Grounding Concepts:

Physical Interaction can Provide Minor Benefit to Category Learning

by

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ABSTRACT

Categories are often defined by rules regarding their features. These rules may be intensely complex yet, despite the complexity of these rules, we are often able to learn them with sufficient practice. A possible explanation for how we arrive at consistent category judgments despite these difficulties would be that we may define these complex categories such as chairs, tables, or stairs by understanding the simpler rules defined by potential interactions with these objects. This concept, called grounding, allows for the learning and transfer of complex categorization rules if said rules are capable of being expressed in a more simple fashion by virtue of meaningful physical interactions. The present experiment tested this hypothesis by having participants engage in either a Rule Based (RB) or Information Integration (II) categorization task with instructions to engage with the stimuli in either a non-interactive or interactive fashion. If participants were capable of grounding the categories, which were defined in the II task with a complex visual rule, to a simpler interactive rule, then participants with interactive instructions should outperform participants with non-interactive instructions. Results indicated that physical interaction with stimuli had a marginally beneficial effect on category learning, but this effect seemed most prevalent in participants were engaged in an II task.

DEDICATION

To my father and mother, Jim and Sally, by who I am.

To my brother, Tyler, for his example of courage and conviction.

To Jeff Stone, for his unexpected friendship.

To Roger Millsap, for his kind wisdom.

To Jessica Chiri, for her faith and love.

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CHAPTER 1

INTRODUCTION

For any given agent, learning can be broken down into several essential parts: the perception of a stimulus, a response, and feedback to that response. When a student taking a test provides an incorrect answer to a question, they are given a grade reflecting their correct and incorrect responses thus providing feedback on how well the student understands the topic. When a child reaches up to touch a stove, a parent may grab their hand, or perhaps the child experiences pain when he burns his hand, teaching the child the dangers of the stovetop. A child sees a dog bearing its teeth and shaking its tail and it only takes a single bite for the child to learn that a dog shaking its tail is not always friendly. The environments in which we find ourselves are defined by many dimensions which can vary greatly and the rules which determine a correct response to these stimuli and environments are not always simple. Actions with this environment often result in feedback which may be delayed, ambiguous, or even completely absent. The challenge, then, is to explain how we are capable of learning given such a difficult scenario.

Traditional Categorization: Simple and Complex Rules

To better understand how we learn “complex” rules, we must also understand how we learn “simple” rules. One of the dominant methods of studying such categorization behavior utilizes two similar yet distinct tasks (Ashby & Gott, 1988). These tasks use stimuli, usually defined by only a few dimensions, which can be separated into different categories by some dimensional rule. When the rule is unidimensional (e.g., if stimulus has dimension X > 5 then it belong in category A) it is called a Rule Based (RB) task. When the rule is multidimensional (e.g., if stimulus has dimension X > dimension Y then it belongs in category B) it is called an Information Integration (II) task. The tasks, while sharing similar cognitive processes such as attention and memory, have different constraints. Namely, the RB task requires only that participants understand one aspect of the stimulus while the II task requires that participants understand a relationship between two dimensions so that a stimulus may be correctly categorized.

As should be expected, Rule Based and Information Integration tasks differ over more than their dimensional definitions. Ashby, Queller, & Berretty (1999) had participants engage in either the RB or II task. Some participants were provided feedback on their categorization responses while others were not. Participants in the RB task were able to learn to correctly categorize stimuli regardless of whether they received feedback or not, while participants in the II task were only able to learn the multidimensional boundary when feedback was provided. They concluded that, in the absence of feedback, individuals will attempt to use the simplest possible rule and it should be noted that these effects are limited to situations in which only two category assignments are possible. A later study by Maddox, Ashby, and Bohil (2003) had participants engage in either RB or II tasks and participants were provided with either immediate feedback for their decisions or feedback that was delayed by 2.5, 5, or 10 seconds. While their results showed that participants made more accurate category judgments in the RB task over the II task, they also showed that participants engaged in the RB task were not affected by the delay in feedback. In contrast, participants in the II task found their performance significantly hindered by the delay in feedback.

Maddox, Ashby, and Bohil (2003) argued that the reason for these differential effects of feedback presentation on category learning between II and RB tasks was due to different underlying neurological mechanisms being utilized by each task. Specifically, they hypothesized that Rule Based learning depends upon executive attention and explicit hypothesis testing, a process which depends heavily on the prefrontal cortex, while information integration relies on an implicit procedural learning system which relies upon a dopamine reward based in the caudate nucleus. As such, the impairing effects of delayed feedback on learning in an II task are explained by the denying or delaying the essential neurological reward signal generated by feedback.

Overcoming Complexity Naturally

This dependency upon feedback for learning to occur in an II task has the significant implication that learning complex categories likely requires both reliable and immediate feedback. Yet, we are likely to have experiences with objects and environments which may not always occur within the presence of an informed and responsive teacher, and naturally occurring feedback may not always be reliable or immediate. Despite these difficulties, there is evidence that we are capable of learning complex rules. Mervis and Rosch (1978) thought of humans (and other organisms) as learning agents within a massively complex environment which struggle to gain the maximum amount of meaningful information from their environment while utilizing the least amount of cognitive effort. An essential part of this argument arose from Rosch et al. (1976), which gave evidence of “basic level” categories; categories which are more easily distinguished from one another because they differ along (comparatively) easily perceivable dimensions and because the rules which designate these categories are related to information meaningful to the individual. For instance, while a dog and a cat have many features in common (in comparison to, say, a bird), an observer with minimal experience is unlikely to confuse one for the other. However, an observer with minimal experience may have a hard time distinguishing between different breeds of dogs because the rules which distinguish the different breeds are either difficult to perceive and/or because little meaningful information is gained from the capacity to distinguish between them.

This theory of basic categories has accurately predicted that participants would categorize objects at the basic level faster than they would for super- or sub-ordinate levels of categorization (Murphy & Smith, 1982). For example, shown an image of a Golden Retriever, most individuals would identify the image as a “dog” rather than the sub-ordinate level category, “Golden Retriever”, or superordinate level category, “mammal” or “animal”. However, this tendency for basic level categories to be the primary level of categorization does not mean that other levels of categorization are inaccessible. Tanaka & Taylor (1991) had dog and bird experts engage in a series of tasks. First, experts and novices listed features for various categories of differing levels: subordinate, basic, and superordinate. Experts listed as many distinguishing, or unique, features for subordinate categories (breeds of dogs or species of birds) as they did for basic level categories; experts perceived subordinate categories to be just as distinct from one another as basic level categories. In a second experiment, experts and novices were shown images of various dogs and birds and asked to identify them as quickly as possible. Experts were significantly more likely than novices to respond with the subordinate category level responses (i.e., calling an image of a Golden Retriever a

Golden Retriever rather than just a dog). Lastly, when shown images of birds and dogs presented with a correct or false subordinate, basic level, or superordinate label, experts responded just as quickly to subordinate level labels as basic level labels. These findings imply that, the basic level of categorization is established by not only the dimensions of the stimuli perceived, but also the meaningful feedback we receive from the environment. As such, complex categories are not beyond understanding, given enough relevant interaction.

The finding of a basic level of categorization, a series of complex yet accessible and learnable rules, potentially poses a challenge to the findings of Ashby, Queller, and Berretty (1999) and Maddox, Ashby, and Bohil (2003) which, as previously stated, claim that complex rules are not learnable without feedback and are difficult to learn when feedback is interrupted or unreliable. There must be an underlying phenomenon by which basic level categories are easily learned without the use of an instructor; wherein feedback is provided by the environment itself by virtue of the individual's experience interacting with the environment. Such an example is provided by Warren (1984) who showed participants of varying heights projected images of stairs. The participants then responded if they believed the stairs were "climbable". As perceived stair height increased, shorter participants would eventually respond that the stairs were no longer climbable. Of note, there was a direct relationship between the probability that a participant would respond that a set of stairs were climbable and the ratio of the height of the stair to the length of the participant's leg. Warren concluded that such perceptual categories exist as a function of the relationship of the agent and the environment, and are not simply due to the dimensions of the environment itself. Furthermore, these interactive categories were immediately perceivable to participants, due to the extent of experience they had interacting with stair-like objects.

This concept of immediately available information was extolled by Gibson (1966) who theorized that a perceptual system is constrained not only by the information which can be sensed in the environment but also by how the observer may act upon such information. These constraints allow for “direct perception” of meaningful information regarding the environment; the immediate perception of information within the environment which is useful to the agent. As an example, the slope of a terrain is considered to provide immediate information to the perceiver of whether it is traversable not only by virtue of the slope of the terrain but also by what the agent understands about its own ability to maneuver through space and along different slopes. These directly perceived possible interactions of the agent with the environment are called “affordances” (Gibson, 1986; Turvey, 1992) and are considered invariant: so long as the agent maintains its capacities to both act and to perceive and the environment continues to maintain its status (e.g. slope and firmness of terrain) the affordances of that environment do not change.

While these examples are related to physically interactive situations, affordances and invariants can also be expressed within the context of limited interactivity. Shepard (1984) tried to address the issue of mental rotation and motion ambiguity; two phenomenon which show that the individuals are capable of manipulating information and images internally. In order to explain these phenomena, Shepard proposed the concept of resonance, which allows for completely external events, partially external events, and even internally imagined events to be biased by the same constraints of the perceived (or imagined) environment and capabilities of the agent. For example, McBeath, Schiano, and Tversky (1997) showed participants symmetric and asymmetric polygons and asked participants to describe them. Participants were more likely to perceive symmetric objects as silhouettes of 3D objects which were being viewed head on, while asymmetric shapes were perceived as being profile or oblique views of similar 3D objects. According to the idea of resonance, these images resonated with the real world invariant that objects tend to be symmetrical about their axis of forward motion. Therefore, symmetric objects are perceived as facing the observer while asymmetric objects are perceived as not facing the observer because the supposed axis of symmetry is directed away from the observer.

This concept of resonance, that our perception of abstractions is still influenced by our capacity for physical interactivity, is strikingly similar to the grounding principle (Clark & Brennan, 1991) which assumes that even abstract concepts are based upon, not only the differences in perceived or imagined features, but also by individual's ability to interact with the perceptions. To illustrate, Anderson (2003) gave the example of a tree stump being referred to as a "chair". Despite the fact that a tree stump has very little in common with most encountered chairs, an observer would understand the reference because the tree stump affords the observer the possibility of sitting just as a chair would. In other words, the abstract concept of "chair" is given meaning, not by just the physical dimensions of a given stimulus, but the capacity that an agent has to interact with it.

The grounding principle also implies that any new thing, despite its possible physical dimensions, may be defined as a chair so long as it affords the agent the same sitting capacity of previously experienced chairs.

