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Does Perceptual Learning from Pre-exposure Affect Category Learning?

by

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Under the Direction of J. David Smith, PhD

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ABSTRACT

Multiple-systems theorists assume that different brain systems facilitate different types of category learning. This project focuses on whether perceptual learning facilitates family-resemblance category learning. Rhesus macaques were tested to see if they were able to learn a single category prototype and also learn about two category prototypes simultaneously through mere exposure. Classic COVIS theory predicted exposure would benefit learning a single category prototype but not learning simultaneously about two category prototypes. COVIS plus theory predicted exposure would benefit in both situations. Results showed that exposure was clearly beneficial when learning a single category, but harmed learning two categories. Results from prototype modeling suggest that relevant exposure did allow the macaques to build two separate prototype representations but did not aid categorization. This was not predicted by either theory. Further research needs to be done to distinguish between the two theories.

INDEX WORDS: Perceptual learning, Exposure learning, Categorization, Comparative cognition, Animal cognition, Rhesus macaques

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DEDICATION

This thesis is dedicated to my family. Without their endless support and love I never would have started this journey. I would also like to thank Chris Wilewicz, for providing encouragement, supporting words, and patience throughout this process.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 INTRODUCTION

Over the past few decades, categorization has been a popular subject of exploration by cognitive scientists and neuroscientists. The ability to make proper category decisions allows us to successfully navigate the world around us. Therefore, researchers have been searching to understand how humans and animals learn perceptual categories (Ashby & Maddox, 2005; Smith & Church, 2018; Smith & Minda, 1998; Smith et al., 2016; Squire & Knowlton, 1995; Vogels et al., 2002; Zaki et al., 2003). Some theorists posit that there is a single system for category learning (Bruner et al., 1956; Hull, 1920; Levine, 1975; Restle, 1962). However, a number of researchers have more recently theorized that humans may be able to learn categories using multiple methods, as opposed to just one (e.g., Ashby et al., 2011; Minda & Smith, 2001; Nosofsky et al., 1994; Smith & Church, 2018; Smith et al., 2016). Multiple-systems theorists have tried to fully understand how different brain systems may facilitate different types of category learning. In the current studies, I focused on whether perceptual learning facilitates family-resemblance category learning. Specifically, I tested rhesus macaques to see if they are able to simultaneously learn about two category prototypes through mere exposure. This had never been tested in rhesus macaques before, and still has not been tested in humans using novel stimuli. This study allowed us to see if prototype knowledge about each category can generalize to new members after receiving exposure and no direct training. I predicted receiving exposure to relevant category members would provide benefit to participants in a later categorization test, as they would have built cortical representations of the prototypes through perceptual learning. This finding could make important contributions to both the categorization and perceptual learning literatures, because it is not predicted by important categorization and perceptual learning theories and can, therefore, distinguish between competing theories in both fields. In the sections that follow, I will begin by detailing the theories of category learning and present evidence of mixed models through patient data. Next, I will discuss the theories of perceptual learning, and compare and contrast evidence for each. I will then describe how a hybrid model that integrates an influential multiple-systems category theory with one of the dominant perceptual learning theories may provide a fuller understanding of category learning, explain why it differentially predicts that primates can learn to distinguish two equally familiar categories from mere exposure, and present the one previous human study that has tried to test this possibility.

2 THEORIES OF CATEGORY LEARNING

Theories of category learning are continuously evolving. There are several major types of category learning theories: categorization by learning defining criteria (rule learning), exemplar comparison, prototype comparison, and associative learning (e.g., Bruner et al., 1956; Medin & Schaffer, 1978; Pavlov, 1927; Rosch, 1973). It has been a long running interest of researchers to determine which of these theories best describes the way humans and animals create and learn categories (e.g., Ashby & Valentin, 2017; Le Pelley, 2014; Newell et al., 2010; Nosofsky 1987; Smith & Minda, 1998).

In the human literature, the classical theory of category learning assumes that we learn categories by discovering defining criteria (category rules). Initially, researchers thought this was the only way categories were formed for humans (Bruner et al., 1956; Hull, 1920; Levine, 1975; Restle, 1962). In this view, humans define perceptual categories by focusing attention to particular stimulus features and explicitly finding those that can correctly define the category. For example, the features four sides of equal length with equal angles sufficiently describes the square category because every entity with these attributes is a square (Ashby & Maddox, 1998). When a stimulus is presented to the subject, the subject retrieves the set of features associated with one of the categories and then the stimulus is tested to see whether it possesses the exact set of features. We rely on working memory (Fuster, 1989) and executive functions (Posner & Peterson, 1990) to evaluate these featural hypotheses. Though many researchers have concluded that rule learning plays a role in human categorization (e.g., Ashby & Maddox, 2005; Bruner et al., 1956; Nosofsky et al., 1994), it quickly became apparent that many natural categories have no clear defining criteria (e.g., an ostrich in the bird category, a peanut in the vegetable category) and there must be other ways to learn categories (e.g., Rosch, 1973, 1975).

As it became evident that not all category learning could be described by the discovery of defining criteria, the prototype comparison theory of categorization was developed (e.g., Rosch 1973, 1975). Prototype comparison theory suggests that we average our experiences with multiple category members into a single schema or prototype that we then compare with new examples to determine if they belong to the category. This theory gained a wide following as it could easily explain many categorization phenomena (Homa et al., 1981; Minda & Smith, 2001; Posner & Keele, 1968, 1970; Reed, 1972; Rosch, 1973, 1975; Smith & Minda, 1998). However, this theory had difficulty explaining people’s ability to learn odd category members that do not share common features with the other members.

To better explain how atypical category members were learned, exemplar comparison theory emerged (e.g., Medin & Schaffer, 1978). Exemplar comparison theory assumes that people categorize a novel object by comparing its similarity to the memory representations of all previous exemplars from each relevant category (e.g., Hintzman, 1986; Medin & Schaffer, 1978; Nosofsky, 1987). Instead of having just one prototype representation of a dog, people have all the different representations of dogs they have seen, and they can compare new furry friends to all these representations to determine overall similarity. This overall similarity to most exemplars determines how quickly or accurately a category decision can be made (the typicality effect; Rosch, 1973, 1975), while still allowing atypical members to be learned over time because of similarity to their exemplars (e.g., Nosofsky, 1987). Exemplar theory has come under criticism for its unrealistic view of memory storage and retrieval, and its inability to accurately predict a number of categorization phenomena (Smith & Minda, 1998, 2001; for review, see Smith, 2014).

As prototype and exemplar comparison theories battled for dominance in the human category learning literature, associative learning theory was dominant in the animal category learning literature (see Smith & Church, 2018). Associative learning, in the category learning literature, focuses on operant learning. Operant learning is a mechanism by which stimuli can be linked to responses through reinforcement. An animal sees a stimulus and it makes a response to that stimulus. If the animal is then rewarded with a reinforcer, the stimulus is associated to the response, making that response more likely to be triggered by that stimulus (or others similar to it) in the future. Research in neuroscience suggests this type of operant associative learning happens slowly across multiple instances and requires time-locked sequences of stimulus-response and reinforcement (see Ashby & Valentin, 2005, 2017). When the subject makes a correct categorization response and receives an immediate reward, dopamine is released to the striatum causing the most recently active synaptic connections between stimulus and response to be strengthened. If there is no reward or it does not arrive during the relatively short time window before activity returns to baseline (Yagishita et al., 2014), then this strengthening does not happen (Yin et al., 2005). Many researchers believe that associative learning is the *only* way animals learn (e.g., Le Pelley, 2014; Le Pelley et al., 2019). This focus on associative learning created a seemingly unbridgeable divide between the human and animal category learning literatures (Smith & Church, 2018).

However, more recently some initial bridging cables have been built as a number of researchers have theorized that humans (and perhaps some animals) may be able to learn categories using multiple methods, as opposed to just one (e.g., Ashby et al., 2011; Minda & Smith, 2001; Nosofsky et al., 1994; Smith & Church, 2018; Smith et al., 2016). These mixed models of category learning have sparked a lot of controversy in the literature. Some single theorists have worked to disprove the idea of mixed models in categorization altogether (e.g., Le Pelley, 2014; Le Pelley et al., 2019). Even those who support mixed models do not agree on exactly how category learning is accomplished. For example, some mixed model researchers theorize that we can switch between comparing possible category members to a prototype or to a limited number of exemplars in memory (e.g., Minda & Smith, 2001). There is evidence showing that humans do in fact default to comparing to a prototype when categories have large numbers of exemplars, but they may simply memorize individuals when a small number of exemplars repeat often (e.g., Minda & Smith, 2001). Smith et al. (2008) used different types of category structures (Shepard et al., 1961) and showed that macaques tend to use prototype comparison. However, by using an exclusive-XOR task, Smith et al. (2008) showed that when an exemplar approach optimizes reward, macaques are able to switch to this approach instead of their default prototype approach. Results from these studies suggest that humans and macaques use either approach depending on the situation, thus supporting mixed model views of categorization. On the other hand, Nosofsky et al. (1994) created a mixed model known as rule-plus-exception model (RULEX). According to this model, we learn categories by creating and testing simple logical rules, and then memorizing the occasional exceptions to the rules (Nosofsky et al., 1994). For each person, one or two rules is stored along with its few exceptions as an exemplar. These rules are learned slowly, on a trial-by-trial basis (Nosofsky et al., 1994). The participant searches for a consistent single-dimensional rule, and once found, the participants can move on to looking for a second, less consistent single-dimensional rule, and so on. This model easily accounts for the individual differences found in the categorization literature, because of differences in the ability to remember the exceptions and strategies for finding rules.

Another mixed model view is the multiple category learning systems theory, COVIS (Competition between Verbal and Implicit Systems). This model has been supported by cognitive and neuroscience findings (for review, see Ashby et al., 2011). This model assumes that category learning can take place by either associative learning or discovering defining criteria (rule learning). Associative learning is thought to be supported by the implicit-procedural system, which learns by associating responses to whole stimuli and generalizing based on similarity. These associations are not conscious or easily verbalizable. Rule learning is thought to be supported by the explicit-declarative system which instead focuses on features of stimuli that are predictive of its category, which are typically verbalizable. There is evidence of this dissociation in the cognitive behavioral literature for both humans (for review, see Ashby & Valentin, 2005, 2017) and monkeys (Smith et al., 2010, 2012).

3 CATEGORIZATION IN PATIENTS WITH BRAIN DAMAGE: SUPPORT FOR MIXED MODELS

Several researchers have focused on testing patients with amnesia’s category and memory decision abilities which has helped us to better understand the role of exemplar memory in categorization. This research focused on what categorization abilities were still intact, when explicit memory for exemplars was absent. For example, Knowlton et al. (1992) investigated whether the ability to classify on the basis of rules can be learned without memory for the specific instances used to teach the rules. They tested patients with amnesia and control participants on an artificial grammar learning task. Patients with amnesia were just as able as control participants to classify letter strings that had been generated according to rules of an artificial grammar (Knowlton et al., 1992). The patients with amnesia were only impaired in their ability to recognize the exemplars that had been used to teach them the rules. They concluded that rule learning does not require intact explicit memory. To follow up, Squire and Knowlton (1995) presented a patient with amnesia, E.P. with 40 dot distortion patterns and then later tested him to determine whether new dot patterns belonged to the category or not, as well as his ability to recognize viewed patterns in a recognition memory task. E.P. exhibited an intact ability to classify novel dot patterns according to whether they did or did not belong to the same category as the training patterns. His intact ability to acquire category-level information occurred despite a complete failure to recognize previously presented dot patterns as familiar. Squire and Knowlton suggested that E.P. performed well on classification, in contrast to recognition, because E.P. was still able to abstract and retain a single prototype after seeing 40 related dot patterns, even though he could not remember the particular exemplars. These studies were taken as evidence against a unitary exemplar comparison theory since the ability to acquire rules and other category-level information was intact despite failures of exemplar memory. However, it is still unclear whether the patients (and controls) in Knowlton et al.’s (1992) study using an artificial grammar task had actually learned the underlying rules or if they simply learned to classify on the basis of similarity to a prototypical string (Servan-Schreiber & Anderson, 1990). If the latter is true, it would suggest that only prototype learning may survive deficits in explicit memory.

Further evidence for prototype formation in patients with amnesia comes from Kolodny (1994), who tested category learning and recognition memory in amnesic patients and controls using dot patterns. Participants were told the patterns fell into three different categories. During a training phase, participants were shown the dot patterns along with its category label (A, B, C). Later, participants were told they would see more clusters of both old and new patterns, but the categories still applied. As the patterns were presented, participants circled A, B, or C on a sheet of paper to categorize the images. The same study was repeated using paintings from three different artists with different styles. Patients with amnesia learned the dot patterns categories at the same rate as controls and showed equivalent transfer. However, the patients with amnesia were not able to categorize the paintings based on style whereas the controls could successfully do so. During a recognition test, the control participants were significantly more accurate at recognizing old and new items with both the dot patterns and paintings than the patients with amnesia. This result suggests that participants were able to learn categories and their labels through training, even when explicit memory was absent. Kolodny suggested that patients with amnesia were successful with the dot-patterns and not the painting classification because the dot-pattern task was a purely perceptual, whereas the painting were more abstract.

To determine whether patients with amnesia could only learn category information at a perceptual level of analyses, Reed et al. (1999) tested the patients’ category knowledge on stimuli that had easily verbalizable discrete features using a mere exposure phase and then a categorization phase. They hypothesized that if exposure items were more discrete and easier to label, the individuals would acquire category knowledge declaratively, that is, explicitly as propositional knowledge about the regularities among the training items (Reed et al., 1999). Results indicated that the patients with amnesia categorized accurately on the basis of discrete features as accurately as controls. This suggested, once again, that even verbalizable rule-like category knowledge can be obtained without explicit memory. These results have been replicated by other researchers testing both typical and atypical populations (i.e., Sinha, 1999; Zaki et al., 2003).

