that learning did occur for non-guessers in the implicit task suggest that implicit category learning is mediated separately from the explicit system in DLPFC. Thus, our results substantiate the dual-system model of categorization, as COVIS is the only theory that could account for our results as it pertains to both the attributions and neural response.

This research was primarily limited by its small sample size (N = 11) and thus its low power, further complicated by the division of the participant group into "guessers" and "non-guessers." A large sample size could account for participants who are not actively engaged in the experiment and simply report guessing as a product. This experiment may have also been limited by the reliability of our self-report measure between participants. It is possible that, despite the given definitions, participants held different interpretations as to what constituted use of the different criteria (guess, intuition, memory, and rule). As such, "guessers" may not have been alike in their report of the guess criterion and vice versa with "non-guessers."

Despite its limitations, we believe this experiment furthers the neurobiological understanding of category learning and further explicates the ways in which learning takes place, particularly in the implicit system. As we come to understand category-learning structures, we can also contribute to improved learning models for categorization and in turn, decrease the margin of error in category decision-making like mammographic cancer screening, for example.

CONCLUSION

This research, to some degree, identifies the acquisition of knowledge in implicit category learning as unconscious to the individual and substantiates the link between behavior and neural activation. The use of subjective measure emphasizes the distinction between explicit and implicit category learning systems. This, in accordance with neuroimaging data, allowed us to establish the efficacy of COVIS as a model for category learning and evidence the claim that category learning is mediated by two separate systems, one explicit and one implicit. Further, this research contributes to our understanding of underlying category learning processes and thus, with more expansive future research, may contribute to superior learning models.

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