These claims are supported by research which indicates that, when participants are dealing with objects with which they have a history of interaction, the visual inspection of the objects also activates the motor capacities involved with interacting with that object (Creem & Proffitt, 2001; Glenberg, Robertson, Kashak, & Malter, 2003). These pieces of evidence suggest that our capacities to learn concepts and to generalize from experiences onto new stimuli are constrained not only by the features of the environment, but are also related to our capacity to interact with the environment. This benefit of interactivity should render individuals capable of understanding complex categories defined by both physical and abstract stimuli so long as the interactive relationship between the participant and the stimulus is made clear (Anderson, 2003; Gick & Holyoak, 1983; Goldstone & Wilensky, 2008).

The Shared Neurology of Perception and Motor Control

The impact of interactivity on categorization is not limited to purely cognitive factors. There are also neurological aspects involved. Faillenot et al. (1997) utilized a variety of neuroimaging techniques to detect differences in neural activation patterns in both a visual recognition task (identifying when two objects were the same) and a motor task (grasping and moving one object at a time). These tasks were not done in any particular order. The researchers found that the intraparietal sulcus was activated for both the visual perception and the interaction with those objects. Jeannerod (2001) hypothesized that there was a motor simulation neural network within the brain that is activated, not only as part of perception and action, but also in regards to imagined actions. Supporting evidence for such a system can be found in work by Frak, Paulignan, and Jeannerod (2001) who found that, when an individual estimates the feasibility of grasping an object, reaction time increases as the object is rotated further away from an ideal interaction, similar to a mental rotation (Shepard, 1978; 1984).

This linking of action to cognition is not limited to simple object interaction tasks. Indeed, there is a body of evidence suggesting that both real and imagined action and other cognitive tasks, such as categorization, share neurological systems. Buccino and colleagues (2005) utilized Transcranial Magnetic Stimulation (TMS) to stimulate “hand” or “leg” areas of the motor cortex while participants listened to sentences containing actions utilizing hands or legs. They found that muscles within participants’ hands and legs were activated when listening to hand and leg action related sentences, respectively. Furthermore, these responses were altered with the application of TMS to the specific motor areas of the brain while the sentence was being heard. These findings were expanded by Glenberg and colleagues (2008) who found motor activation and subsequent effects of TMS on motor activation during the comprehension of sentences with abstract actions (e.g. delegating tasks or issuing orders) as well as concrete actions. These findings indicate an intimate functional relationship between motor action and language processing.

While TMS offers the opportunity to alter brain function temporarily, the relationship between motor activation and sentence comprehension has been investigated in individuals with permanent damage to motor areas. Parkinson’s disease, damages dopamine receptors and destroys them over time resulting in a gradual loss of motor control. Boulenger and colleagues (2008) found that individuals with Parkinson's disease, when off of their dopaminergic medication, have more difficulty understanding action related words but their medication status does not affect their understanding of concrete nouns. Further interactions between motor functions, action related neurotransmitters, and the brain's activation patterns and the comprehension of words are well established (see Mahon & Caramazza, 2008 for a summary). These findings indicate a strong link between actual and imagined motor control and cognitive capacities of the individual to process interactive stimuli.

This detrimental effect of damage to dopaminergic systems is not limited to interactions and interactive concepts. Parkinson's disease patients have been shown to perform comparably with normal participants when engaged in artificial grammar learning and in distinguishing category members from non-category stimuli (Reber & Squire, 1999), implying that damage to dopaminergic areas of the brain has little impact on perceptual learning tasks, such as information integration. However, Maddox and Filoteo (2001) compared Parkinson's patients to control participants in their capacity to learn RB and II tasks. They found that Parkinson's patients were just as likely to fail to learn in a RB task as controls, but were more likely to fail to learn in an II task than similarly aged controls. Maddox and Filoteo concluded that, although the basal ganglia (and its dopaminergic functions) are implicated in both RB and II task performance, different areas are utilized for each task; success in RB tasks depends upon the prefrontal cortex and the head of the caudate nucleus, while success in II tasks depends more upon the tail of the caudate nucleus (Ashby & Waldron, 1999). These findings imply that the learning of artificial grammar, RB, and II tasks all require unique neural pathways, despite their sharing multiple neural modules. Furthermore, the impact of Parkinson's disease on both motor control and category learning indicates that areas of the brain associated with motor control are also involved in the learning of category structures which, in turn, implies that these functions may be related.

The nature of this interaction between sensory motor regions in the brain and verbal cognition has been the cause of some debate as there have been several prominent theories which purport to explain these effects. The most radical of these theories, aptly identified as the *embodied cognition hypothesis* (ECH) (Glenberg, 1997), stipulates that all conceptual knowledge is inseparable from the motor and sensory systems of the individual; all memory and cognitive capacities of the individual are defined and constrained by their physical capacities to sense and interact with the environment. The weakness of this theory lies in its explanation of how we come to have and consistently utilize abstract concepts such as justice, beauty, or patience. Such concepts often do not rely on a single set of experiences actions: these concepts may be applied to a diversity of individuals, actions, or environments, yet the same concept is employed to encapsulate them. It should be noted that the presence of abstract concepts within individuals is nothing new in categorization literature (Posner & Keele, 1968; Minda & Smith, 2001; Homa, Hout, Milliken, & Milliken, 2011) and there is some evidence that the occurrence of such abstractions can arise from a cognitive system which stores such a vast array of individual experiences as unique exemplars (Nosofsky & Zaki, 2002; Zaki, Nosofsky, Stanton, & Cohen, 2003). However, the occurrence of abstract knowledge is still somewhat problematic to theories which stipulate a cognitive system which is rigidly constrained to interactivity.

To account for such abstract knowledge, two other theories have been posited which stipulate the existence of “disembodied” concepts within the cognitive system: that certain concepts cannot be reliably and directly understood or generated by motor activation alone (Mahon & Caramazza, 2008). The antithesis of the ECH is the disembodied cognition hypothesis (DCH) which stipulates that the relationship between motor activation and conceptual understanding is simple conditioning; concepts exist as abstract knowledge and the activation of the motor response system is a byproduct rather than a cause of the activation of that abstract knowledge. DCH, while explaining the finding that motor and sensory areas of the brain are activated during cognition (Hauk et al. 2004; Pulvermüller, 2005), fails to acknowledge the previously discussed impact of motor and sensory capacity on word recognition (see also Neininger & P Pulvermüller, 2003) or sentence comprehension (see also Glenberg & Kaschak, 2002). In essence, there is sufficient evidence to conclude that sensation and motor capacity are involved in concept formation and utilization, particularly when such concepts are active (e.g., hammer, kicking, chair). However, the embodied cognition hypothesis stipulates that concept use it constrained to specific instances and actions (Glenberg & Gallese, 2012) and therefore has difficulty explaining more abstract concepts such as justice or beauty which can be applied to multiple unique contexts.

Mahon and Caramazza (2008), in an attempt to explain all of these aspects of concept formation and utilization stipulated the Domain-Specific Sensory-Motor (DSSM) hypothesis which argues for the presence of abstract categorical knowledge which is grounded within, but not limited to, physical sensation and interaction. To explain this, they provide the following example regarding the concept “beautiful”:

> Consider the concept BEAUTIFUL. There is no consistent sensory or motor information that corresponds to the concept BEAUTIFUL. The diversity of sensory and motor information that may be instrumental in the instantiation of the concept BEAUTIFUL is unlimited: the mountains can be beautiful, or an idea, or the face of the beloved. The 'abstract' and 'symbolic' representation BEAUTIFUL is given specificity by the sensory and/or motor information with which it interacts in a particular instantiation. Of course, this claim could be interpreted as indicating that anything that 'happens' to be activated in the mind/brain when a given concept is instantiated is 'part of' that concept. In this regard, the analogy to spreading activation during lexical access in speech production is relevant. So for instance, when a person says to another – you are beautiful – the activation of the phonological encoding system is not, in any sense, 'part' of the concept BEAUTIFUL. On the other hand, one may be inclined to say that the perception of the setting sun behind the beloved, is in a relevant sense, part of the instantiation of the concept BEAUTIFUL in the utterance – you are beautiful.

This example illustrates that, in the using of the concept of "beautiful" the individual accesses an abstraction which has been generated from a summed experience with other sensations which are also instances of "beautiful", even if those specific sensations are not direct facsimiles of the current experience. If applied to more "interactive" concepts, such as "hammer", the concept is grounded to specific instances of hammer interaction but the concept is abstract in that the instances need not be identical. Indeed, they can be extremely diverse; even a brick can be conceived of as a hammer just as a tree stump can be conceived of as a chair (Anderson, 2003).

If concepts are indeed grounded to our interactions and perceptions, then stimulus interactivity presents an opportunity to affect, and perhaps improve, category learning. If a visual stimulus is grounded to an interactive concept, such as weights which are separated into “heavy” and “light”, then the presentation of a stimulus activates not only the visual but also motor areas of the brain associated with that stimulus (Martin, 2007). Indeed, the possibility that new concepts may be easier to learn if grounded in previously learned concepts was predicted by Seger and Miller (2010) who argued that, because brain activity involved in executive functions, motor capacities, and vision have a shared neurological workspace (basal ganglia), it is possible that activation of motor loops may facilitate in the learning process, even if those activations are the result of a resonance from imagined interactions.

Putting the Pieces Together

As has been shown, there is ample evidence to predict that there is an effect of stimulus interactivity with category learning and categorization behavior. First and most likely, there is good reason to believe that interaction may aide in participants’ learning in an II task. While II tasks typically involve the difficult process of combining sensory information from two dimensions, interactivity offers a potential method to circumvent this difficulty, given the proper context. In essence, when the rule separating categories in an II task can be expressed as a simple, unidimensional, interactive rule such as when stairs, a complex visual rule, can be expressed as a unidimensional interactive rule such as stairs being “climbable” or “non-climbable” (Warren, 1984) or a ball being catchable or not catchable (McBeath, Shaffer, & Kaiser, 1995; Oudejans, Michaels, Bakker, & Dolne, 1996). This effect should occur even when interaction is only imagined (Frak et al., 2001).

Second, there is evidence that physical interaction may engage neurological systems upon which both RB and II task performance depend. This shared neurological workspace could imply that information from one system could be informative and instructive to the other. If so, it would be fairly reasonable to expect that physical interaction with stimuli should improve accuracy in both tasks. However, RB task performance is usually not difficult for participants (Ashby, Noble, Filoteo, Waldron, & Ell, 2003). Therefore, both participant learning and end categorization performance should be unlikely to improve as participant performance should begin at nearly peak levels. Also, the presence of additional, irrelevant information such as a co-occurring task has been shown to impair learning during a RB task (Waldron & Ashby, 2001) and, therefore, the presence of additional, non-diagnostic information gained from interaction may actually impede learning. As such, the inclusion of a task irrelevant interactivity may harm performance during the RB task, potentially even to the point of impairing learning.