There is also evidence from patient work that categorization can depend on implicit-procedural processes. For example, to examine probabilistic category learning, Knowlton and colleagues (1994) examined amnesia patients' performance on the weather prediction task in comparison to healthy controls. The patients with amnesia exhibited normal learning of the probabilistic relationship between the cues and outcomes during the first 50 training trials (Knowlton et al., 1994). These results suggested that categorization was not dependent on short-term memory but instead depended on a more long-term, nondeclarative process. In addition, a variety of patient groups are known to have deficits in both rule-based learning and tasks thought to require associative learning, yet they show normal prototype distortion learning when asked to decide whether items belong to the category or not (Ashby & Maddox, 2005). This includes patients with Parkinson's disease (Reber & Squire, 1999), schizophrenia (Kéri et al., 2001), and Alzheimer's disease (Sinha, 1999).

Taken together, these patient studies suggest that people *can* acquire category information about even complex stimuli without a conscious memory for exemplars or rules (Knowlton et al.,1992; Lewicki et al.,1988; Reber & Allen 1978), even with deficits in associative learning. All of which supports the idea that multiple category learning systems may support different *types* of category learning. From a neuroscience perspective, we know a lot about the brain systems involved in learning exemplars (Palmeri, 2014), associative learning (Yin et al., 2005), and rule learning (Ashby & Ell, 2001). However, we know less about the neural underpinnings of prototype formation, though there is an assumption that it is part of basic perceptual processing (Goldstone, 1998) and may under some circumstances come about because of perceptual learning.

4 PERCEPTUAL LEARNING THEORIES

To better understand how perceptual learning may allow for prototype formation, it is important to understand the theories behind perceptual learning. Perceptual learning has been defined as “a relatively permanent and consistent change in the perception of a stimulus array, following practice or experience with this array” (Gibson, 1963). Perceptual learning and categorization are both sources of perceptual structuring of our environment (Carvalho & Goldstone, 2016). For example, a color wheel is made up of various shades of color. If we were to perceive it directly, we would see a continuous set of shades. However, what we actually see is a series of different colors that can be named and defined. This example demonstrates how our perception can be influenced by categories. Categorization not only provides organization to a complex world but also works to adapt the perceptual features used to perceive this world. Categorization is thus the result of perceptual experience and simultaneously a pervasive influence on that same perceptual experience (Goldstone, 2000; Goldstone et al., 2000; Schyns et al., 1998; Schyns & Murphy, 1994). Since perceptual and category learning constitute two different levels of processing information (e.g., their specificity and level of abstraction), they have had separately developing literatures (Carvalho & Goldstone, 2016). However, here I hope to provide a bridge between the perceptual and category learning literatures. Theories of perceptual learning historically fall into three main categories.

4.1 Representational Theories

Goldstone (1998) first defined representational theories of perceptual learning when he introduced the ideas of unitization and differentiation to the perceptual learning literature.

Differentiation involves an increased ability to discriminate between dimensions or stimuli that were psychologically fused together (Carvalho & Goldstone, 2016). Once separated, discriminations can be made between percepts that were originally indistinguishable. Differentiation can happen with whole stimuli as well as parts within stimuli. Simple pre-exposure to stimuli to be distinguished promotes their differentiation. Gibson and Gibson (1955) showed that even when no feedback is provided, practice in identifying visual scribbles increases their discriminability. Discrimination training is often highly specific to the task. Trained performance on a horizontal discrimination task frequently does not transfer to a vertical version of the same task (Fahle & Edelman, 1993; Poggio et al., 1992), to new retinal locations (Shiu & Pashler, 1992), or even from the trained eye to the untrained eye (Fahle et al., 1995).

Unitization is roughly the counterpart to differentiation. Here, the person perceives the stimulus as a single property as opposed to perceiving its distinct properties. For example, those who read in English fluently do not view familiar words as the distinct letters, but rather view those letters as a single word. Czerwinski et al. (1992) described a process by which conjunctions of stimulus features are “chunked” together so that they become perceived as a single unit. Shiffrin and Lightfoot (1997) argued that even separated line segments can become unitized following prolonged practice with the materials. One obvious role for perceptual learning processes in category learning could be the unitization of prototype representations. Representational views assume that exposure or training actually change the way that stimuli are perceptually represented, and those representations are believed to be potentially more unitized and/or more distinguishable from other representations than representations that have not been pre-exposed (Church et al., 2013).

4.2 Associative Theories

Another dominant explanation of perceptual learning comes from associative theories. The classic gradient interaction theory suggests that positive excitatory gradients of generalization develop around reinforced stimuli, while negative inhibitory gradients surround nonreinforced stimuli (Spence, 1937). An individual's ability to discriminate is governed by the summation of these gradients. When reinforced and nonreinforced stimulus gradients are overlapping and difficult to discriminate, they will cancel each other out, and learning will proceed more slowly. If the gradients are overlapping but are more separated their summation will produce a stronger difference between the reinforced and nonreinforced stimulus that can generalize (see McLaren et al., 1989; McLaren & Mackintosh, 2000). Elemental-associative theory, referred to as MKM after the authors (McLaren, Kate, & Mackintosh) assumes that learning requires associations between the perceptual inputs and responses (McLaren et al., 1989). The MKM model proposes that stimuli are made up of a combination of similar and unique elements that differentiate stimuli. The authors of this model assume it is more difficult to discriminate stimuli when they have several shared common elements, which may seem obvious. However, a less obvious assumption of this model is that when elements co-occur, there will be a reduction in the salience of those elements. This is often referred to as latent inhibition. For example, if you have two stimuli, AX and BX, they will have unique elements (A and B elements) but will share some things in common (X elements). The X elements are the basis for any generalization between them. So, if BX is pre-exposed for some time before AX is paired with an unconditioned stimulus, less conditioning will generalize to BX, as compared with a control group that received no pre-exposure because the X elements will be latently inhibited (therefore having reduced salience) by pre-exposure. These inhibited elements will then be overshadowed by the A elements which will acquire the most associative strength to the unconditioned stimulus, leaving less strength to accrue to the X elements and hence generalize to BX (McLaren & Mackintosh, 2000). Consequently, one of the principal effects of pre-exposure is that elements that frequently co-occur reduce in salience more quickly than elements that rarely co-occur (Milton et al., 2019). This means that the unique elements that discriminate one stimulus from another will tend to be higher in salience than the common elements that both stimuli share, because the common elements will have been presented more often and because they are good predictors of one another. According to MKM theory this preferential processing of the unique elements, which discriminate between items, compared with the common elements, which do not discriminate, is what leads to the increased differentiation of stimuli after pre-exposure (Milton et al., 2019; McLaren et al., 1989).

4.3 Attentional Theories

Attentional theories have been a dominant explanation of perceptual learning, especially in the visual domain. There are two primary types of attentional theories of perceptual learning, attentional weighting and attentional spotlight theories. Although they are both considered attention-based theories, their assumptions are quite different, and therefore it is important to understand each individually.

Attentional spotlight theories typically involve participants using some sort of search process to find the unique aspects of the representation, and once found, the participant can pay attention to these particular aspects and not others (Pashler & Mozer, 2013). Participants intentionally direct their attention to the various stimulus dimensions until the most relevant is identified. This happens suddenly through insightful explicit discovery. Once they identify the most relevant dimension, they perceive it more minutely (e.g., Pashler & Moser, 2013). This is a very explicit, intentional, and often quick process.

Attentional weighting on the other hand, involves something more akin to associative processes. Attentional weighting theories assume that there are incremental changes in the attention to relevant perceptual dimensions. Attentional weighting models utilize activation of artificial visual cortical neurons with fixed response profiles as inputs to associative learning-based artificial networks. Researchers that utilize these models have suggested that associative weights represent weights of attention (Lu et al., 2011). These models use incremental attentional weighting to gradually learn which visual features are shared across different events and which are unique to each event (Petrov et al., 2005). During learning, unique elements become more strongly associated with the output over time. If a novel event activates these elements to a greater degree than a trained stimulus, an individual will respond more to the novel event (e.g., Lu et al., 2011). The idea is that the input of certain sensory representations to a decision, for example, those with location, orientation, and spatial frequency that correspond to the trained stimulus, should be strengthened, while other irrelevant inputs are down-weighted in the decision (Dosher & Lu, 2009). When presented with a stimulus, the output neuron will calculate an activity level by multiplying activity in each input neuron by the weight of the connection. Then, these values for each input are summed together. The assumptions for attentional weighting are as follows: 1) there is a fixed stimulus representation; 2) learning involves decreasing the absolute value of weights on parts of that representation that are irrelevant for discriminating; and 3) learning involves increasing the absolute values of weights on parts of the representation that are critical for making a discrimination (Wisniewski et al., 2019).

4.4 Evidence for Perceptual Learning Theories

To investigate how perceptual learning may aid in category learning, it is important to compare and contrast the evidence behind the theories just discussed. A lot of the evidence supporting attentional weighting and spotlighting theories comes from the visual perceptual learning literature using simple stimuli with basic visual features (Song et al., 2005). If the stimuli are easy to discriminate, it is hard to tell how much *learning* is truly taking place. Several studies have shown that many examples of perceptual learning are highly specific to the training situation (e.g., Ball & Sekuler, 1982; Fiorentini & Berardi, 1980; Karni & Sagi, 1991; Poggio et al., 1992). Participants' enhanced discriminability produced by experience was restricted to the stimulus orientation and retinal position used in training and did not transfer to situations in which these were changed (Dwyer & Mundy, 2016). The neurons with the requisite location and orientation specificity are found in primary visual cortex and not further along the visual processing stream (Dwyer & Mundy, 2016). One observes a high degree of specificity when simple stimuli are used because it is happening so early in the visual system, and this has been taken to suggest that perceptual learning cannot involve actual representational change because these early areas of visual cortex are thought to be fixed and relatively unchanging early in development. However, when one uses more complex stimuli, perceptual learning is not as basic as was once thought. For example, one study used event-related potentials to test whether perceptual learning of different complexities of stimuli involved different levels of visual cortical processing (Song et al., 2005). For simple stimuli, learning effects were focused over the occipital cortex. For complex stimuli, learning effects were focused over the central/parietal regions (Song et al., 2005). This suggest that perceptual learning modifies the response at different levels of visual cortical processing related to the complexity of the stimulus. A PET study showed that perceptual learning of visually complex stimuli enhanced the activity of inferior temporal regions (Dolan et al., 1997). This again suggests that perceptual learning is not always happening as early in the visual system as once believed and suggested by some attentional theories.

Support for attentional theories has also come from studies looking at easy-to-hard effects. Attentional spotlighting theory suggests that initial easy trials direct learners' attention to the relevant dimensions. Once the most relevant dimension is spotted, learners ignore the irrelevant dimensions and pay more attention to those they have found to be relevant. Several studies have tested attentional spotlighting theories directly to see if they can adequately explain easy-to-hard effects (progressive training) in perceptual learning (Wisniewski et al., 2017; Wisniewski et al., 2019). According to attentional spotlighting views, the benefits from progressive training are the result of discovering the relevant dimensions through an explicit search process. Therefore, any benefit of progressive similarity should generalize for the critical dimension to a new frequency space in an auditory task (Pashler & Mozer, 2013). In contrast, learning theories based on how representations are reorganized and modified, predict that benefits should be partially specific to the feature values of trained stimuli. Wisniewski et al. (2017) showed in an auditory task that participants trained to discriminate the rate of periodic, frequency-modulated tones in one frequency range (300-600 Hz or 3000-6000 Hz) only showed an advantage of progressive training if they were tested in the *same* frequency range. Perceptual learning theories that suggest experience-dependent changes in stimulus representations predict the observed specificity of easy-to-hard effects, whereas attentional-spotlighting theories do not (Wisniewski et al., 2017). Attentional spotlighting theory also incorrectly predicts that when a participant's attention is explicitly and repeatedly drawn to relevant dimensions early in training (e.g., by the presentation of easy contrasts in one range of that dimension), then he or she should show no within-subject benefits of progressive training (e.g., Pashler & Mozer, 2013, Wisniewski et al., 2017). In contrast to the attentional-spotlighting, representational modification/reweighting learning mechanisms (e.g., Saksida, 1999) are able to account for the specificity of easy-to-hard effects to trained sounds and the presence of an easy-to-hard effect when relevant dimensions are clearly revealed. In another study, predictions of attentional theories were pitted against representational theories by testing how “easy” initial levels should be to yield easy-to-hard effects (Wisniewski et al., 2019). Representational theories predict that extremely easy trials will make it less likely that representations will be modified enough to aid discrimination on a harder version of the task. Attentional spotlight models predict that the easy trials should facilitate performance as long as the discrimination-relevant dimension is made obvious. Results showed that training protocols where initial blocks are too easy or too difficult produce less benefit than blocks of intermediate difficulty (Wisniewski et al., 2019). This result, which was observed for two different acoustic dimensions, was predicted by representational accounts of learning, and runs counter to predictions of attentional spotlighting.

Another study pitted representational theories against associative models like MKM. Church et al. (2013) examined whether the sequencing during pre-testing exposure to the stimuli mattered. Progressive sequencing of stimuli during pre-exposure led to a more accurate performance with the critical difficult contrast and greater generalization to new contrasts in the task, compared with equally variable training in either a random or an anti-progressive order. This greater accuracy was even evident when participants experienced the progressively sequenced stimuli in an incidental learning task that did not involve direct training for the test. The results suggest that progressive training advantages cannot be fully explained by direct associations between stimulus features and the corresponding responses. Therefore, the advantage of progressive training cannot be explained by elemental-associative or selective incremental attention theories that assume that the advantage is caused by learning task-relevant features. Taken together, it does not seem as though associative or attentional theories can fully explain all phenomena of perceptual learning. Overall, this research suggests that perceptual learning may often reflect representational change producing differentiation or unitization of perceptual representations.

5 COMBINING MIXED MODELS OF CATEGORIZATION AND MODELS OF PERCEPTUAL LEARNING

The classic COVIS theory assumes that family resemblance information is learned implicitly. On the other hand, single atypical exemplars are learned explicitly through memorization. Classic COVIS suggests that learning single family-resemblance categories can be learned without feedback because of fluency. This happens because the prototype induces a graded pattern of activation in the visual cortex, and the group of cells will fire more rapidly to the presentation of this prototype pattern (Ashby & Maddox, 2005). These same cells will repeatedly fire throughout exposure of the category members, causing an enhanced visual response to the category stimuli (Ashby & Maddox, 2005). When the variable nonmember stimuli are shown, the same cells will not fire, and therefore activation will be slower. During the transfer or testing phase of the experiment, the participant can use the increased sensitivity of the cell group to respond accurately. This fluency can be used as a cue to category membership. A participant in a task can rely on feelings of familiarity/fluency to decide which stimuli belong in the category. This view makes the clear predictions that there will be problems learning more than one category simultaneously by exposure. Using the classic COVIS model logic, both categories would become familiar, as the exemplars from prototype A would cause cell group A to fire faster, and the exemplars from prototype B would cause cell group B to fire faster. During the categorization phase, stimuli from *both* categories would elicit an enhanced visual response (Ashby & Maddox, 2005). So, As and Bs will all feel familiar; therefore, they cannot be differentially categorized. This view predicts that we can learn to discriminate single family-resemblance categories without feedback, but not to discriminate between two family-resemblance categories.

However, this classical COVIS view is not the only possibility. If the cortical activation during exposure doesn't simply create faster future activation but rather creates a unitized representation of the prototypes (representational theories of perceptual learning), it should aid learning in both situations. To instantiate this possibility, I hypothesize a COVIS plus theory. This theory would still support the idea of separate implicit and explicit systems; however, it would suggest that we can build *real* cortical representations of prototypes through perceptual learning, and therefore, family resemblance learning from exposure does not have to be based on fluency or feelings of familiarity. By building actual representations of the prototypes, we would be able to more quickly map stimuli that share similarity with those prototypes, old or new, to categories. This view would predict that initial exposure to category members would create representations that would aid family-resemblance category learning in both single category learning and in discriminating between two categories.

6 EVIDENCE FOR LEARNING TWO CATEGORIES THROUGH EXPOSURE

Currently, no studies have directly investigated whether humans or macaques show a benefit in an A-B (two category) categorization task and then transfer prototype knowledge to novel stimuli after being exposed to exemplars from each category. However, there is one study that has provided related results to the proposed study indicating that exposure to two categories can change family-resemblance categorization in humans. Milton et al. (2019) examined the effect that prior exposure to perceptual stimuli has on the prevalence of overall similarity (family-resemblance) categorization in a free classification task. To do this, the researchers exposed participants to either relevant or irrelevant stimuli of two categories before giving them a free-sort task. The researchers were specifically interested in how people naturally form categories without any feedback. Previous work has shown that many natural categories appear to possess a family resemblance or overall similarity structure (e.g., Rosch & Mervis, 1975; Rosch et al., 1976) in which categories are organized around a number of characteristic but not defining features. If an item has enough features characteristic of a category, it can be considered a member of that category even if it does not have a particular feature (Milton et al., 2019). However, early work suggested that when participants are asked to group items without any feedback, they have a strong tendency to create categories based on a single dimension and rarely sort by overall similarity (e.g., Ahn & Medin, 1992; Ashby et al., 1999; Imai & Garner, 1965; Medin et al., 1987). Milton et al. (2019) predicted that the categories created in these laboratory studies did not reflect the assumed underlying structure of natural categories because the participants had little or no exposure to the stimuli before classifying a very limited number of items (e.g., Ahn & Medin, 1992; Medin et al., 1987; Milton & Wills, 2004). Milton et al. (2019) believed that the lack of familiarity/experience with the stimuli contributed to the lack of family-resemblance categorization in these studies. To test their theory, two stimulus sets were used, one containing artificial lamps, and the other artificial boats. Each set was made up of 10 stimuli. The stimuli consisted of four binary-valued dimensions, and were organized around two prototypes, each representative of one of the categories. One prototype was constructed by taking all of the positive values on the dimensions, whereas the other category prototype was created by taking all of the zero values on the dimensions. Stimuli were mild distortions of these prototypes (a change in 1 feature). Participants were randomly assigned to the same-stimuli (relevant) exposure, or unrelated-stimuli (irrelevant) exposure conditions. In the same-stimuli condition, participants were exposed to the exact same stimuli that they would later categorize. In the unrelated-stimuli condition, participants were exposed to different stimuli than those they would later classify (e.g., they were exposed to boat stimuli but had to classify lamp stimuli). Participants were exposed to all 10 stimuli twice in each exposure block. During the exposure blocks, one of the stimuli from the set appeared in the middle of the screen for 3,000 ms, and then participants were instructed to press a labeled “x” if they had seen the stimulus already during this block, and press “m” if they had not. At the end of each block, feedback was given. Participants were given 16 blocks of 20 trials each. In the categorization blocks, participants were told they could classify stimuli however they saw fit. Categorization blocks began with the two category prototypes presented at the top of the screen representing categories A and B, and then below in the center was one of the 10 stimuli. Participants categorized the stimulus as belonging to category A or B. No feedback was provided for the categorization phases. All stimuli in the set appeared once in each block. In between each categorization block, participants were asked to write down their strategy for classify the stimuli to see if a similarity strategy was used or not, and then moved on to the next categorization block (six in total). Results indicated that participants who were pre-exposed to the same stimuli showed greater levels of overall similarity sorting than those in the unrelated-stimuli conditions. Further testing showed that this was modulated by the perceptual difficulty of the stimuli. Pre-exposure increased the overall similarity sorting for perceptually easy stimuli but not the difficult stimuli (Milton et al., 2019).

These results are important for the current study. Overall, this study indicates that participants experience an ease of family resemblance comparison after exposure to the exact exemplars they later categorized. However, Milton et al. did not test whether this advantage generalizes to novel category members, and testing generalization to novel members is necessary to differentiate between our theories of interest.

7 THE CURRENT STUDY

Evidence for multiple systems has been growing in the human and animal categorization literature. It has been shown that humans are able to learn slowly through associative processes, as well as through hypothesis testing and rule creation (Ashby & Valentin, 2005). We can also change strategies between prototype and exemplar comparison approaches (Minda & Smith, 2001), and even categorize without intact declarative memory (Knowlton et al., 1992). Research with rhesus macaques also supports the idea that they can successfully complete rule-based and information-integration tasks (Smith et al., 2010), as well as utilize prototype and exemplar comparison strategies (Smith, 2014). For the purpose of this study, I focused on comparing the classic COVIS model (Ashby et al., 2011) that assumes prototype learning strategies are generally part of the reinforcement based implicit memory to a model that adopts many of the assumptions of COVIS, but assumes that prototype formation can occur without the striatum via cortical perceptual learning (e.g., Church et al., 2013; Goldstone, 1998). To do this, I focused on how perceptual learning during a stimulus exposure phase affected category representation. In the classic COVIS model, this type of exposure learning is thought to produce basic perceptual priming (perceptual fluency) that could be used to guide judgments about whether items belong to a new family-resemblance category or not (A-not-A tasks), but could not be used to differentiate between two equally primed categories (A-B tasks) (for review, see Ashby &

Maddox, 2005), because no actual prototype representations are formed/changed. However, theories that assume perceptual learning can produce representational unitization would predict that prototype formation during exposure could aid category learning in both types of tasks (e.g., Church et al., 2013; Goldstone, 1998; Wisniewski et al., 2019). Therefore, this COVIS plus model predicts that both types of category tasks should benefit from previous exposure. As seen above, studies have shown that humans, including patients with amnesia, are able to learn single category tasks through mere exposure (e.g., Reed et al.,1999). Studies have also shown that rhesus macaques are able to learn single category tasks (A-not-A) and are able to transfer their prototype knowledge to novel stimuli using reinforcement (Smith et al., 2008). Previous to the current studies, no one had tested whether rhesus macaques can learn this task through mere exposure. My goal was to investigate this, and then determine if the macaques could also show a benefit in a two-category discrimination task (A-B) after exposure.

Initial piloting to find a working methodology had started with human participants. However, due to COVID19 restrictions, piloting with humans ended before a working methodology could be refined. Testing occurred with rhesus macaques instead. The type of learning being tested should not differ between species (Mitchell & Hall, 2014). The tasks for humans and macaques would only differ in that humans could receive written or verbal instructions on how to complete the task, whereas the macaques required an initial training phase to teach them that they need to categorize stimuli on the basis of visual similarity. Also, because of the small number of macaques, an ABA small-N research design was used (Task 1, Task 2, Task 1 again), but with humans I would have counterbalanced order of task across participants.

The design of this study differed in several ways from the Milton et al. (2019) task design. In this study, since I was looking to see if exposing participants to exemplars causes a mental representation of the prototype to be built, I did not expose the participants to the prototype or ask participants to group exemplars based on the prototype on screen. Instead, the prototype was mixed in with other exemplars during the categorization phase to see if participants were able to correctly identify the A vs B prototypes. Feedback was also provided to participants during the categorization phase since I was interested in how exposure benefits category learning and not how participants naturally divide the stimuli. Another critical difference is that participants were asked to categorize novel stimuli that they were not previously exposed to. I predicted that if a representation of the prototype was created, participants would successfully categorize novel stimuli for both categories.

For this study I used prototype distortion tasks instead of free classification tasks. Prototype distortion tasks are often used when testing family-resemblance category learning. In these tasks, categories are created by first generating a category prototype, and then exemplars are made by generating distortions of varying (but controlled) similarity to the prototype (Posner & Keele, 1968, 1970). Stimuli used are often dot patterns, or polygon shapes. A-B and A-not-A tasks are popular prototype distortion tasks. In an A-B task, participants are presented with exemplars based on two category prototypes (A and B). Participants must then correctly label each stimulus on each trial. In an A-not-A task there is a single, central prototype (A) from which category members are generated and random foils. Participants must decide if the stimulus on each trial is part of the category by responding “Yes” or “No.” Researchers can then look at the endorsements of the distortions to see if the participant was able to learn the prototype from the distortions.

The main goal of the pilot study was to see if macaques learned an A-not-A task through mere exposure and transferred the category knowledge to novel members, as this had never been tested before. The pilot also allowed me to find a working methodology that promoted successful learning and generalization of a single category through exposure on an A-not-A task. It also helped to determine the proper proportion of distortion levels (how similar/dissimilar the exemplar is from the prototype) during the exposure phase to aid categorization, as well as how many exposure trials were needed. After this was established, I was able to conduct the next experiment using two categories (A-B), as opposed to one category and random stimuli, to assess if it is possible to learn two categories through mere exposure. Each macaque completed a condition that provided no relevant pre-exposure of category members (irrelevant task) as well as two tasks that used pre-exposure to category members (relevant task). This allowed a comparison to be made to see how beneficial pre-exposure was to learning categories. This initial finding was necessary because all theories predict that pre-exposure should aid performance in an A not A task; so, it is an important methodological check. The procedure for the pilot task is below, and then follows the A-B task.

8 METHODS: PILOT STUDY

8.1 Participants

Four male rhesus macaques Murph, Lou, Han, and Obi (approximately, 27, 27, 18 and 17 years of age) were tested. All had been previously trained to respond to computer-graphic stimuli by manipulating a joystick (Washburn & Rumbaugh, 1992). The macaques were tested in their home cages and given access to the testing apparatus whenever they choose. They also had free access to water at all times. They worked for fruit-flavored primate pellets. They were not food deprived for the purposes of this or any other experiment. They received daily fruits and vegetables independent of task participation.

8.2 Apparatus

Testing took place at the Language Research Center using a computerized testing system, comprised of a computer, joystick, color monitor, pellet dispenser, and programming code written in Turbo Pascal 7.0. Trials were presented on a 17-inch color monitor with 800 X 600 resolution. Joystick responses are made with a Logitech Precision gamepad, which is mounted vertically to the test station. Monkeys manipulated the joystick, which extended horizontally through the mesh of their home cages and produced movements of a graphic cursor on the screen. Touching the correct response with the cursor provided them a 64-mg fruit-flavored chow pellet (Bio-Serve, Frenchtown, NJ) using either a Med Associates ENV-203-45 or a Gerbrands 5120 dispenser interfaced to the computer through a relay box and output board (PIO-12 and ERA-01; Keithley Instruments, Cleveland, OH; or ADU252; Ontrak Control Systems, Ontario, Canada).