The current experiment was structured to test if the grounding principle is applicable in category learning and, if so, when and to what extent. In opposition to this principle are the disembodied theories of category learning: that experience and stimulus dimensional values are all that determine accuracy in categorization and, furthermore, that the potential interactivity of a participant with the stimuli has no impact on their capacity to grasp conceptual structure. Participants engaged in a Rule Based task or an Information Integration task and were given one of four different instructions: (1)

visually inspect these stimuli and then identify them as members of category A or category B, (2) visually inspect these stimuli and then identify them as one of two types of children's toy (Type A or Type B), (3) visually inspect these stimuli and then imagine interacting with these objects and then identify them as members of category A or B, or (4) visually inspect these stimuli and then physically interact with the object and then identify them as members of category A or B. If embodied cognition is capable of impacting category learning, we should predict that, if participants can ground dimensionally complex categorization rules into simpler, interactive terms they should, therefore, be able to learn to categorize stimuli into those categories easier than participants who lack such grounding. On the other hand, traditional, non-embodied explanations of category learning would predict that interactivity would not alter the learning in the II task. Given the previously discussed difficulties in predicting the effects of interactivity on RB task performance, it was unclear if any benefit of interactivity was capable of overcoming the difficulty of additional, non-diagnostic information. As such, it was predicted that there would be no effect of interactivity on performance in a RB task.

To make specific hypotheses, it was predicted (1) that participant accuracy would increase across blocks and (2) participants engaged in the RB task would reduce the number of errors made within a block faster than participants engaged in the II task. Furthermore, if category grounding though embodied cognition aides in the learning of complex categories, but not simple categories, then there should be a significant interaction between block number, instruction group, and categorization task. Follow up model analysis comparisons will compare models which either treat responses from participants in different instruction groups as responses from unique populations to models which treat all participants' responses the same. If category grounding aides in the learning of complex categories, then models which treat participant responses from interactive instructions as separate from participant responses from non-interactive instruction groups should fit the data better than models which treat those groups as the same.

CHAPTER 2

METHODS

Participants

Participants were 280 ASU undergraduate students sampled from the Psychology 101 student pool. These participants signed up for the study through the SONA system run through the ASU website. Participants were granted ½ credit hours of their participation. These credit hours are needed for the participants to receive a grade for their class.

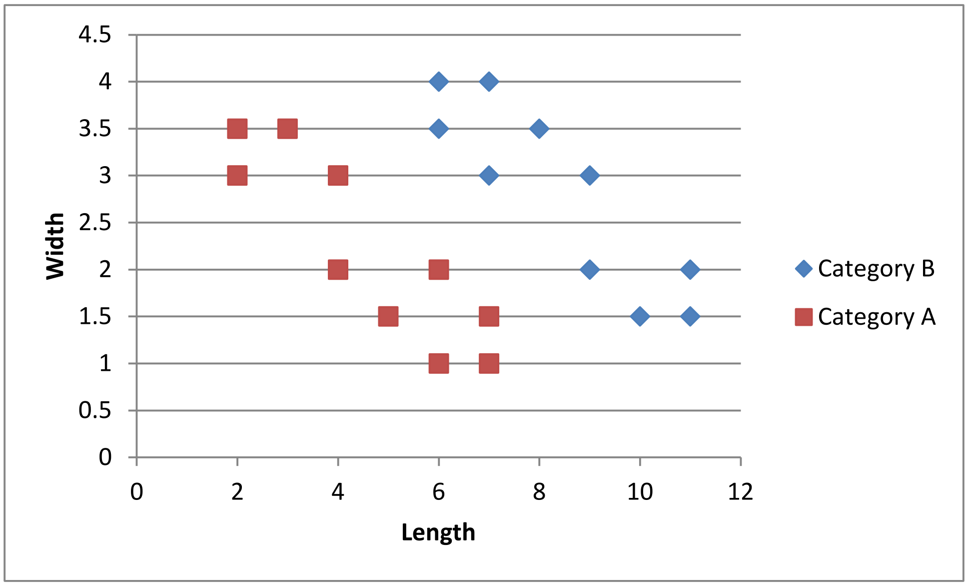
Stimuli

Stimuli were 20 wooden blocks each with a handle that was ½ in. x ½ in. x 1 in. These stimuli varied in length from 2 to 11 inches and in width from 1 to 4 inches. The stimulus dimensions are shown in Figure 1 and images of the actual stimuli are shown in Figures 2a and 2b.

Category Structure

Category structure, as experienced by participants, was determined by the feedback they were provided. In the II task, the rule to distinguish between the two categories was (as shown in Figure 1) multidimensional. For this task, stimuli for which $L > 9 - W$ (in inches) are members of category A, and stimuli for which L < 9 – W (in inches) are members of category B. In the RB task stimuli with width greater than 2.5 in. were members of group A and stimuli with width less than 2.5 in. were members of group B.