8.3 Stimuli

Prototypes were created using nine points that were randomly selected from a 50 X 50 grid. The distortions (exemplars) were created by applying a series of probabilities that determines whether each dot kept the same position it had in the prototype, and if not, how far it moved. Once prototypes were established, distortions were built by probabilistically moving each dot into one of five areas that covered the 20 X 20 grid of pixels that surrounded it (for specific algorithms see Minda & Smith, 2002; Smith et al., 2008). Different levels of distortions were arranged by adjusting the probabilities that dots would make small or large movements away from their original position. Each pixel position in the distortion algorithm was mapped to a 3x3 pixel square on the screen, and the dot was placed in the center of the appropriate 9-pixel cell on the screen. Level 2 (lowest), level 3 (low), level 4 (low-medium), level 5 (medium), and level 7 (high) distortions of the prototype were used. The Draw Poly procedure in Turbo Pascal 7.0 connected successive dots with lines and filled the resulting polygon shape in purple. This follows the common practice of presenting dot distortions as random polygon shapes (Homa et al., 1979, 1981). Figure 8.1 presents examples of possible prototypes and their different distortion levels.

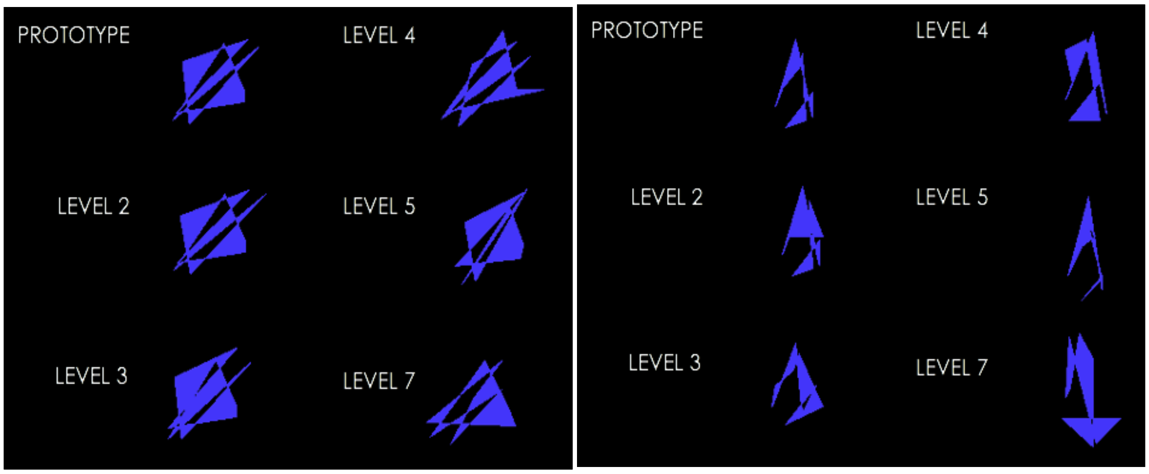


Figure 8.1 Examples of Stimuli. Illustrating randomly generated prototypes and examples of its varying distortion levels.

8.4 Procedure

Each monkey completed one training task, three exposure tasks and three categorization tasks. The first task was always a training task, followed by a relevant exposure task and categorization task, then an irrelevant exposure task and categorization task, and then another relevant exposure and categorization task. Relevant here means that the exemplars created during the exposure phase were based on the same prototype that was used during the categorization phase. Irrelevant task means that exemplars were based off of a different prototype than the one that was used in the categorization phase. The initial training task was simply a categorization task (described below) without pre-exposure in which half of the shapes were based on a single prototype and half randomly generated.

In the exposure phases, the monkeys saw 120 shapes total, 60 belonging to a category and 60 random shapes. For the first relevant exposure phase, half of the monkeys received the category members as their first 60 shapes, and the random shapes as their second 60. The other half of the monkeys received the 60 random shapes first and then the 60 category members during their first relevant exposure phase. For the irrelevant exposure phase, all shapes were unrelated to the category in which they would be tested in the categorization task. Then, in the third exposure phase (the second relevant task), the order in which the monkeys received the stimuli the first time was reversed. Those who originally saw category members first and random shapes second, now received random shapes first and category members second. This allowed me to look for primacy and recency effects in the subsequent categorization task. Table 8.1 shows the exposure schedule for each monkey in each task. The exposure category shapes consisted of 20 level-3, 20 level-5, and 20 level-7 prototype distortions. The shapes appeared in the center of the screen, and the monkeys used their joystick to simply touch the shape. In this task, pellet rewards were given for every three shapes that were touched by the cursor.

After each exposure phase, a categorization task was present. In the categorization tasks, half of the polygon shapes belonged to the category and the other half did not. The categorization tasks that were presented after relevant exposure used the same category prototype. The categorization task presented after the irrelevant task used a new prototype for the category. The shapes used for the categorization tasks were comprised of 5% prototype, 5% level-2, 10% level-3, 10% level-4, 10% level-5, 10% level-7 prototype distortions of the category. The shape appeared in the center of the screen, beneath the shape appeared a Y to the left of a cross cursor, and an N to the right of the cursor. The objective was for the monkey to move their joystick to the left or right to decide if the shape that appeared was a part of the category (Y), or not (N). They received a pellet reward and heard a familiar whooping sound when they selected Y for correct category members and selected N for nonmembers. If they made the wrong categorization decision, a familiar buzzing sound was played, and they received a 20 second timeout. The monkeys automatically moved to the next task after reaching a criterion of 85% accuracy over approximately 120 trials. The program automatically transitioned to the next task by looking at the last 120-trials, however the program uses an internal array to keep score which automatically starts at 50% accuracy. This allows the monkey to potentially move on in less than 120 trials. The program generated random prototypes for each task. If a monkey did not finish a task (exposure or categorization task) before the program was closed out, they restarted with the last exposure task and a new prototype. For example, if they had finished Training, Task 1-exposure, and were working on Task 1-categorization test but had not finished it, the next time the program was reopened they started on Task 1-exposure with a different prototype than before.

Table 8.1 Order of Tasks.

	Relevant 1	**Irrelevant**	**Relevant 2**
Murph	60 Relevant- 60 Random	60 Random-60 Random	60 Random- 60 Relevant
Han	60 Relevant- 60 Random	60 Random-60 Random	60 Random- 60 Relevant
Obi	60 Random- 60 Relevant	60 Random-60 Random	60 Relevant- 60 Random
Lou	60 Random- 60 Relevant	60 Random-60 Random	60 Relevant- 60 Random

Note. Relevant stimuli were made from the same prototype as category members in the categorization phase, and random were random shapes not part of a category. No stimuli from the exposure phase repeated in the categorization phase.

9 PILOT RESULTS

9.1 Trials to Criterion

All four monkeys completed all tasks for the pilot experiment, and their proportion correct and trials to criteria can be seen in Table 9.1. Figure 9.1 A shows the number of trials it took to complete each task (including unfinished sessions) and Figure 9.1 B shows the number of trials it took to meet criterion in their last session for each task. Murph finished his first relevant task (relevant shapes then random shapes during exposure) in one session, and it took 586 trials to meet criterion. It took Murph three sessions to finish his irrelevant task, in which he met criterion in 785 trials. In his second relevant task (random shapes first then relevant shapes), he met criterion in his first session in 265 trials. Both relevant tasks were completed in fewer trials/number of sessions than the irrelevant task. Obi, in his first relevant task (random shapes then relevant shapes), met criterion in 136 trials in his first session. Obi met criterion in the irrelevant task in 913 trials across three sessions. Obi completed his second relevant task (relevant shapes then random shapes), in 303 trials during his first session. Han finished his first relevant task (relevant shapes then random shapes) in 127 trials in his first session. Han attempted his irrelevant task but was not able to meet criterion. He completed over 5,000 trials across eight different sessions. Since he completed over 5,000 trials without performance above chance, he was moved to the next task. It took Han five sessions to finish his second relevant task. This time he received 60 random shapes and then 60 category members and it took 2,287 trials to meet criterion. Lou finished his first relevant task (random shapes and then relevant) in 409 trials across two sessions total. He completed his irrelevant task in two sessions, 958 trials total. In the second relevant task (relevant shapes and then relevant), Lou met criterion in 116 trials in his first session.

Table 9.1 Proportion Correct in Each Task

HAN	**Trials to Criterion**	**Total Trials Prop. Correct**	**Trials in Last Session**	**Prop. Correct Overall Last Session**	**Prop. Correct First 120 Last Session**
Rel-Rand(1)	127	0.84	127	0.84	0.83333
Irrelevant	*5163*	0.59	*1066*	0.71	0.62
Rand-Rel(2)	2286	0.57	283	0.74	0.65
MURPH	**Trials to Criterion**	**Total Trials Prop. Correct**	**Trials in Last Session**	**Prop. Correct Overall Last Session**	**Prop. Correct First 120 Last Session**
Rel-Rand(1)	586	0.73	586	0.73	0.68
Irrelevant	785	0.68	689	0.68	0.63333
Rand-Rel(2)	265	0.82	265	0.82	0.81
OBI	**Trials to Criterion**	**Total Trials Prop. Correct**	**Trials in Last Session**	**Prop. Correct Overall Last Session**	**Prop. Correct First 120 Last Session**
Rand-Rel(1)	136	0.81	136	0.81	0.8
Irrelevant	913	0.75	608	0.77	0.66
Rel-Rand(2)	303	0.74	303	0.74	0.63333
LOU	**Trials to Criterion**	**Total Trials Prop. Correct**	**Trials in Last Session**	**Prop. Correct Overall Last Session**	**Prop. Correct First 120 Last Session**
Rand-Rel(1)	409	0.71	299	0.71	0.64
Irrelevant	958	0.76	665	0.75	0.69
Rel-Rand(2)	116	0.88	116	0.88	0.88

Note. Rel-Rand represents the relevant exposure task in which relevant category members were first and shape shapes second. Rand-Rel represents the opposite exposure schedule. The number in parentheses indicates whether that monkey received that exposure schedule as the first or second relevant task. Italicized numbers indicate the task was never finished.

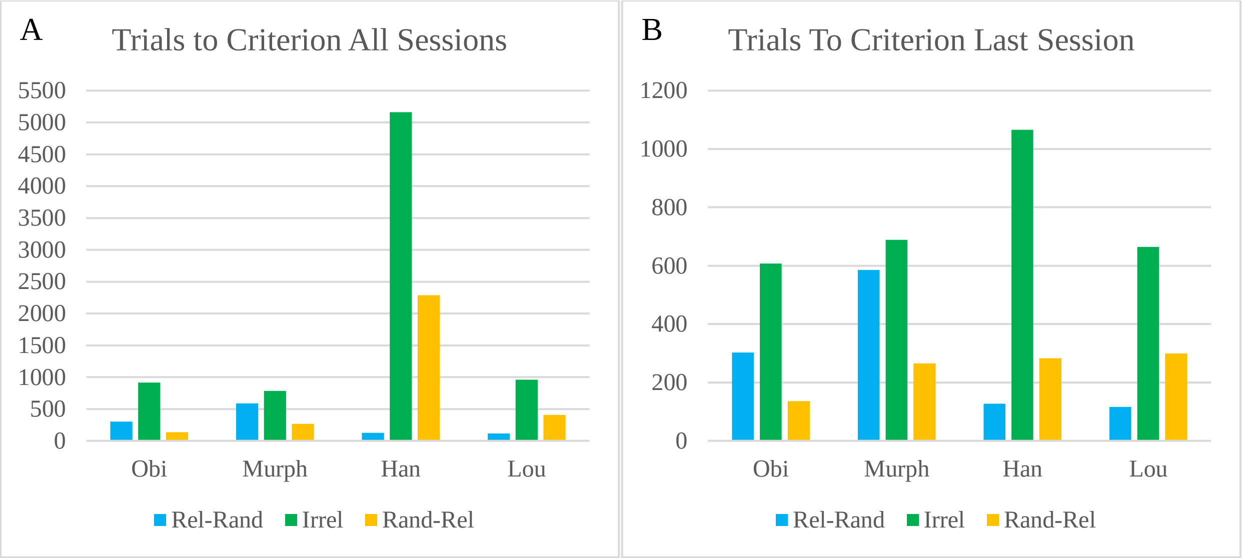


Figure 9.1 Trials to Criterion

Note. Rel-Rand represents the relevant exposure task in which relevant category members were first and shape shapes second. Rand-Rel represents the opposite exposure schedule. Han never completed his irrelevant task, therefore trials to criterion last session contains his longest single session.

Table 9.2 presents the means (*M*) and standard deviations (*SD*) information for the trials to criterion for each task. Due to the small N design and the strong directional predictions, all analyses use an alpha level of .10. Han's data have been excluded in analyses looking at trials to criterion that make comparisons with the irrelevant task, as he never met criterion. Looking at the relevant tasks combined and irrelevant task, there was a significant difference between relevant and irrelevant trials to criterion, *t*(5) = 6.569, *p* < .001 , *d* = 4.164. Additional analyses were done to investigate possible order of task effects on trials to criterion. There was a significant difference between the first relevant task and the irrelevant task, *t*(2) = -3.024, *p* = .094, *d* = 1.746, and the irrelevant and second relevant task , *t*(2) = 6.853, *p* = .021, *d* = 3.957. There was no significant difference of trials to criterion between the first relevant task and the second relevant task, *t*(2) = -.728, *p* = .519. Differences between tasks based on exposure schedule was also investigated. There was no difference in trials to criterion between the two relevant tasks *t*(2) = .372, *p* = .758. There was a significant difference between the relevant task with relevant shapes first and random shapes second and irrelevant task, *t*(2) = 2.927, *p* = .100, d = 1.690, and between the relevant task with random shapes first then relevant shapes and the irrelevant task, *t*(2) = 7.572, *p* = .017, d = 3.357.

Table 9.2 Means and Standard Deviations of the Total Trials to Criterion

Overall Trials to Criterion	***M***	***SD***
Relevant All	528.5	728.21
Relevant 1	314.5	223.35
Relevant 2	742.5	1032.16
Relevant-Random	283	219.42
Random-Relevant	774	1014.15
Excluding Han's Trials		
Relevant All	302	176.42
Irrelevant	885.33	89.76
Relevant 1	377	226.7
Relevant 2	228	98.84
Relevant-Random	335	136.62
Random-Relevant	270	136.57

Note. Relevant 1 indicates the first relevant task, Relevant 2 indicates the second relevant task. Relevant-Random represents the relevant category member then random shape exposure schedule. Random-Relevant represents the opposite exposure schedule.

Each time the pilot program was restarted, a monkey received a new prototype. Therefore, if a monkey was in the middle of a categorization task and the program had to end for scheduling reasons, the next session would restart in the last exposure phase with a new prototype. For this reason, analyses were also performed looking specifically at the number of trials to criterion in the session of each task in which they met criterion, excluding trials from previous session where criterion was not met. Once again, because Han did not meet criterion in the irrelevant task, his data were excluded for all analyses in which comparisons are made with the irrelevant task. Table 9.3 presents the means (*M*) and standard deviations (*SD*) for the trials to criterion in their last session. There was an overall significant difference in trials to criterion in their last session of each task when comparing the relevant trials and irrelevant tasks trials, *t*(5) =

-5.071, *p* = .002, d = 2.129. I also investigated to see if there was an effect of order. There was a significant difference between the irrelevant task and the second relevant task, *t*(2) = 11.348, *p* = .008, d = 6.551. However, there was no significant difference between the first relevant task and the irrelevant task, *t*(2) = 2.550, *p* = .125, or between the two relevant tasks, *t*(3) = .369, *p* = .737. Analyses were also done to look for differences in the trials it took to meet criterion in the last session due to exposure schedule. The key finding here is there was no significant difference between the two relevant exposure schedules, *t*(3) = .301, p = .783. There was also no significant difference between the irrelevant exposure schedule and the relevant then random schedule, *t*(2) = 2.474, p = .132. There was a significant different between the irrelevant and random then relevant tasks exposure schedules *t*(2) = 13.727, p = .005, *d* = 7.929.

Table 9.3 Means and Standard Deviations of the Number of Trials to Criterion for the Last Session

Last Session Trials to Criterion	***M***	***SD***
Relevant All	264.375	152.99
Relevant 1	287	214.43
Relevant 2	241.75	85.26
Relevant-Random	283	219.42
Random-Relevant	245.75	74.27
Excluding Han's Trials		
Relevant All	284.167	168.688
Irrelevant	654	41.6
Relevant 1	340.33	227.83
Relevant 2	228	98.84
Relevant-Random	335	236.63
Random-Relevant	233.333	85.99

Note. Relevant 1 indicates the first relevant task, Relevant 2 indicates the second relevant task. Relevant-Random represents the relevant category member then random shape exposure schedule. Random-Relevant represents the opposite exposure schedule.

9.2 Categorization Performance

Data from the last session were used for each task to look at each monkey's categorization performance. This is the session in which they met criterion, except Han, who was never able to meet criterion in his irrelevant task. To statistically compare categorization performance, the Fisher's exact test was used to compare the overall performance difference between the relevant tasks and irrelevant task. Cochran's Q test was used to look at performance for the first 120 trials. Friedman's ANOVA was used to look at overall performance. The first 120 trials were tested because I predicted that the monkeys would build a prototype representation during relevant exposure, and therefore would be able to more quickly identify whether a shape was a category member or not. In the irrelevant tasks, category learning would not take place until the first categorization trial, so performance at the beginning was predicted to not be as successful. For the individual analyses, alpha was set at .05. Analyses using pairwise comparisons to look at all three tasks have had a Bonferroni correction applied, and is denoted with cp. This correction multiplies the significance value to the number of comparisons in order to reduce Type 1 error, this can result in a *p*-value over 1.000 which is denoted here as *p* = 1.000.

Figure 9.2 depicts Murph's category endorsements for the first 120 trials, overall, and last 120 trials. In his first 120 trials, Murph was most successful endorsing the prototype in the second relevant task. He also was at chance with the random shapes in the early trials of both the irrelevant and first relevant tasks. Looking at his endorsements in all trials in Figure 9.2C, Murph shows the expected general trend of higher endorsements with the prototype and lower distortion levels and then declines with the level 5 and 7 distortions. However, he was generally more successful in his prototype and lower distortion level endorsements in the two relevant tasks. There was an overall significant difference in Murph's performance between the relevant tasks and the irrelevant tasks, $\chi^2(1) = 9.906$, $p = .002$, $\varphi = .002$. The Cochran's Q test confirmed that there was a significant difference between Murph's performance on the tasks in the first 120 trials $\chi^2(2) = 9.139$, p = .010. Planned pairwise comparisons showed that his performance was significantly higher in the second relevant task (random shapes then relevant) than the irrelevant task ($cp = 0.011$). There was no significant difference between the first relevant (relevant shapes then random shapes) and the irrelevant task ($cp = 1.00$) or between the two relevant tasks ($cp = .082$). Friedman's ANOVA test showed that there was a significant difference in overall performance to criterion, χ^2 (2) = 27.607, $p < .001$. Pairwise comparisons showed that his performance was significantly different between his second relevant task (random then relevant shapes) and his irrelevant task ($cp = .001$). There was no significant difference between the two relevant tasks ($cp = .080$), or between the first relevant task (relevant shapes and random) and the irrelevant task ($cp = .455$).

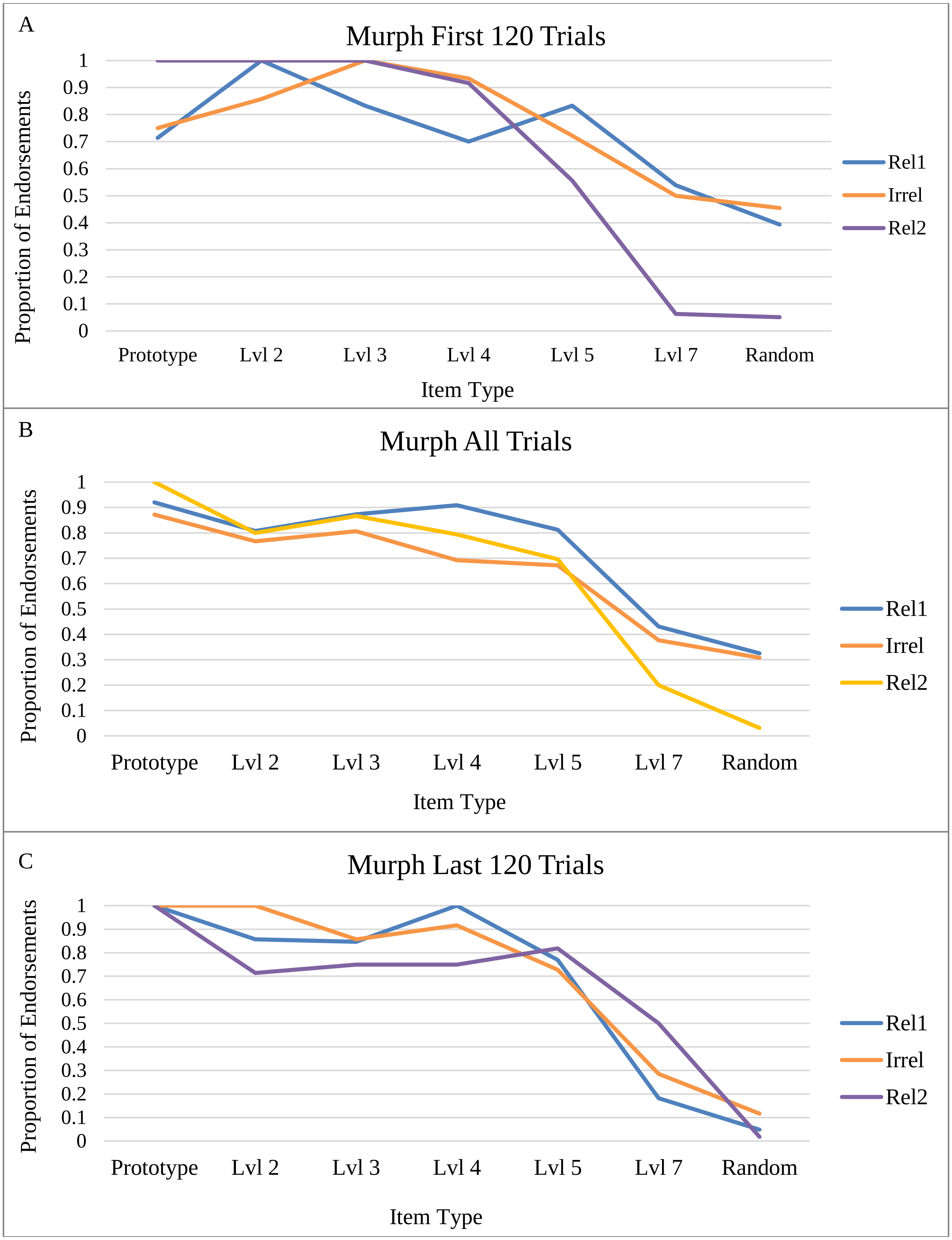


Figure 9.2 Murph's Proportion of Endorsements

Note. (A) The proportion of endorsements for each item type in Murph's first 120 trials for each task. (B) The proportion of endorsements for each item type in all of Murph's trials for each task. (C) The proportion of endorsements for each item type in the last 120 trials for each task.

Figure 9.3 depicts Obi's category endorsements for the first 120 trials, overall, and last 120 trials. In his first 120 trials, Obi was able to successfully endorse the prototype every time in all tasks. However, he was at chance with the random shapes in the irrelevant and second relevant tasks. Figure 9.3C depicts Obi's endorsements in all trials. He endorsed the prototype every time throughout all tasks. Overall, Obi did very well endorsing the prototype and lower level distortions regardless of task.

There was no overall significant difference in Obi's performance between the relevant tasks and the irrelevant task, $\chi^2(1) = .213$, $p = .644$. Looking at the tasks individually, the Cochran's Q test confirmed there was a significant different in performance for Obi between tasks in the first 120 trials, $\chi^2(2) = 9.562$, $p = 0.008$. Pairwise comparisons showed that there were significant differences between the two relevant tasks ($cp = 0.012$), and the irrelevant and first relevant task (random shapes then category members) ($cp = .044$). There was no significant difference between the irrelevant and second relevant (relevant then random shapes) ($cp = 1.00$). Obi's overall performance was also significantly different between tasks, $\chi^2(2) = 11.415$, $p = 0.003$. Pairwise comparisons show that there was a significant difference again between both relevant tasks ($cp = .004$), and the irrelevant and first relevant task (random then relevant shape order) ($cp = .045$). There was no significant difference in the overall performance between the irrelevant task and the second relevant task (relevant then random shape order) ($cp = 1.000$). For Obi, performance was significantly better when the relevant shapes were presented right before the categorization task.

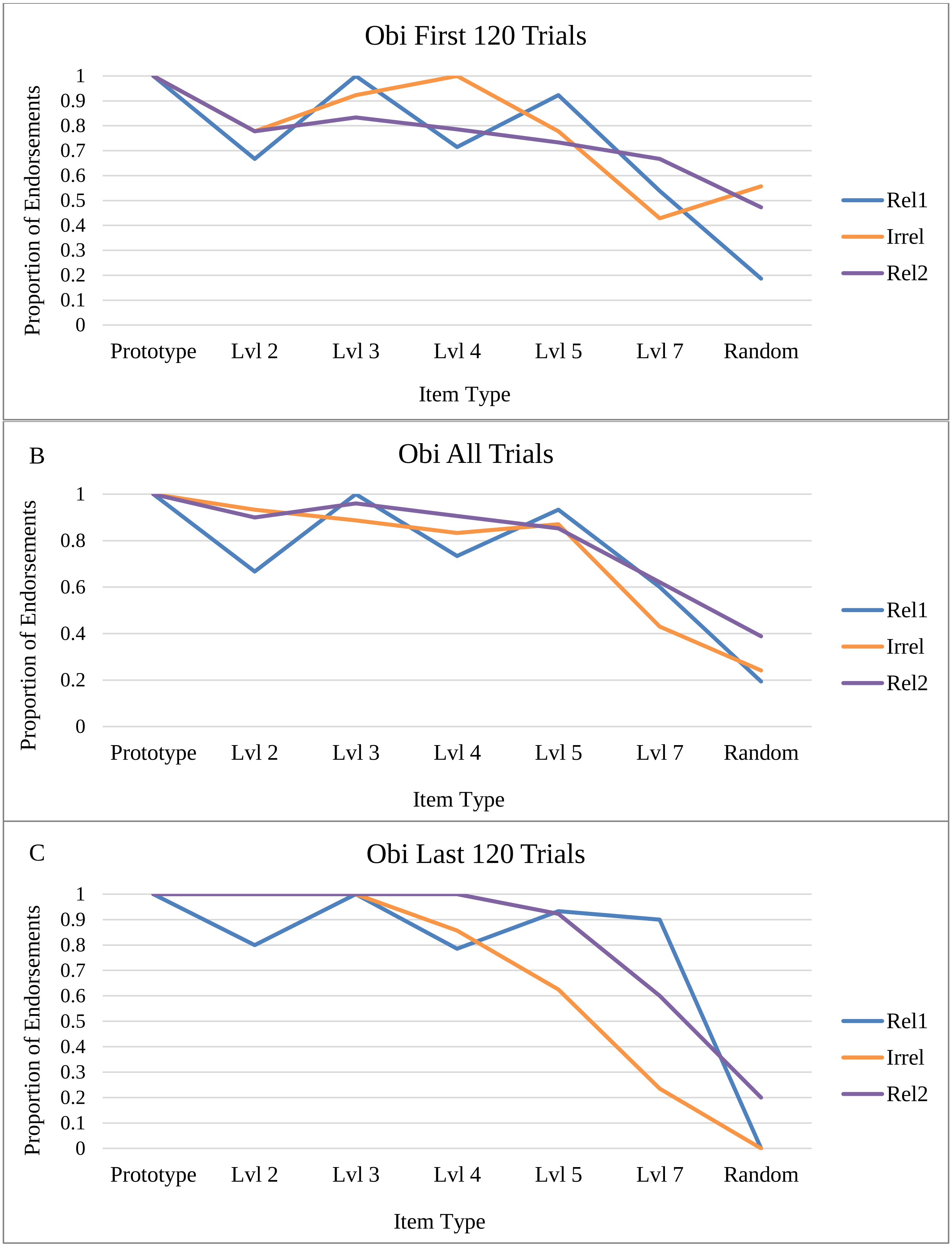


Figure 9.3 Obi's Proportion of Endorsements

Note. (A) The proportion of endorsements for each item type in Obi's first 120 trials for each task. (B) The proportion of endorsements for each item type in all of Obi's trials for each task. (C) The proportion of endorsements for each item type in the last 120 trials for each task. Obi finished the first relevant task in 136 trials.