Information Integration Category Structure



Rule Based Category Structure

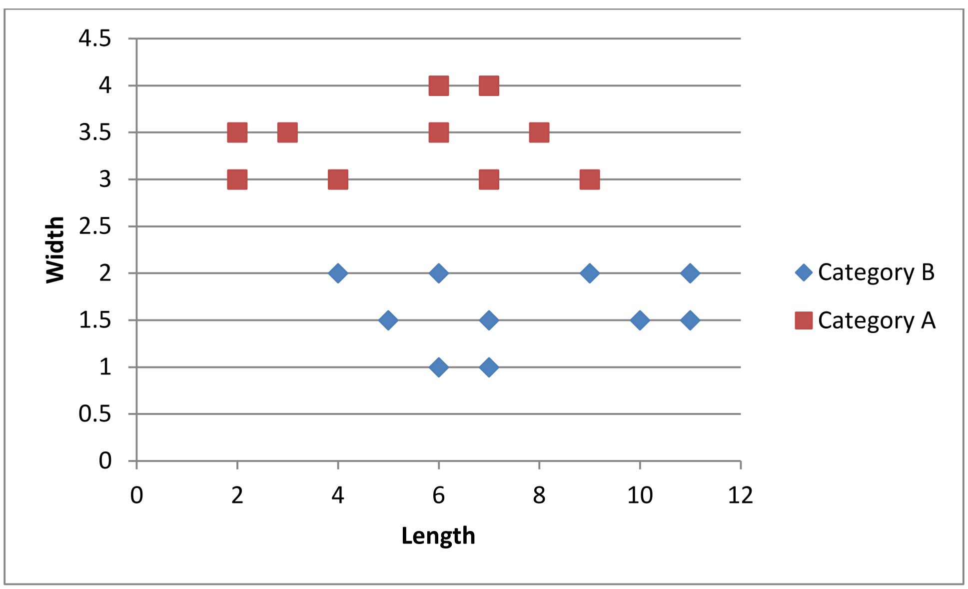


Figure 1. Stimulus Dimensions and Category Membership

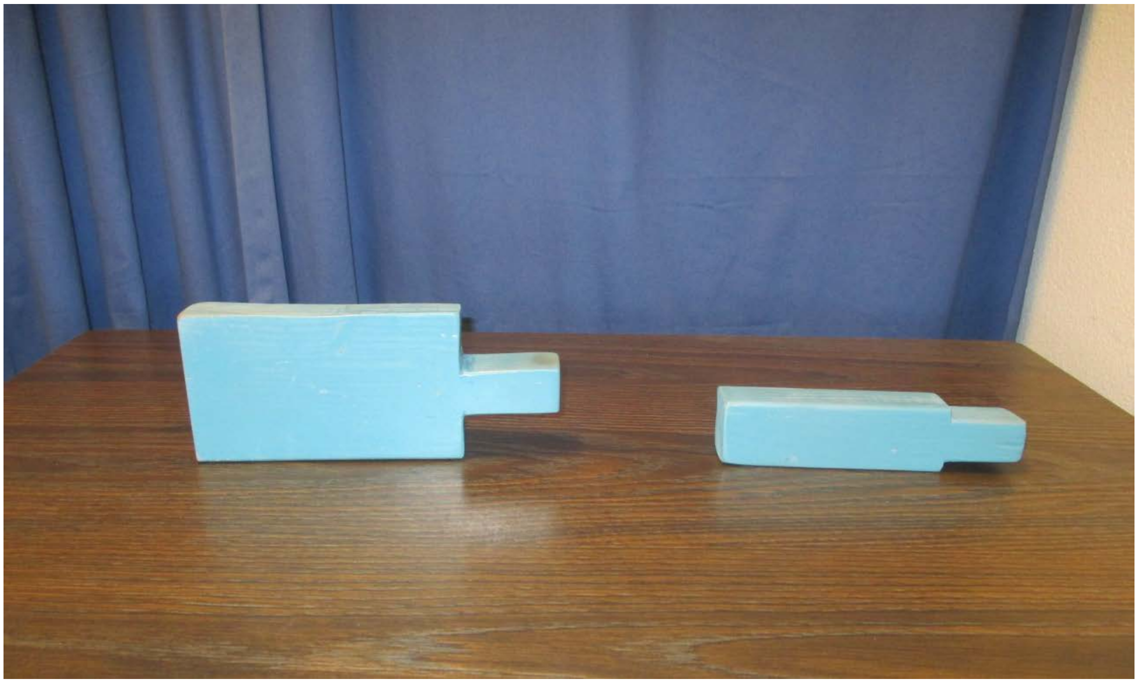


Figure 2a. Stimulus Example as viewed by participants

Figure 2b. Entire Stimulus Set

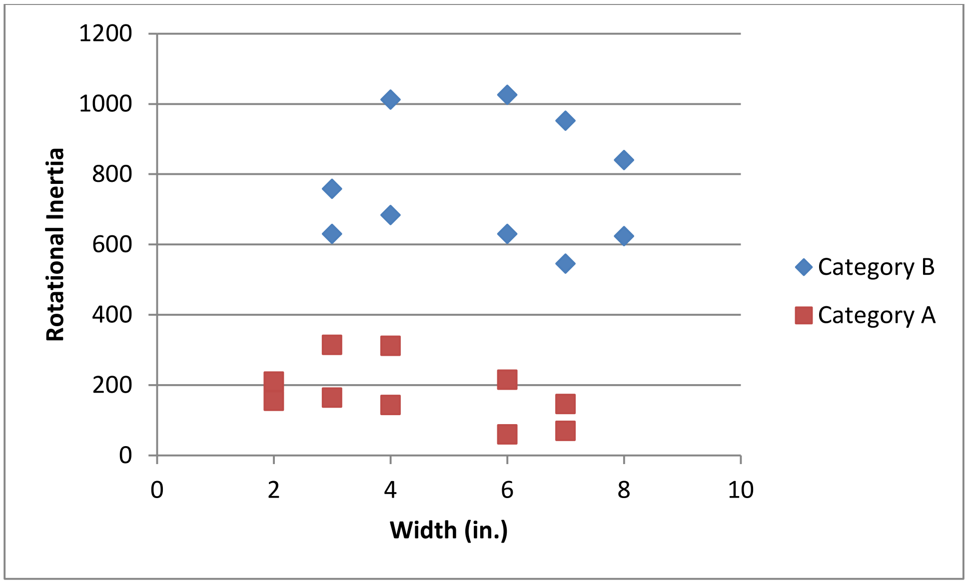


Figure 3a. II Category Structure by Rotational Inertia

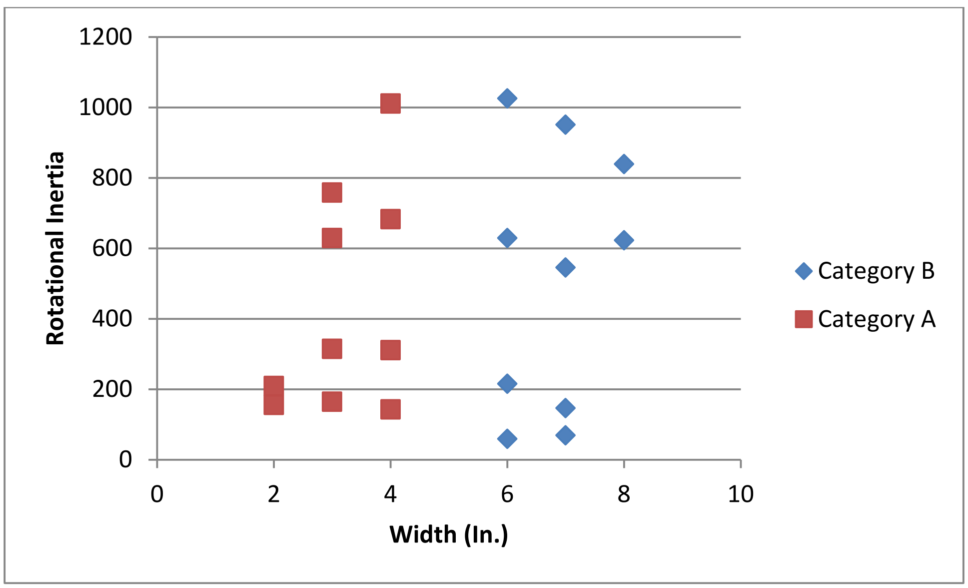


Figure 3b. RB Category Structure by Rotational Inertia

It is important to point out that the dimensions of the stimuli in the II task generate two categories which are also distinguishable by total rotational inertia such that stimuli from category B require more torque to handle than stimuli from category A. This is shown in Figures 3a and 3b which show the two different category structures as defined by width and rotational inertia where rotational inertia was roughly estimated such that a cubic inch of material at one inch distance from handle would equal one unit of torque.

Procedure

Instructions

Participants were first instructed that they will be learning to sort objects into two categories. They were then given one of four different instructions: (1) some were simply told that the stimuli belong to two different categories and they should look at the stimuli and then make their choice, (2) some were told the objects were simplistic children's toys but were instructed only to look at the stimuli, (3) some were told to imagine holding the stimuli by their "handles" and to imagine moving them around, while the object remained on the table, and (4) some were told to actually hold the stimuli by the "handles", pick them up, and manipulate them freely. The exact instructions may be found in Appendix A.

Learning

Participants went through 6 blocks of 20 trials each. On each trial, a stimulus, selected randomly without replacement, would be placed on the table in front of the participant. They would then obey their instructions (see above) and make a category assignment. They were immediately provided feedback on their judgments and the next trial would begin. Between each block, participants were given a brief reminder of their instructions.

Backwards Learning Curve

Concerns regarding aggregate data have been a constant concern in cognitive psychology, including in Multidimensional scaling of similarity data (Ashby, Maddox, & Lee, 1994) and even categorization behavior (Maddox, 1999;). The basic concern within these writings, particularly within categorization literature, is that this averaging process leads to an incorrect understanding of the behaviors of individuals. In order to investigate the effects that the instructions would have on individual behavior, rather than aggregate behavior of their groups, individual participant data was analyzed with an exploratory Backwards Curve analysis (Hayes, 1953; Estes, 1956).

For this analysis, each participant was given a score dependent upon the block in which they made half or fewer errors than the previous block. It was assumed that, prior to any experience with the stimuli, the participants would perform at chance (10 errors). The outcome of this analysis would assign to each participant a value between 1-7 defining the block in which that participant made a significant improvement in accuracy for their categorization judgments. To illustrate, a hypothetical participant, *w*, makes 4 errors on block one. He is given a score of 1 because he has made 50% or fewer errors than the initial estimate of chance performance (10 errors). Another participant, *x*, makes a total of 8 errors on block one and then 4 on block two. X is given a score of 2, because he has made 50% or fewer errors on block two than in block one. Participant Y makes 10 errors in block one, 12 in block two, then 6 in block three and is given a score of 3. However, participant Z makes 10 errors, then 9, 8, 7, 6, and finally 4. Despite having made fewer errors in each block than in the preceding block, he has never made a significant improvement, and is therefore given a score of 7.

CHAPTER 3

RESULTS

Traditional Analyses

Instruction Groups

Errors on blocks were subjected to a repeated measures analysis where block was treated as the repeated measure and participant instructions and category task were treated as between subject variables. As can be seen in Figures 4a and 4b, the results show participants made fewer errors across blocks (main effect of block), $F(5, 268) = 138.740$, $p < .001$, $\eta^2 = .721$ and participants made fewer errors in the RB task than in the II task, $F(1, 272) = 112.153$, $p < .001$, $\eta^2 = .292$. These variables interacted, $F(5, 268) = 7.825$, $p < 0.01$, $\eta^2 = .127$, such that participants made fewer errors faster in the RB task than in the II task. Lastly, the interaction between block and instructions was not significant $F(5, 810) = 1.404$, $p = .138$, $\eta^2 = .027$, and the three way interaction between block, instructions, and task was also not significant, $F(15, 810) = 1.217$, $p = .252$, $\eta^2 = .025$. All other effects and interactions were non-significant.

Interaction Groups vs. Non-Interaction Groups

Exploratory analyses were done in which the groups with “interactive” instructions (“Interact” and “Imagine”) were grouped together and the “non-interactive” instruction groups (“Kids Toys” and “A or B”) were grouped together. As can be seen in Figures 5a and 5b, the results show participants made fewer errors across blocks (main effect of block), $F(5, 272) = 138.073$, $p < .001$, $\eta^2 = .717$ and participants made fewer errors in the RB task than in the II task, $F(1, 199) = 52.520$, $p < .001$, $\eta^2 = .290$.

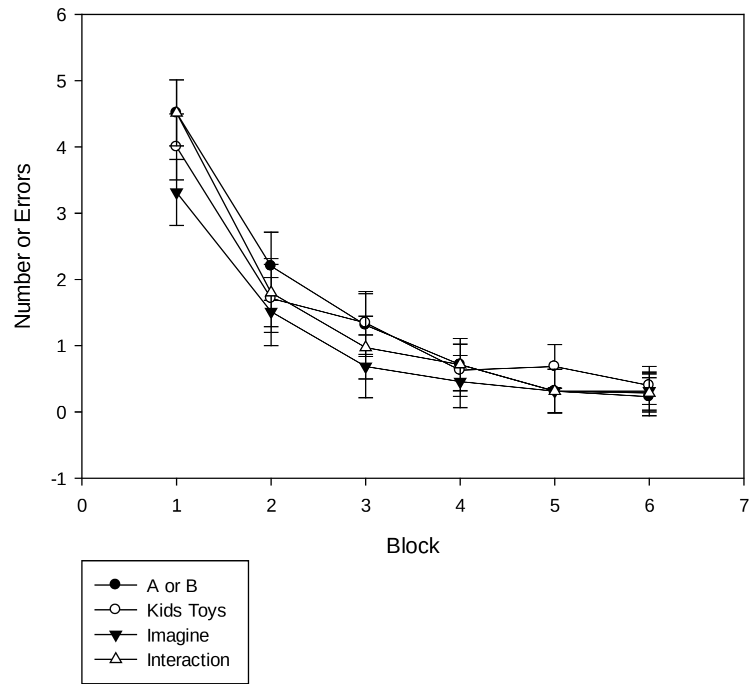


Figure 4a. Rule Based Task Errors for All Instruction Groups

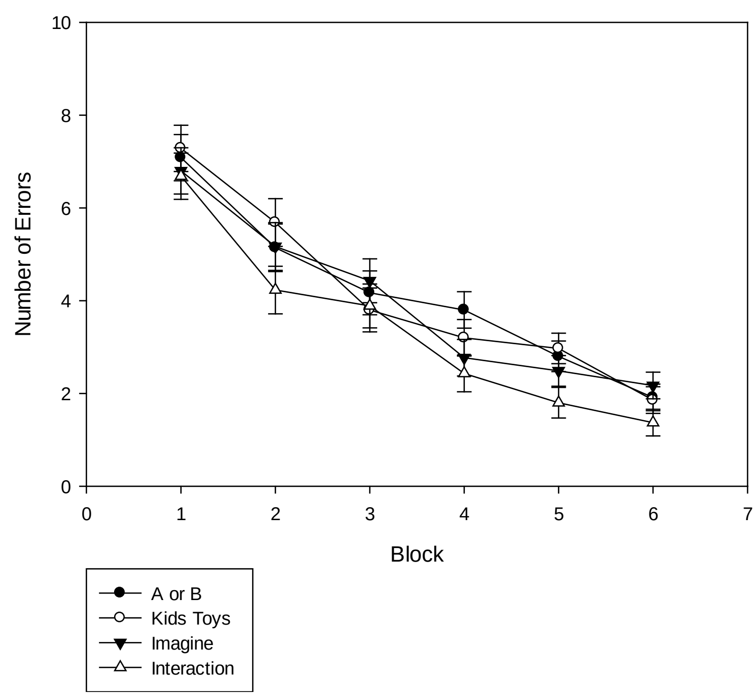


Figure 4b. Information Integration Task Errors for All Instruction Groups

These variables interacted, $F(5, 272) = 7.913$, $p < 0.001$, $\eta^2 = .127$, such that participants made fewer errors faster in the RB task than in the II task. Lastly, while the interaction between block and instructions was not significant $F(5, 272) = 1.773$, $p = .119$, $\eta^2 = .032$, there was a significant three way interaction between block, instructions, and task, $F(5, 272) = 2.368$, $p = .040$, $\eta^2 = .042$. This interaction implies that participants' improvement across blocks was significantly affected by interactive definitions in the II task, but not in the RB task. Again, referring to Figures 5a and 5b, this effect was not linear (implying that the difference in learning between interactive and non-interactive stimulus definition groups was not that one was simply more accurate than the other). Post-hoc contrast analyses confirm that this effect is not linear, $F(1, 276) = .163$, $p = .687$. All other effects and interactions were non-significant.