Figure 9.4 depicts Han's category endorsements for the first 120 trials, overall, and last 120 trials. In his first 120 trials, Han was at chance for the prototype and distortion levels 2-5 in the irrelevant task. In the first relevant task, Han endorsed the prototype every time. Han struggled to endorse the prototype in the second relevant task but was still above chance. He was also at chance with the random shapes in the irrelevant and second relevant task. Figure 9.4C depicts Han's endorsement for all trials. He continued to endorse the prototype every time in the first relevant task.

There was an overall significant difference in Han's performance between the relevant tasks and the irrelevant tasks, $\chi^2(1) = 77.271$, $p < .001$, $\varphi = .281$. The Cochran's Q test shows that in the first 120 trials, there was a significant difference between tasks, $\chi^2(2) = 33.083$, $p < 0.0001$. The pairwise comparison shows that there are significant differences between the two relevant tasks, (*cp* = .018), the irrelevant and first relevant task (relevant then random shapes) (*cp* < .001), and the irrelevant and the second relevant task (random then relevant shapes) (*cp* = .008). The Friedman's ANOVA also showed significant differences on his performance over all trials in his last session of each task, $\chi^2(2) = 35.204$, $p < 0.001$. Pairwise comparisons show again, the two relevant tasks are significantly different (*cp* = .025), and the irrelevant and first relevant task (relevant then random shapes) (*cp* < .0001). There was no significant difference between the irrelevant and second relevant task (random then relevant shapes) (*cp* = .144).

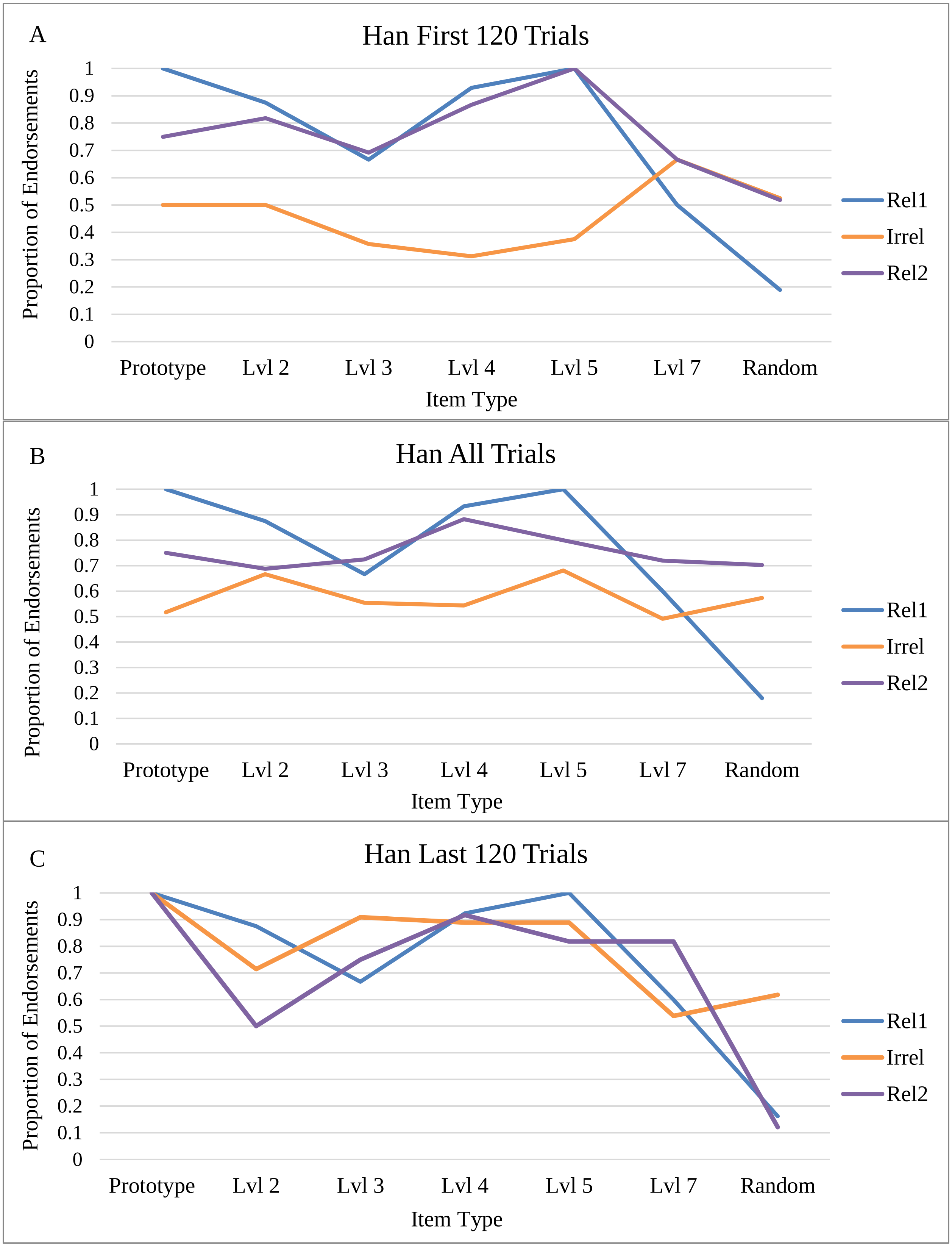


Figure 9.4 Han's Proportion of Endorsements

Note. (A) The proportion of endorsements for each item type in Han's first 120 trials for each task. (B) The proportion of endorsements for each item type in all of Han's trials for each task. (C) The proportion of endorsements for each item type in the last 120 trials for each task. Han never met criterion in the irrelevant task, information represents his last session.

Figure 9.5 depicts Lou's category endorsements for the first 120 trials, overall, and last 120 trials. In his first 120 trials, Lou successfully endorsed the prototype every time in each task. Lou did well endorsing the lower distortion levels in all tasks. However, Lou was at chance for the random shapes in the irrelevant task and was endorsing the majority of random shapes as category members in the first relevant task. Figure 9.5C depicts Lou's endorsements for all trials. He remained successful in his endorsements for the prototype and lower level distortions in all tasks. He remained inaccurate with the random shapes in the irrelevant and first relevant task.

There was no significant difference between his overall relevant and irrelevant task performance $\chi^2(1) = .020$, $p = .942$. The Cochran's Q test shows that in the first 120 trials, there was a significant difference in task performance $\chi^2(2) = 16.935$, $p < 0.001$. The pairwise comparisons show that there is a significant performance difference between the two relevant tasks ($cp < .001$), and with the irrelevant task and the second relevant task (relevant then random shapes) ($cp = .006$). There was no significant difference between the irrelevant task and the first relevant task (random then relevant shapes) ($cp = 1.000$). Friedman's ANOVA shows there is also a significant difference in task performance when looking at all trials in the last session, $\chi^2(2) = 16.935$, $p < .001$. Pairwise comparisons show that there was a significant difference in performance between the two relevant tasks ($cp = .014$). However, there was no overall difference between the irrelevant and first relevant task (random then relevant shapes) ($cp = 1.000$), or between the irrelevant and the second relevant task ($cp = .147$).

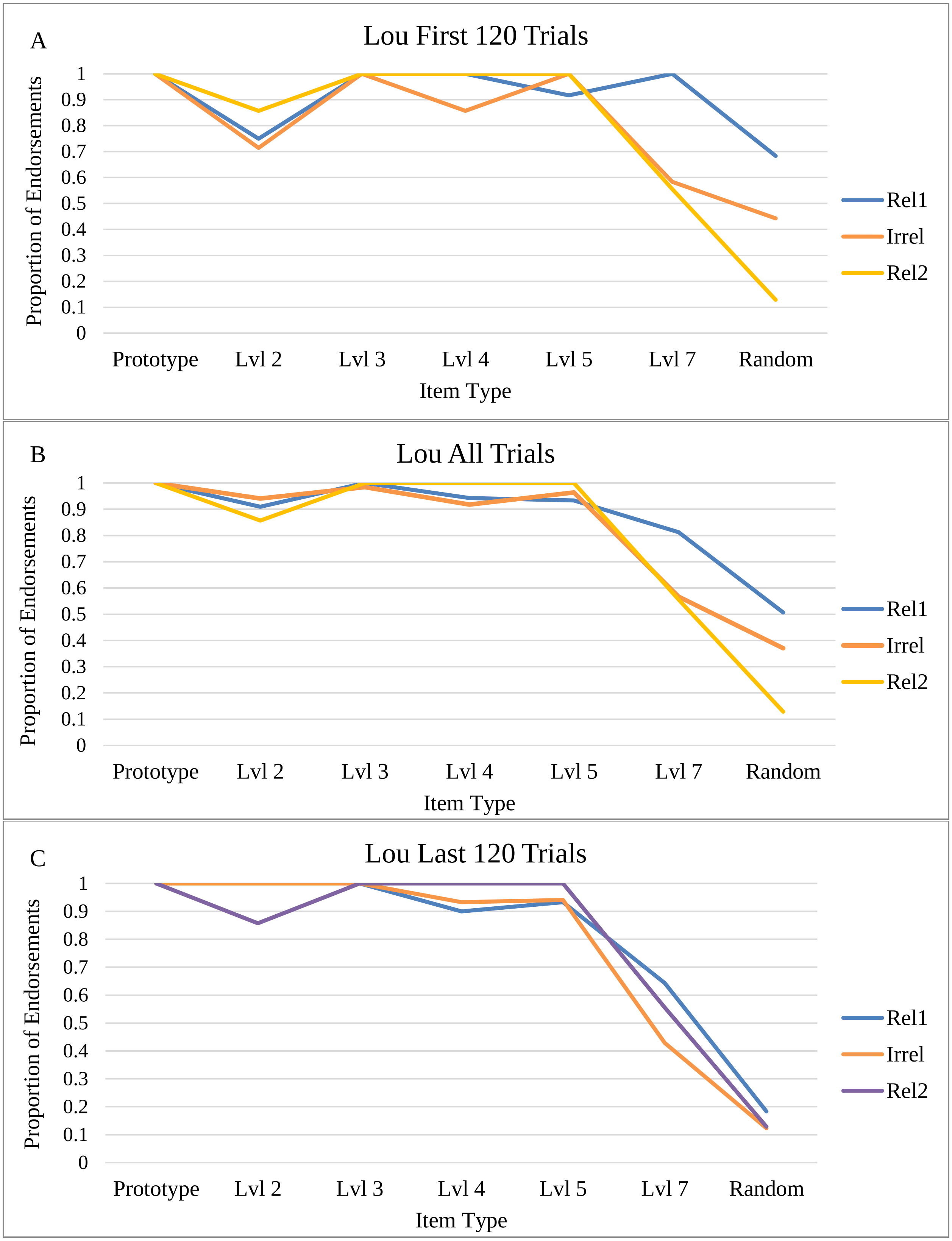


Figure 9.5 Lou's Proportion of Endorsements

Note. (A) The proportion of endorsements for each item type in Lou's first 120 trials for each task. (B) The proportion of endorsements for each item type in all of Lou's trials for each task. (C) The proportion of endorsements for each item type in the last 120 trials for each task. Lou completed his second relevant task in 116 trials.

9.3 Prototype Modeling

Prototype modeling was done for each monkey for each task. The prototype model assumes that the participants are comparing the to-be categorized items (TBCIs) to the category prototype to make their category membership decisions. Therefore, this modeling is helpful in determining whether the findings fit the supposition that a mental representation of the prototype was created during exposure. If they were able to create this prototype representation, I would expect them to have good fit to the prototype model. The model compares a TBCI to the prototype, and the psychological distance between them is converted to a measure of similarity. Psychological distance, in this particular case, is the actual physical distance of the nine-dimensional Pythagorean distance between the distortion and the prototype. This physical distance is then converted into a similarity measure. It is not a perfectly precise measure, as the dot configurations will affect the mind differently as they form different lines or angles.

TBCI types for the pilot included the prototype, Level 2, Level 3, Level 4, Level 5, Level 7 distortion, and randoms. For experiment 1, TBCI types included the prototype, Level 2, Level 3, Level 4, Level 5, Level 7 distortions for both the A and B categories. The psychological similarity between the TBCIs *(i)* and the category prototype *(p)* is estimated in order to predict the strength of category endorsement for each item type. The model used the following parameters in the equation: R_{Cat} = category response, S_i = given item type, η= psychological similarity, k = criterion quantity (a proportionalizing free parameter), P = prototype. The criterion quantity represents the general similarity between the items and members of other categories. The equation below states the probability of category endorsement, given the TBCI type:

(A)

$$P(\mathrm{R}_{\mathrm{Cat}} \mid \mathrm{S}_i) = \frac{\eta_{ip}}{\eta_{ip} + k}$$

The psychological similarity between the TBCI type (*i*) and the prototype (*p*) is compared with the proportionalizing threshold *k*. The psychological similarity is calculated by taking the average Pythagorean distance that the corresponding dots were moved between the patterns of the (*i*) and (*p*) (Smith et al., 2008). This psychological distance measurement is set equal to the equation ln (1+ mean Pythagorean distance). It has been well documented that the average logarithmic distances between the prototype and the prototype, Level 2, Level 3, Level 4, Level 5, Level 7 and randoms are 0.0000, 0.4497, 0.6401, 0.8687, 1.094, 1.762, and 2.8479 (Church et al., 2010; Smith et al., 2008). These distances are transformed into psychological similarities using an exponential-decay function that incorporates a sensitivity parameter (c), the prototype model’s second free parameter. The sensitivity parameter is a measure of the participants sensitivity to the perceptual distance from the prototype. This parameter reflects the steepness of the decay of similarity around the prototype. The similarity between a transfer item type and the prototype is represented below:

(B)

$$\eta_{ip} = e^{-cd_{ip}}$$

Psychological similarity (η) is entered into the choice rule (A) above, and the probability of endorsement (model-predicted endorsement) is calculated for each item type.

9.3.1 *Model Fitting*

Hill-climbing procedures were used to find the best possible prototype model fits to the data. This algorithm maximized the fit by minimizing the differential between the predicted and observed profiles. Hill-climbing procedures have been used reliably in categorization research and involve seeding the model to find the best fit (e.g., Smith et al., 2008). Seeding the model is a process in which a random configuration of the parameters (sensitivity and criterion) is selected and then the predicted categorization probabilities for the item types according to that configuration is calculated. The degree of fit between the predicted and observed categorization probabilities is the sum of the squared deviations (SSD) between them. Then the hill-climbing mechanism makes small adjustments to the provisional best-fitting parameter settings, and the new settings are adopted if they produced a better fit (i.e., a smaller SSD between predicted and observed performance). The directional changes are always very small (1/10,000,000 for criterion and 1/10,000 for sensitivity) and respect the upper and lower bounds of the free parameters (0.0000001 and .1 for criterion and .0001 and 10 for sensitivity). This can happen hundreds of times before finding the best fit. The sum of squared deviation (SSD), best fit, sensitivity (*c*), and criterion (*k*) free parameters are recorded once the best fit has been determined. A higher SSD denotes a worse fit and a lower SSD would indicate better fit. I compared the fits for each monkey on each task and determined in which task their observed endorsements were closest to the predicted. I hypothesized that the monkeys would be building prototype representations during the exposure phase, and therefore I expected that each monkey showed better fit for this model in the relevant tasks than the irrelevant task.

Table 9.4 shows the criterion, sensitivity and fit in the first 120, and all trials for each monkey in each task. The fit (SSD) value for each monkey in each task was low, which represents a good fit. When looking at the first 120 trials, Han's best fit is in the irrelevant task. When looking at his overall performance, his best fit in is the relevant task where he received random shapes and then relevant shapes during exposure. Obi's best fit in the first 120, and overall trials is in the relevant task when exposure was presented with relevant then random shapes. Murph's best fit in the first 120 and overall trials was in the relevant task with relevant then random shape exposure order. Lou's best fit in all cases was in the relevant task when the random then relevant shapes were presented.

Table 9.4 Prototype Modeling

Task	**Monkey**	**Overall Criterion**	**Overall Sensitivity**	**Overall Fit**	**120 Criterion**	**120 Sensitivity**	**120 Fit**
Rel-Rand	Han	0.1241	0.3578	0.132	0.133	0.4018	0.179
	Obi	0.0663	0.8745	**0.0324**	0.1284	0.7806	**0.019**
	Murph	0.1466	0.5852	**0.1072**	0.1858	0.5122	**0.09**
	Lou	0.0601	0.5517	0.1355	0.0601	0.5517	0.136
Rand-Rel	Han	0.2992	0.0861	**0.0263**	0.1475	0.635	0.091
	Obi	0.1518	0.3235	0.1404	0.1648	0.3222	0.169
	Murph	0.2427	0.2388	0.4174	0.1155	0.2846	0.206
	Lou	0.0172	1.4419	**0.0057**	0.0015	2.5102	**0.077**
Irrel	Han	0.6277	0.2244	0.0342	0.6277	0.2244	**0.034**
	Obi	0.1155	0.5838	0.1398	0.0974	0.8912	0.128
	Murph	0.2838	0.3846	0.1083	0.1095	0.9157	0.093
	Lou	0.0492	0.9743	0.0676	0.0709	0.9106	0.106

Note. Rel-Rand represents the relevant exposure task in which relevant category members were first and shape shapes second. Rand-Rel represents the opposite exposure schedule. Irrel represents the irrelevant task. The best fit for each monkey is depicted for the overall, and first 120 trials in bold.

10 DISCUSSION

Criterion was met significantly faster in the relevant tasks when looking at all sessions and the last session. There were no significant differences between the exposure schedules of the relevant tasks for meeting criterion indicating that the relevant shapes being exposed before or after the random shapes did not affect how quickly the monkeys were able to meet criterion.

Murph and Han’s performance was significantly better in the relevant tasks (combined) than in the irrelevant task. Looking at individual tasks, Murph and Obi had significantly better performance in the relevant task in which the relevant shapes were shown second. Han and Lou both had significantly better performance on the opposite relevant task, when relevant shapes were presented before random shapes.

Overall, relevant exposure, in at least one of the relevant tasks, provided benefit in the later categorization task. The results may be due to building a representation of the prototype during the exposure phase. This is the first time that macaques have been tested in an A-not-A task with mere exposure. Not only did they learn the category, but they were able to transfer their category knowledge to novel shapes. Due to the recency effect shown by two of the monkeys in the relevant task with random shapes first and relevant shapes shown second, Experiment 1 used a different exposure schedule.

11 METHODS: EXPERMENT 1

Four male rhesus macaques Murph, Lou, Han, and Obi were tested in the same way as in the pilot study with the same apparatus. Stimuli were made in the same way as mentioned in the pilot. The main difference was that instead of creating random non-category members for comparison, a second prototype was created as the basis for a B category during both exposure and test, and they had to decide during the categorization phase if the shape belonged to category A or B. The distortion types and proportions for the B category were the same as for the A category described earlier.

11.1 Procedure

Just as in the pilot, each monkey completed one training task, three exposure tasks and three categorization tasks. The tasks were presented in the same order as before: training, relevant exposure and categorization task, irrelevant exposure and categorization task, and relevant exposure and categorization task. In the training task, half of the polygon shapes belonged to category A and the other half belonged to category B. The shapes were comprised of 5% prototype, 5% level-2, 10% level-3, 10% level-4, 10% level-5, 10% level-7 prototype distortions from each category. The shape appeared in the center of the screen, then beneath the shape appeared an A to the left of a cross cursor, and a B to the right of the cursor. The objective now was for the monkey to move their joystick to the left or right to decide if the shape that appeared belonged to category A or category B. They received a pellet reward and heard a familiar whooping sound when they selected A for category A members, and B for category B members. If they made the wrong categorization decision, a familiar buzzing sound was heard, and they received a 20 second timeout. The monkeys automatically moved to the next task after reaching a criterion of 85% accuracy over approximately 120 trials. Due to a strong recency effect found for some monkeys in the pilot, the category A and B stimuli were randomly intermixed at the beginning and end of the exposure phases, and in-between there were alternating blocks of 10 Category A and Category B members. In one of the relevant tasks, the exposure phase presented 20 trials with Category A and B members intermixed, then 10 Category A members, 10 Category B members, 10 Category A members, 10 Category B members, 10 Category A members, 10 Category B members, 10 Category A members, 10 Category B members, and 20 intermixed exposure trials. For the other relevant task, the first and last block consisted of 20 trials Category A and B members intermixed, then the alternating blocks began with 10 Category B members, and then 10 Category A members, etc. The category shapes consisted of 20 level-3, 20 level-5, and 20 level-7 prototype distortions from each category during exposure. The shapes appeared in the center of the screen, and the monkey used their joystick to simply touch the shape. In this task, pellet rewards were given for every three shapes that were touched by the cursor. After each exposure phase, the monkeys completed a categorization task. A shape appeared in the center of the screen, and the monkey used his cursor to select A if it belonged to category A and B if it belonged to category B. The program generated random prototypes for each task. If a monkey did not finish a task (exposure or categorization task) before the program closed, they were restarted at the last exposure task (completed or not) with two new prototypes.

12 EXPERIMENT 1 RESULTS

12.1 Trials to Criterion

Three of the four monkeys completed all three tasks. Their proportion correct and trials to criteria can be seen in Table 12.1. Figure 12.1A shows the number of trials it took to complete each task (including unfinished sessions), and Figure 12.1B shows the number of trials it took to meet criterion in their last session for each task. Murph finished his first relevant task (Category A shown first after intermixing) in two sessions, it took 275 trials to meet criterion. It took Murph one session of 190 trials to meet criterion in his irrelevant task. In his second relevant task (Category B presented first after intermixing), Murph met criterion in one session, 152 trials. Obi met criterion in his first relevant task (Category B presented first after intermixing) in his first session of 170 trials. In his irrelevant task, Obi met criterion in his first session in 114 trials. In his second relevant task (Category A presented first after intermixing), Obi met criterion after two sessions with 617 trials. Lou finished his relevant task (Category B presented first after intermixing) in eight sessions with 603 trials. In his irrelevant condition, Lou met criterion in his first session in 306 trials. Lou met criterion in his second relevant task (Category A presented first after intermixing) in three sessions after 624 trials.

Table 12.1 Proportion Correct in Each Task

MURPH	**Trials to Criterion**	**Total Trials Prop Correct**	**Trials in Last Sess**	**Prop Correct Last Sess**	**First 120 Last Sess**	**Prop Correct Cat A**	**Prop Correct Cat B**
Rel-AB (1)	275	0.64	233	0.66	0.51	0.71	0.68
Irrelevant	190	0.84	190	0.84	0.82	0.69	0.98
Rel-BA (2)	152	0.75	152	0.75	0.7	0.85	0.65
OBI	**Trials to Criterion**	**Total Trials Prop Correct**	**Trials in Last Sess**	**Prop Correct Last Sess**	**First 120 Last Sess**	**Prop Correct Cat A**	**Prop Correct Cat B**
Rel-BA (1)	170	0.75	170	0.75	0.73	0.68	0.84
Irrelevant	114	0.85	114	0.85	0.85	0.8	1
Rel-AB (2)	617	0.55	294	0.68	0.58	0.63	0.72
LOU	**Trials to Criterion**	**Total Trials Prop Correct**	**Trials in Last Sess**	**Prop Correct Last Sess**	**First 120 Last Sess**	**Prop Correct Cat A**	**Prop Correct Cat B**
Rel-BA (1)	603	0.59	230	0.78	0.68	0.77	0.78
Irrelevant	306	0.73	306	0.73	0.63	0.76	0.71
Rel-AB (2)	624	0.5	304	0.73	0.68	0.72	0.75

Note. Rel-AB represents the relevant exposure when the Category A members were presented first after intermixing both categories. Rel-BA represents the relevant exposure conditions when Category B was presented first after intermixing. The 1 or 2 represents whether it was the first or second relevant task for that monkey.

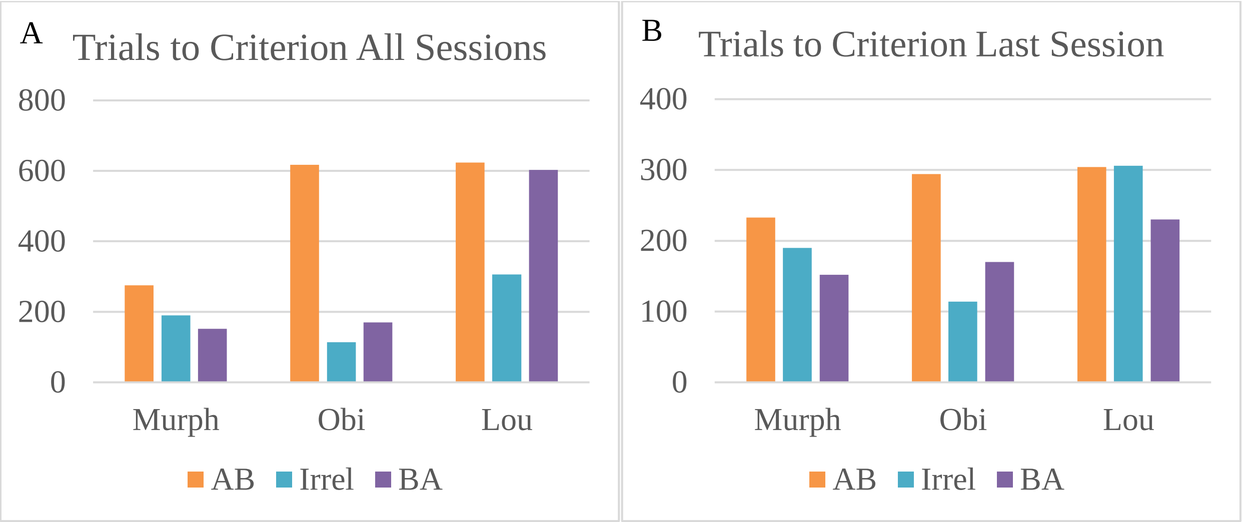


Figure 12.1 Trials to Criterion

Note. AB represents the relevant exposure when the Category A members were presented first after intermixing both categories. BA represents the relevant exposure conditions when Category B was presented first after intermixing.