Backwards Learning Curves: Instructions

A univariate ANOVA was run comparing the Backwards Learning Curve data between instruction groups. Participants engaged in the RB made significant improvements in accuracy in earlier blocks (M=1.64) than participants engaged in the II task (M=3.48), $F(1, 272) = 76.900$, $p < .001$, $\eta^2 = .220$.While there was no significant difference between instruction groups alone, $F(1, 272) = 1.713$, $p = .165$, $\eta^2 = .019$, there was a significant interaction between instruction group and category structure, $F(3, 272) = 2.654$, $p = .049$, $\eta^2 = .028$. As can be seen in Figure 6a, participants engaged in the RB task did not vary highly as a result of instruction group, while instructions had a significant impact on participants engaged in the II task.

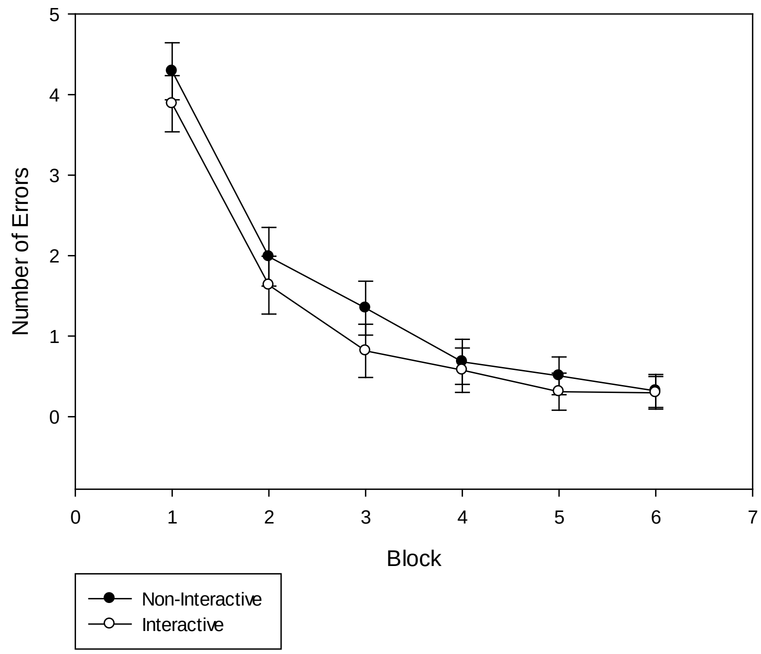


Figure 5a. Rule Based Task Errors for Interactive and Non-Interactive Definitions

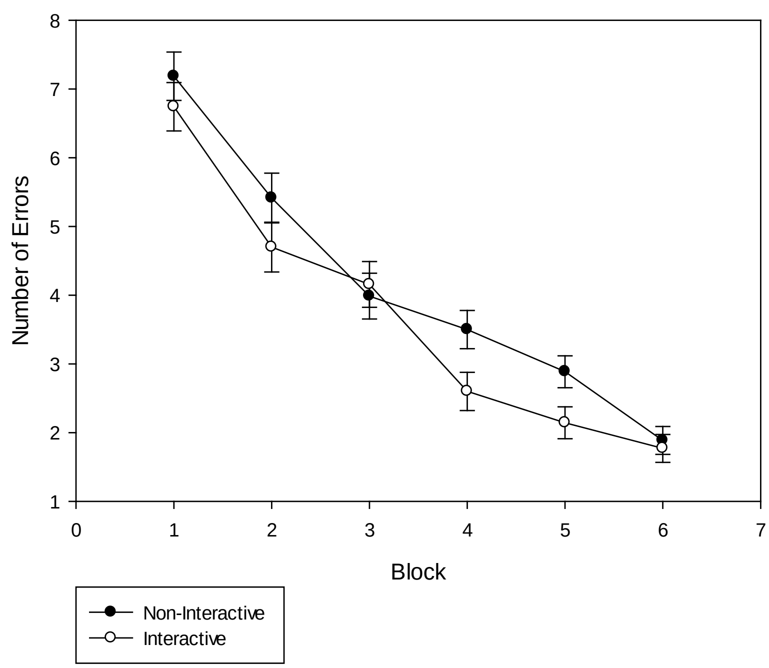


Figure 5b. Information Integration Task Errors for Interactive and Non-Interactive Definitions

Backwards Learning Curves: Interaction Groups

Just as with the learning data, another analysis was done comparing the Backwards Learning Curve data between Interactive groups with non-interactive groups (See Figure 6b). Just as before, participants engaged in the RB task made significant improvements in their accuracy earlier than participants engaged in the II task, $F(1, 276) = 75.554$, $p < .001$, $\eta^2 = .215$. Participants with Interactive stimulus (M=2.36) made marginal improvements (not significantly) earlier in learning than participants with non-interactive definitions (M=2.76), $F(1, 276) = 3.560$, $p = .060$, $\eta^2 = .013$. There was no interaction between stimulus definition group and task, $F(1, 276) = 0.549$, $p = .549$, $\eta^2 = .002$.

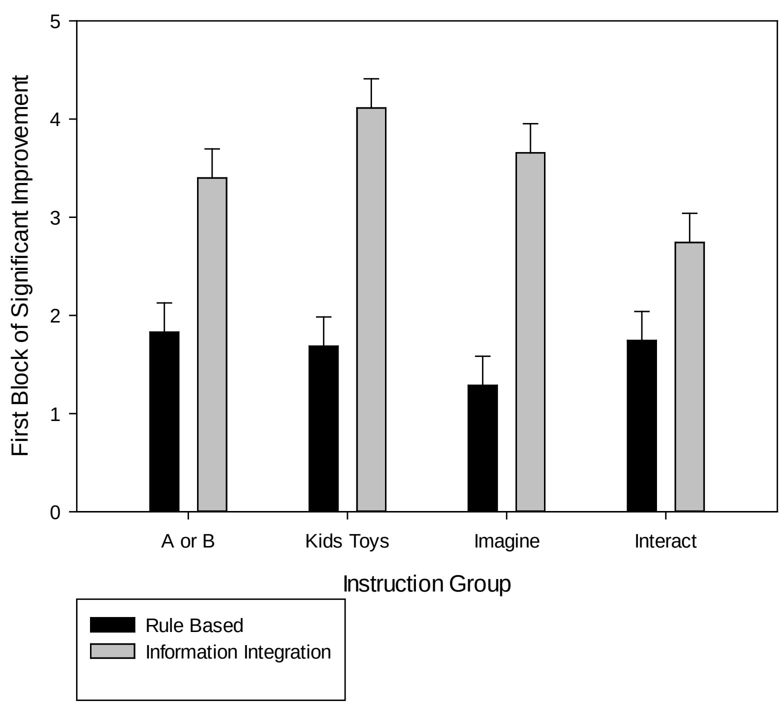


Figure 6a. Significant Improvement Block by Instruction Groups

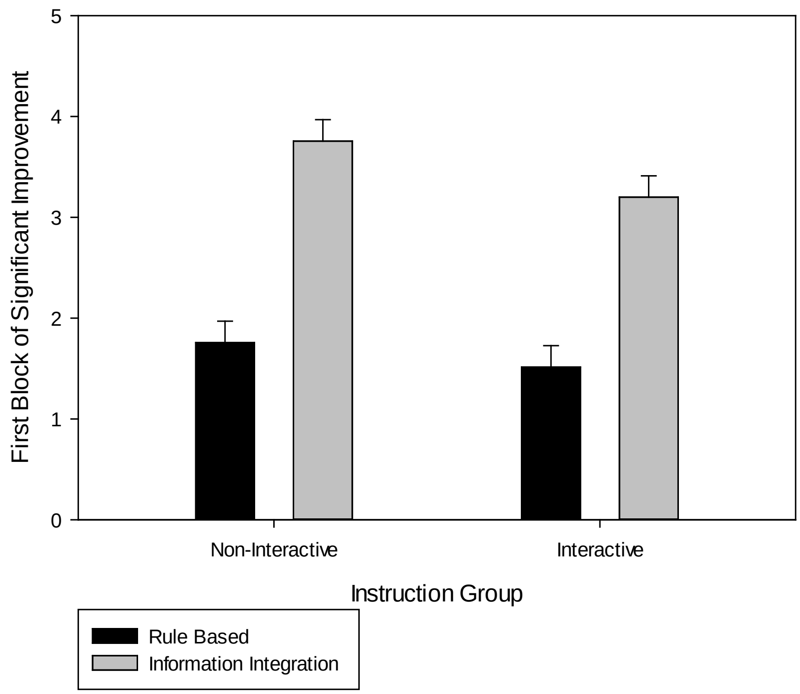
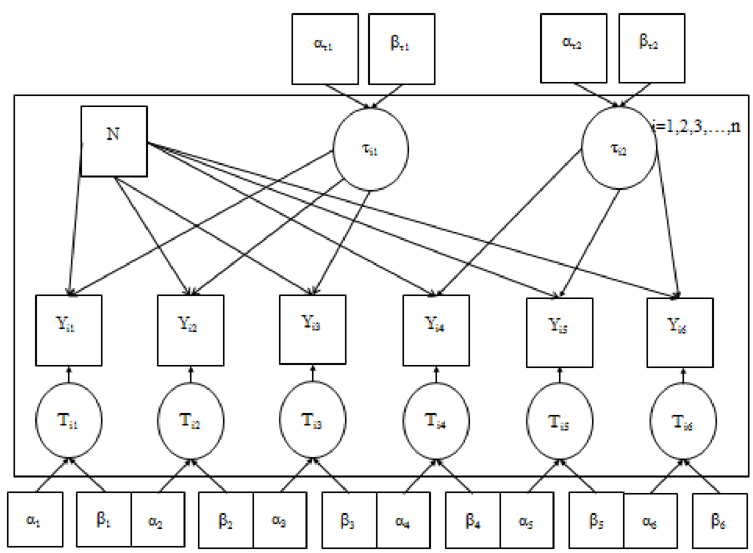


Figure 6b. Significant Improvement Block by Interaction Groups

Bayesian Model Comparisons

To further investigate these results, three different Bayesian models were measured for the degree to which they fit the results presented. All models are based around the same basic structure shown in Figure 7. In essence, the function of each model is to attempt to predict, given the parameters and their interactions with one another, the number of errors a sampled participant will make within each block. As such, the model has a number of interacting parameters. The simplest parameter, N, is the number of trials (and therefore possible errors) in a given block. This value is fixed at 20. The next parameters to consider are T_1 through T_6. These parameters are meant to imply the degree of accuracy of the participants sampled in blocks 1 and 6, respectively. These parameters are multiplied by the total number of possible errors, N, to predict the number of errors in each block. As such, the greater the value of T, the more errors the model predicts that participants will make in that given block. T is not a fixed value, and is instead given a distribution of possible values; a beta distribution, bounded to be between 0 and 1 (100% accuracy and 0% accuracy respectively). Finally, this predicted number of errors is expected to vary, and so the predicted outcome from the interaction of N and T is given a precision of τ, or tau. This precision can be more easily understood if conceived of as variance, where the variance of the estimated number of errors is equal to 1/ τ. As such, the greater the value of τ, the more accurate the model assumes its predictions will be. Tau is given a gamma distribution, which is bounded between 0 and infinity, (which prevents the model from predicting negative variance) and assumes that lower values are more likely than higher values (assumes greater variance than less). In sum, the basic model attempts to predict the number of total errors on a given block of trials (Y) by integrating the other parameters of the model, N, T, and τ.



Note. Priors, including the distributions utilized for each parameter are given in the appendix.

Figure 7. Basic Bayesian Model

As a reminder, the basic process of Bayesian inference takes these prior distributions of possible values for a given variable (in this instance T) and updates them depending upon the distribution of probable scores given the data. WINBUGS, the software used for this modeling, uses Gibbs sampling to construct this posterior distribution. In brief, this method assigns values to the variables being analyzed (for the AGSL this means T for block 1, T for block 2, etc.). The software then attempts to choose a new value for one of the variables, say T1, by (1) choosing a random new value for T1 and then (2) sampling from the data. If the new value for T1 or the current value of T1, combined with the values for the other variables, T2-T6, fits the sampled data better, the model updates T1 to the new value. If not, it keeps the old value. The software then attempts to update the next variable in the sequence, T2 using the same methods and the new, or old, value of T1. This continues on through each variable until all variables have been updated. One run through all variables is considered a single “sample”. After a large number of samples have been taken, what is left is a distribution of possible values for each variable and with the best fitting values being more likely to be sampled; thereby giving those parameter values the highest probability density with similar values also having high probability.

The measure used to determine model fit is the Deviance Information Criterion (DIC). A model’s DIC is a measure of how well the variable values sampled from the distributions deviate from the data. The lower the DIC, the better the variables approximate the data. The DIC also incorporates a measure called ‘p_D’ which increases a models DIC for each parameter added. This, in essence, penalizes models for adding extraneous parameters to account for variability. The procedure, then, is to have a measure of DIC for each model such that the model with the lowest DIC is considered to be the best model fitting the data.

The three models analyzed using these methods were different from one another not in the basic construction of the model, but in how many iterations of the model were utilized to fit to participant responses and how participants' data were entered into those versions. The hypotheses of the present experiment questioned if interaction, even imagined interaction, would allow for participants to learn complex categories faster than participants who lacked any interactive insight. The first model is called the "All Groups Same Learning" (AGSL) model, and it assumes that there was no difference between participants learning over blocks as a result of instructions. It uses only the basic model and it lumps all participant responses for a given block into the same distributions regardless of their instruction group. The second model is called the "All Groups Different Learning" (AGDL) model. It stipulates four different iterations of the basic model for each instruction group. The third model is the "Interactive Groups Different Learning" (IGDL). It utilizes two iterations of the basic model which samples participants' errors for a given block depending upon whether they were given interactive ("Interact" or "Imagine") or non-interactive ("Kids Toys" or "A or B") instructions. These three different models, their assumed distributions, and their priors are detailed in the appendix.

Multiple Sampling Chains

When generating each model, each parameter was given a random initial value. In order to prevent these initial values from biasing the final distributions, each model was given three different sets of initial parameters, or 3 "chains". These chains were first run through 10,000 samples after which it was assumed that they were no longer biased by their initial starting values. These 30,000 samples (total) were not included in any analyses. Then an additional 100,000 samples using these three chains (for 300,000 total) were run to generate the posterior distributions and to gain the measure of the DIC.

Bayesian Modeling Results

As can be seen in Table 1, AGSL had the lowest DIC, followed by the IGDL and finally the AGDL for not only the RB task but also for the II task, regardless of whether or not the data contained only participants who reached the learning criterion. It should be noted that the IGDL model always fit the data better but the additional parameters of the IGDL model increase its DIC such that the AGSL was always considered to be the better model to describe the data gathered.

Table 1. Model DIC

II Task Data

Model	D_{Bar}	p_D	DIC
AGSL	4178.970	7.969	4186.940
AGDL	4179.820	25.301	4205.120
IGDL	4175.660	13.864	4189.530

RB Task Data

Model	D_{Bar}	p_D	DIC
AGSL	3383.270	7.737	3391.010
AGDL	3386.690	22.365	3409.050
IGDL	3382.770	12.946	3395.720

CHAPTER 4

DISCUSSION

The present experiment was designed to determine if stimulus interactivity, imagined or otherwise, would aide in the learning of complex categories. While averaged accuracy of participants showed no significant beneficial effect of interactive instructions on learning, individual analysis of participants' improvement across blocks revealed that participants with interactive instructions made significant gains in learning during earlier blocks than participants with non-interactive instructions. Furthermore, while the Bayesian model comparisons showed that the AGSL model was the best fitting model, the IGDL model was actually a better predictor of participant accuracy and is described as a less fitting model only due to the additional parameters of the model. These results seem to indicate a consistent, albeit minor, effect; that stimulus interactivity provided a small benefit to category learning.

By no means should one consider this study and its results a full-throated confirmation of this potential benefit. Rather, this claim should be considered with the understanding that this study was aimed at detecting the presence of an effect given the most basic of experimental constraints. The only real differences between the present experiment and other similar categorization experiments conducted with the same category structures (e.g., Ashby & Gott, 1988; Maddox, Ashby, & Bohil, 2003) was the nature of the instructions and the use of physical rather than computer generated stimuli.

Yet, these simple differences resulted in a non-trivial impact on participants' categorization accuracy. It is, therefore, likely that there exist more impactful alterations to instructions and to the stimulus dimensions, which may allow participants who interact with stimuli a more potent benefit to category learning and concept formation.

That being said, the structure of the categories in the II task was designed such that interactivity would allow participants easy access to an interactive, unidimensional rule, rather than having to rely on a difficult to learn multidimensional visual rule. Therefore, it is not unreasonable to have expected that participants with interactive access should have learned to categorize at similar rates when engaged in either the II or RB tasks. However, when considering just those participants with interactive instructions, participants engaged in the RB task made their first significant improvement an entire block sooner (M=1.743) than participants engaged in the II task (M=2.743). While this difference is too large to claim that participants in the two groups made significant improvements in categorization accuracy with similar amounts of experience, it should be noted that, participants who were given different instructions, showed larger differences in learning between task types (RB vs II). For participants with A or B instructions, participants engaged in the RB task made their first significant improvement in accuracy nearly two blocks sooner (M= 1.829) than participants engaged in the II task (M=3.400) and similar effects are found when considering participants with Kids Toys instructions (M=1.686 vs M=4.114) and with imagined interaction instructions (M= 1.286 vs M=3.657). We can, thereby, say with some small amount of confidence that participants who actually interacted with the stimuli were able to access the unidimensional rule of torque when engaged in the II task, making the learning of category structure easier.

Instructions and Interactions

The qualitative self-report of participants also supports this claim. Among those participants who engaged in the II task, many who received interactive instructions reported categorizing stimuli according to some measure of torque or weight; they used the difficulty they experienced when manipulating the stimuli in their judgments of category membership, rather than visual information. In contrast, very few participants, even among those who were instructed to imagine picking up the objects, made similar reports. They instead often offered overall object size (e.g. B's are bigger than A's) as an explanation for their categorization decisions. It should be noted that there were some participants who engaged in the II task who also reported using stimulus "weight" in their judgments outside of the interaction instruction group. However, these cases were much less frequent.

Perhaps surprising, instructions seemed to impact the self-reported explanations for categorization behavior for participants in the RB task as well. Several participants in both the imagined and actual interaction instruction groups reported using an interactive categorization rule of "difficulty to pick up". In this paradigm, stimuli in category B (the thinner category in the RB task) were perceived as more difficult for participants to pick up due to an insufficient distance between the handle and the table for the participants' thumbs to fit under to allow for lifting the block. Again, just as with the reports from the

II task, this effect was not universal, with many participants in both the imagined and actual interaction instruction groups reporting using the visual rule of stimulus width to determine a stimulus' category membership.

This illuminates what is likely the aspect which most cripples the formation of any bold conclusions for the current experiment: for those participants engaging in the II task, the unidimensional, interactive rule was not universally perceived and learned by participants who could physically interact with the stimuli. This is an important factor in establishing the context of current marginal results. It suggests a significant difference between the perception of the stimuli from the current experiment and the perceptions of stimuli such as stairs (Warren, 1984) or passable gaps such as doorways (Warren & Whang, 1986). One of the critical differences between these examples and the present experiment was that the categories in the present experiment are defined by an interactive definition which delimitates a level of difficulty, rather than the boundary between possible and impossible action. This represents a qualitative distinction between the present experiment and previous experiments regarding the immediately perceived affordances or non-affordances of the environment.

The nature of affordances is that they are immediately perceived aspects of the environment based not only on the dimensions of the environment but also upon the *capacity* of the agent perceiving them to interact with them (Gibson, 1979). In essence, affordances are binary dimensions: they either exist or do not. A surface is either considered stable, solid, and angled properly so that it can be traversed, or it is not, and this is immediately perceived by the agent, guiding its action. If cognition is to be grounded by way of these affordances, such as in the example of the chair, it may be difficult for such a system of perception and action to deal with complex category boundaries which are not interactive absolutes; the “ease of action” is not as easily perceived as the “capacity for action”.

Yet, while it is a reasonable explanation that the weak effects expressed in the current experiment are due to this distinction between ease of action and capacity for action, it forgoes the fact that we are capable of understanding that certain tasks are easier than others. It is easier to hit a thrown ball with a bat if the ball is traveling at 25 miles per hour than if it were traveling at 95, yet the capacity for both actions exist. We are just as capable of sitting down on a tree stump which is 3 feet wide as a tree stump 1 foot wide, although we understand that one is easier to balance on than the other (as well as being more comfortable). In essence, it is possible that complex stimuli and environments may be definable by unidimensional, interactive rules, some of which are absolute while others are relative. However, it is a safe assumption that we learn and utilize absolute boundaries, such as the capacity for action, differently than relative boundaries, such as ease of action. Whether this is a function of perceptual input or feedback is at this time unclear. However, given the findings of Tanaka and Taylor (1991), these boundaries, even absolute boundaries, may only become clear with extensive experience.

The Bigger Picture

Taken in whole, the results of this experiment indicate important aspects regarding the relationship between stimulus interactivity and categories and concepts by which we define those stimuli. First, given that instructions had differential impacts on participants’ category learning as a result of category structure, it is concluded that stimulus interactivity has a strong connection to categorization behavior when categories and concepts are intimately tied to interactive capacities between the stimulus and the agent. However, when dealing with category structures which are not well defined by interactivity (such as the RB task in the present experiment) or instances in which interactivity is not explicitly used in the construction of categories, interactivity is not related to concept formation or use.

While it tempting to derive conclusions on the strength of the various embodied cognition theories given the present results, such a step would not be wise at this time. The current results do show that individuals are more likely to incorporate interactivity into their category definitions when they are allowed to actually interact with the stimuli. However, this does not necessarily eliminate the viability of disembodied cognitive explanations. The interactive category rule in the II task is unidimensional, and should, therefore, be dominant (Ashby, Queller, & Berretty, 1999). As such, rather than considering the finding that some participants with interactive instructions utilized the interactive rule to be a surprising result, it could actually be considered odd that participants with interactive instructions did not utilize the simpler rule more reliably. We must also consider the knowledge that a great deal of support for embodied theories of cognition rely on tasks using imagined interactivity, such as the imagined grasping of objects (Frak, Paulignan, & Jeannerod, 2001). In the present experiment, however, participants who imagined lifting and wielding these objects in the present experiment showed no to little benefit to categorization accuracy in the II task, compared to participants who actually interacted with the objects. This is more a curiosity than a strong test of embodiment and indeed the sum of these findings do not allow for a strong confirmation or disconfirmation of embodied theories of concept learning and use, allowing only the conclusion that stimulus interactivity may be used in concept learning in instances where interactivity is not only active, as opposed to imagined, but also uniquely informative (II task).

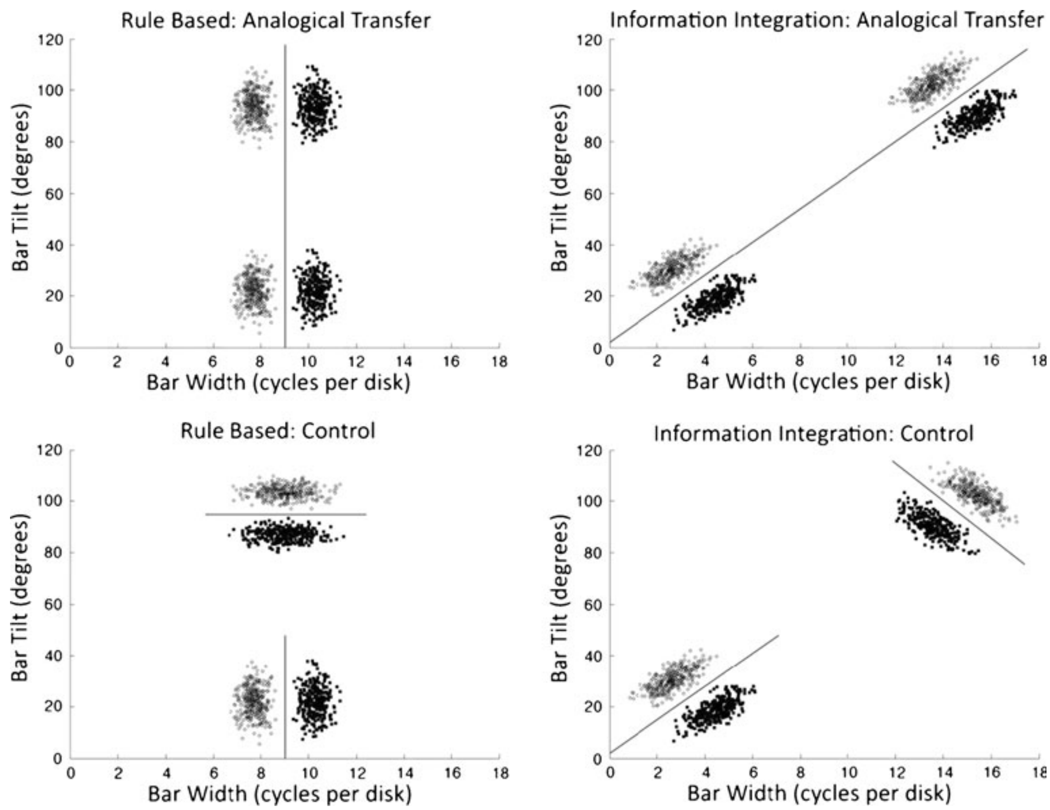
However, determining graspability is innately tied to physical interaction while mere identification does not necessarily require interactivity. Therefore, it is possible that imagined interaction may yet yield results similar to actual interaction when it comes to affecting category learning, but this may be limited to instances in which the goal of the interaction with a stimulus is more than identification. For example, one of the vital points for learning the differences between chairs and tables, which share a great deal of important characteristics both physical (solid, sturdy, above ground level, etc.) and interactive (e.g., a surface to support weight that also allows objects placed on it to remain in place), is that they are used to support different objects; namely that chairs are meant to support people while tables are meant to support objects. Individuals may, therefore, benefit from using imagined interactions when learning to differentiate between these two concepts. In fewer words, imagined and actual interactions may show similar effects on concept formation when concepts are defined by an interactive goal which depends upon a dimensional rule rather than when the concept is defined by the dimensional rule alone.

If the goal or intent of interaction is vital to concept formation, then the impact of interactivity on concept formation may well be found within such interactive concepts such as hammers, stairs, and chairs. However, it is still unclear if interaction, with or without intention or goals, will have any impact on the learning of more abstract concepts such as “beauty” or “justice”. While it may be the case that interactivity is the progenitor of many concepts and categories, it may be just as difficult to define the specific interactive origins of such abstract concepts as it is to confine those defining interactions to a specific intention. The concept of justice, for example, may be invoked by many potential interactions. A thief may be imprisoned, fined, have his hand cut off, or even be forced to apologize and return the stolen goods. These interactions are unique, and so are their intentions: some are meant to be deterrents, some are meant to isolate, and some are meant to recompense those injured. While there are likely significant differences in how an individual defines justice, each of these instances can be said to be representative of the concept of justice for that individual. As such, it may be that the diversity of both the defining interaction and intentions may limit the impact of interactivity on the use of such abstract, diverse concepts despite the possibility that interactivity is essential for the learning and formation those same abstract concepts,

Future Directions

The results of the present experiment present several opportunities for future research. The first aims to improve upon the construction of the present experiment through some minor alterations. As previously stated, it is likely the effects witnessed in the present experiment may have been tempered due to the categories' interactive rule being defined by ease of action, rather than absolute capacity. Ideal future learning tasks could perhaps increase the beneficial effects found in the present experiment by having the rule come closer to these more absolute rules. Of course, these interactive rules are subject to the interactive capacities of the individual (Gibson, 1979; Warren, 1984; Warren & Whang, 1986), so establishing the rule for "capacity to interact" will be subject to alterations between participants. There is also the possibility that merely coming close to this capacity to interact will improve learning. Say, for instance, that a future experiment, utilizing similar stimuli establishes category B as being heavier than category A by virtue of a multidimensional rule just as in the present experiment. However, unlike the present experiment, several members of category B should be nearly impossible to lift/manipulate. Perhaps access to absolute interactivity would increase the likelihood of participants utilizing the interactive rule, thereby avoiding the difficulties inherent in the II task.

Next, there exists the possibility that conceptual grounding may aide in the transfer of rule information to new experiences. Casale, Roeder, and Ashby (2012) looked at the capacity of participants to extend a learned linear categorization rule, either unidimensional (RB task) or multidimensional (II), to new stimuli with dimensions which placed them close, in psychological space, to that same rule (see Figure 8). They found that participants were much more successful transferring the rule to new stimuli in the RB task compared to the II task. They argued that such "analogical" transfer is difficult for rules learned in the II task because such learning is dependent upon knowledge of unique perceptual combinations rather than an attention based assessment of a single dimension (Maddox & Filoteo, 2001). Here, again, the possibility of conceptual grounding offers a potential, beneficial effect. If interactivity allows for participants to express multidimensional, vision-based categorization rules in terms of a unidimensional, interactivity-based rule, then it is likely that interactivity may allow participants to transfer a supposedly II rule as if it were a RB rule. The potential benefit of allowing individuals to easily transfer supposedly complex distinctions to new stimuli with relative ease represents a huge potential benefit which should not be ignored.



**Note.* This figure has been adapted from "Analogical transfer in perceptual categorization." By Casale, M., Roeder, J., & Ashby, F. (2012), *Memory and Cognition, 40*, 434-449. Copyright 2012 by the American Psychological Association.

Figure 8. Analogical Transfer in II and RB tasks

There also remains the possibility that the reason interactive instructions lacked any strong effect in the present experiment was due to the task: participants were learning to identify objects rather than on how to interact with them. This task demand may have caused participants to attend more to visual dimensions of stimulus (length and width) and less upon the interactive dimensions (weight/wieldability) of the stimuli. As such, it may be possible that participants with actual or imagined interactions may be more likely to use interactivity in their categorization of stimuli if their learning of categories was defined by the learning of an interactive goal. To illustrate, let us consider the possibility of teaching a young child the difference between a hammer and a wrench. To an adult, this difference may be intuitive, yet to a child who is first experiencing these objects, their visual similarities (e.g., thinner on one end, weighted on one end, metallic, etc.) may lend themselves to confusability. Even early interactions may not necessarily allow for distinction as simply lifting and wielding the objects will not necessarily illuminate their unique functions. It is when each tool is paired with its interactive partner, the hammer with a nail and a wrench with a bolt, that the tools are easily distinguishable. To test this possibility in a future experiment, participants could learn to sort the same stimuli as the present experiment into two groups, however, in interacting with the objects they would be asked to use the stimuli to hammer small pegs into a board. In such a setup, those stimuli with more "weight" would be better "hammers" in essence allowing the same interactive rule to imply an interactive use to the object rather than an interactive rule left unrelated to object use.

Finally, there remains the grand, yet distant outcome of utilizing grounded cognition to aide in the learning and instruction of complex, and potentially abstract concepts. It has been theorized that abstract concepts, such as mathematics, are embodied concepts; grounded to our capacity to interact with the world (Nuñez, 2000). A strong piece of evidence said to support this claim has been the findings that instructors frequently utilize gesture in their explanations and descriptions of a variety of rules in mathematics and physics. Indeed, children taking a test covering a mathematical principle performed better when given prior instructions which included instructional pointing than when given instructions without pointing (Valenzeno, Alibali, & Klatsky, 2003). However, this type of research is the exception rather than the rule regarding the potential influence of conceptual grounding to the learning of complex information. A large portion of the research on this topic has focused on describing the actions of teachers attempting to explain this material to students, with little concern for its efficacy (see Alibali & Nathan, 2012 for a summary). Additional research, akin to that of the present experiment as well as the work of Valenzeno et al. (2003) should seek to offer greater insight into the potential impact of conceptual grounding to the learning of complex concepts by controlling the types of instructions students receive, rather than by simply observing it.

Conclusions

Grounded cognition offers a potentially beneficial and easily accessible method to aide in the learning of complex concepts by simplifying them to a more immediately available relationship between the individual and the environment. This possibility has important implications in potentially understanding how we learn complex rules and offers potential learning aides, so investigating it further is worthwhile. While the current results allow for some small confidence in the capacity of conceptual ground and stimulus interactivity to aide in learning, there remains much work to be done to flesh out the extent and limitations of this strategy.

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APPENDIX A

INSTRUCTIONS GIVEN TO PARTICIPANTS

To all participants:

"Thank you for your participation. If at any time you feel as though you cannot continue, you may stop the experiment at no penalty. Your task today will be to learn how to sort a series of objects into two distinct groups. You have never seen or interacted with these objects before so, at the beginning of the experiment you will have no idea as to which group an object belongs to, but you will learn, and here's how: I will take these objects one at a time and place them on the table in front of you."

Then the instructions diverge

A or B:

"You will then look at, but not touch, the object and then make your best guess as to whether it is an "A" or "B". "

Kids Toys:

"The objects are simplistic children's toys made out of wood. You will look at, but not touch these toys, and make your best guess as to whether it is a "Type A" or "Type B" toy."

Imagined Interactions:

"You will look at each object and imagine picking it up with your right hand on the right side of the object. Imagine manipulating the object: waving it around, swinging it, etc. I only ask that you don't imagine rotating the object so that you could see the opposite side. After imagining interacting with the object, make your best guess as to whether the object is an "A" or "B"."

Actual Interactions:

“You will look at each object and the pick it up by the right side with your right hand. Feel free to manipulate the object: waving it around, swinging it, etc. I only ask that you don’t rotate the object so that you could see the opposite side. After imagining interacting with the object, make your best guess as to whether the object is an “A” or “B”.”

Then the instructions converge

“After you have made your judgment, I will tell you if you are correct or incorrect. Then I will take the object behind the curtain and replace it with another. And the process will repeat. After going through each object once, we will repeat the process again, going through each object randomly. We will go through a total of 6 rounds. At the beginning of this experience, you will be simply guessing, but as we go through more and more stimuli, you will get better. Do you have any questions?”

APPENDIX B

BAYESIAN MODEL PRIORS

$N = 20$

$\tau_1 \sim \text{dgamma}\ (\alpha_{\tau 1}, \beta_{\tau 1})$

$\alpha_{\tau 1} = 1$

$\beta_{\tau 1} = 1$

$\tau_2 \sim \text{dgamma}\ (\alpha_{\tau 2}, \beta_{\tau 2})$

$\alpha_{\tau 2} = 1$

$\beta_{\tau 2} = 1$

$T_k \sim \text{dbeta}(\alpha_k, \beta_k)$

All $\alpha = 2$

All $\beta_1 = 2$

All $\beta_2 = 3$

All $\beta_3 = 4$

All $\beta_4 = 5$

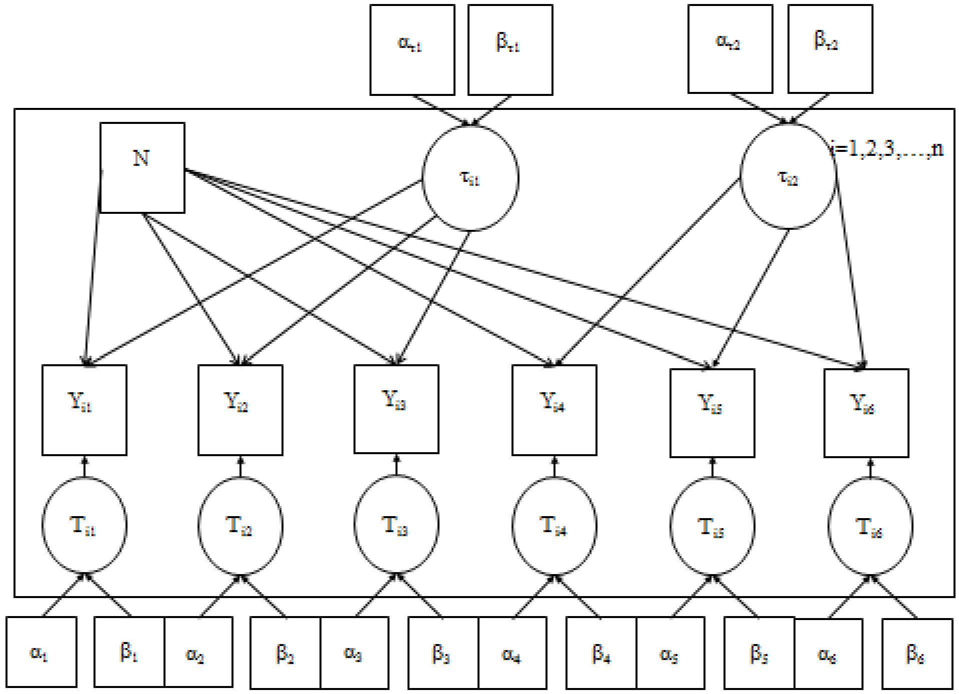
All $\beta_5 = 6$

All $\beta_6 = 7$

APPENDIX C

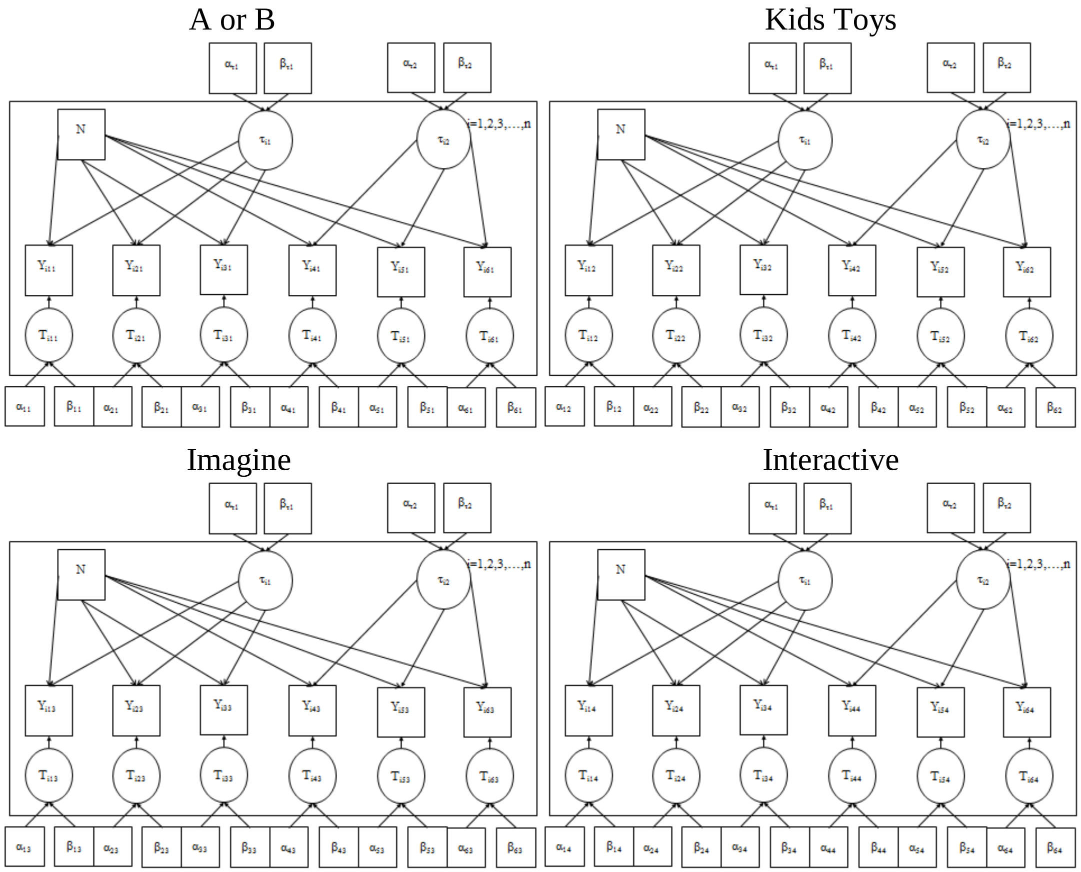
BAYESIAN MODELS

AGSL Model



ατ1
βτ1
ατ2
βτ2
N
τi1
τi2
i=1,2,3,…,n
Yi1
Yi2
Yi3
Yi4
Yi5
Yi6
Ti1
Ti2
Ti3
Ti4
Ti5
Ti6
α1
β1
α2
β2
α3
β3
α4
β4
α5
β5
α6
β6

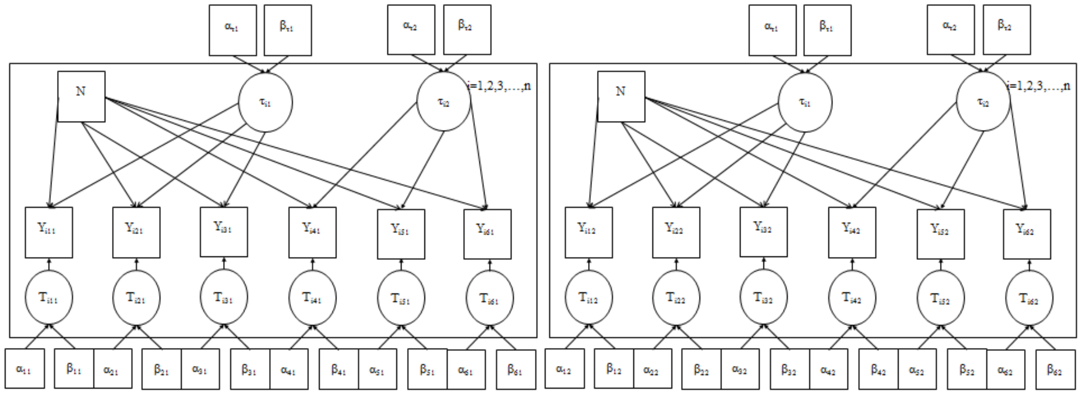
AGDL Model



IGDL Model

Non-Interactive

Interactive



BIOGRAPHICAL SKETCH

Thomas Crawford is a Cognitive Psychologist with a research interest focused primarily on categorization behavior with a strong focus in complex rule learning, physical stimuli, and order effects on categorization behavior. He also has other interests in ecological psychology and dynamic/complex mental processes. He will begin teaching psychology at Bethel University in the Fall of 2014.