Table 12.2 presents the means (*M*) and standard deviations (*SD*) information for the trials to criterion for each task. Due to the small N design and the strong directional predictions, all analyses use an alpha level of .10.

Looking at the relevant tasks combined and irrelevant task, there was no significant difference between relevant and irrelevant trials to criterion, *t*(7) = 1.4215, *p* = .198. Differences between tasks based on exposure schedule was also investigated. There was no difference between the relevant task in which Category A was presented first and the irrelevant task, *t*(2) = 2.497, *p* = .130, or the relevant task in which Category B was presented first and the irrelevant task *t*(2) = -1.053, *p* = .403, or between the two relevant tasks, *t*(2) = 1.534, *p* = .265.

Table 12.2 Means and Standard Deviations of the Total Trials to Criterion

Overall Trials to Criterion	**M**	**SD**
Relevant All	406.83	231.61
Relevant 1	349.33	225.86
Irrelevant	203.33	96.69
Relevant 2	464.33	270.51
Rel-AB	505.33	199.50
Rel-BA	308.33	255.34

Analyses were also performed looking at the number of trials to criterion only from the session in which they met criterion for each task. Table 12.3 presents the means (*M*) and standard deviations (*SD*) for the trials to criterion in the last session. There was no overall significant difference in trials to criterion in the last session of each task when comparing the relevant trials and irrelevant tasks trials, *t*(8) = .617, *p* = .458. Analyses were also done to look at differences in the trials it took to meet criterion in the last session due to exposure order. There was a significant difference between the two exposure schedules, *t*(2) = 5.950, *p* = .027, *d* = 3.433. There was no significant difference between the relevant task in which Category A was presented first and the irrelevant task , *t*(2) = 1.346, *p* = .311, or between the relevant task in which Category B was presented first and the irrelevant task, , *t*(2) = .493, *p* = .671.

Table 12.3 Means and Standard Deviations of the Number of Trials to Criterion for the Last Session

Last Session Trials to Criterion	**M**	**SD**
Relevant All	230.33	96.69
Relevant 1	211	35.53
Irrelevant	203.33	96.69
Relevant 2	250	85.02
Rel-AB	277	40.84
Rel-BA	184	40.84

Note. Rel-AB represents the relevant exposure when the Category A members were presented first after intermixing both categories. Rel-BA represents the relevant exposure conditions when Category B was presented first after intermixing.

12.2 Categorization Performance

Data from the last session was used from each task to examine each monkey's categorization performance. This only includes the session in which criterion was met. To statistically compare categorization performance, the Fisher's Exact test was used to compare the proportion correct between the relevant tasks and irrelevant task. Cochran's Q test was used to look at performance for the first 120 trials. McNemar's test was used to see if there was a significant difference in performance with Category A and Category B members. For the individual analyses, alpha was set to .05. Analyses using pairwise comparisons to examine all three tasks have a Bonferroni correction applied, denoted as cp. This correction multiplies the significance value to the number of comparisons in order to reduce Type 1 error, this can result in a p-value over 1.000 which is denoted here as p = 1.000.

Figure 12.3 depicts Murph's category endorsements for the first 120, and all trials. In his first relevant task, Murph learned the prototypes of each category equally by the end. However, in his first 120 trials, he was at chance with the prototypes and level 2 and 3 distortions for both categories, suggesting he had not learned the correct response for the categories yet. In the irrelevant task, performance was perfect for the prototype of Category B throughout the task, but he was at chance with the prototype of Category A even by the end of the task. His endorsements of Category A also did not show the normal typicality gradient. In the second relevant task, he learned the Category A prototype perfectly by the end, but he was only 78% correct with the Category B prototype. However, both categories showed a normal typicality gradient.

A Fisher's Exact test found Murph's performance was significantly better in the irrelevant task than the relevant tasks, $\chi^2(1) = 10.742$, $p = .0012$, $\varphi = -.138$. The Cochran's Q test confirmed this significant difference between Murph's performance on the tasks in the first 120 trials $\chi^2(2) = 27.136$, $p < .001$. Planned pairwise comparisons show the proportion correct in the irrelevant task was significantly better than in the first relevant task ($cp < .001$), and the proportion correct in the second relevant task was significantly high than the first relevant task ($cp = .005$). There was no significant difference between the second relevant task and the irrelevant task ($cp = .124$).

McNemar's test found a significant difference in proportion correct between two categories in the irrelevant task ($p < .001$), and in the second relevant task ($p = .006$), indicating Murph learned one category significantly better than the other. There was no significant difference in Category A and Category B performance in the first relevant task, $p = .200$.

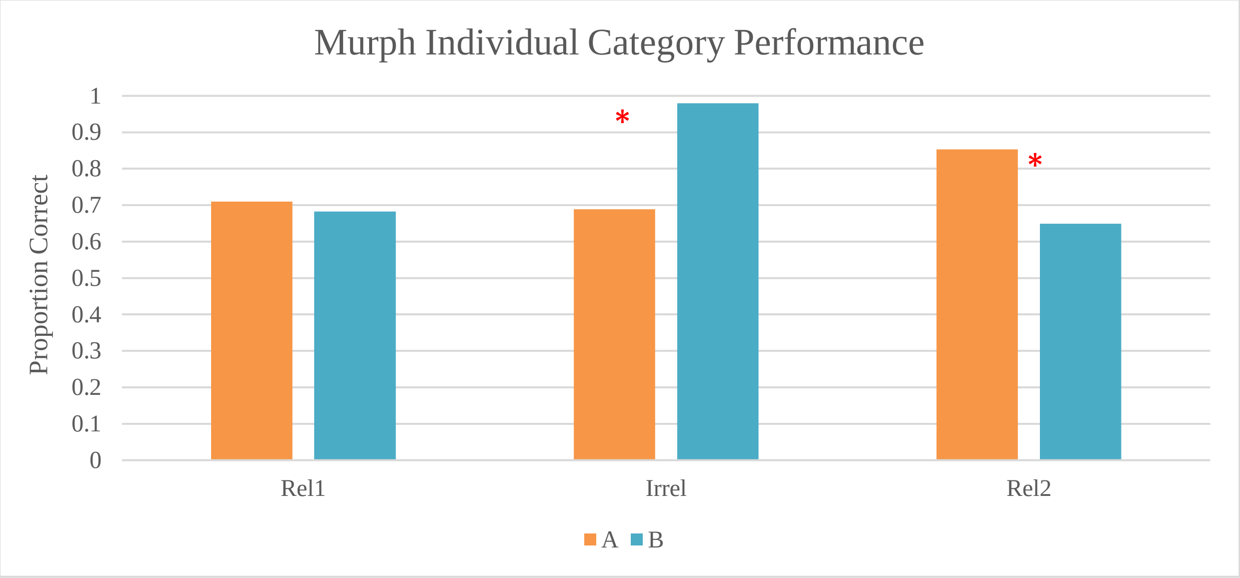
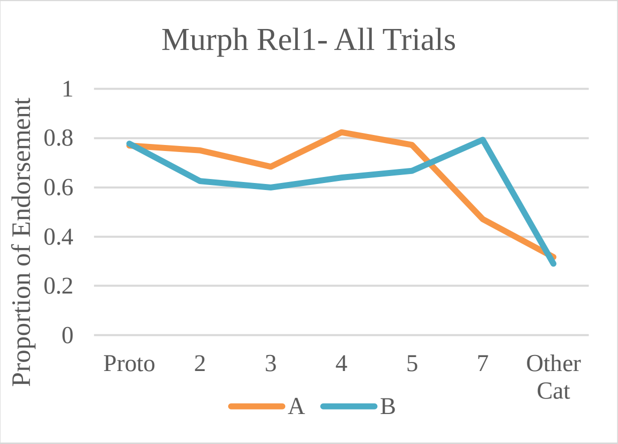
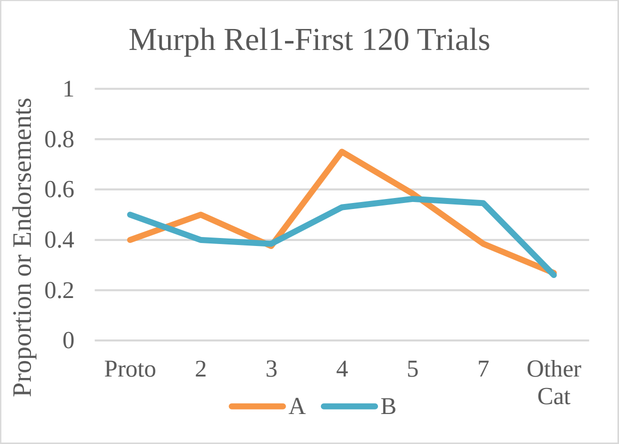
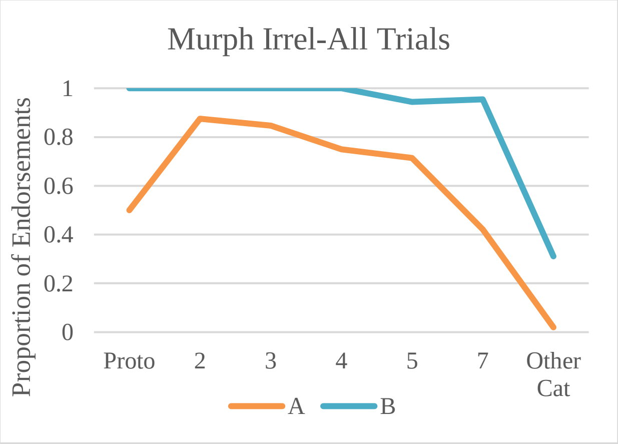
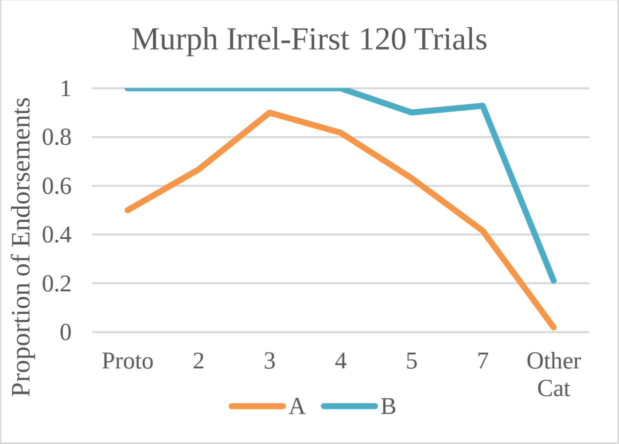


Figure 12.2 Murph's Category Performance









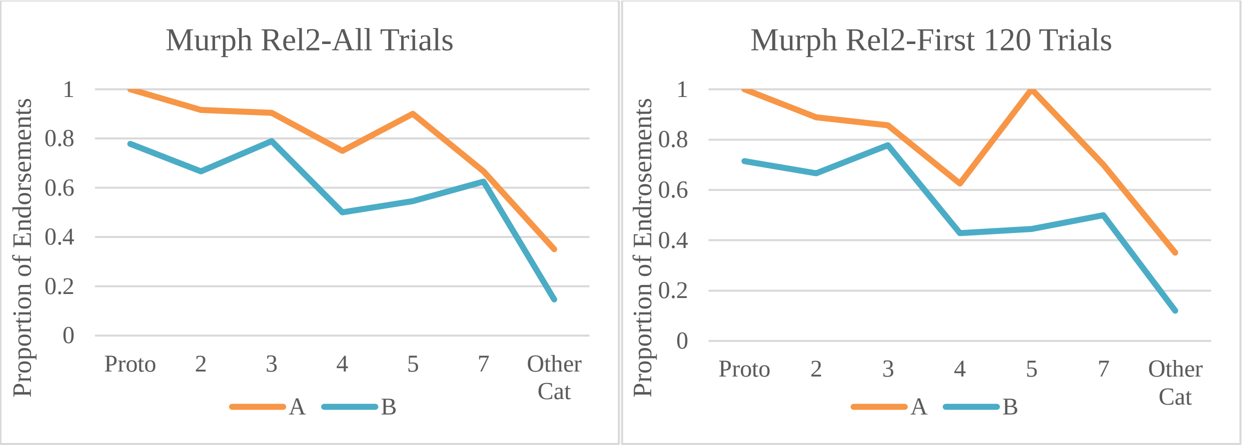


Figure 12.3 Murph's Proportion of Endorsements

Figure 12.5 depicts Obi's category endorsements for the first 120, and all trials. In the first relevant task, Obi correctly endorsed the Category B prototype every time, and correctly categorized the Category A prototype 89% of the time overall. In the irrelevant task, Obi had perfect performance with all of Category B, exemplars and also endorsed the Category A prototype every time it was presented. In the second relevant task, Obi endorsed the Category A prototype every time, but was at chance with the Category B prototype.

The Fisher's Exact test found an overall significant difference in Obi's performance between the relevant tasks and the irrelevant tasks, $\chi^2(1) = 16.951$, $p < .001$, $\varphi = -.171$. The Cochran's Q test confirmed a significant difference between Obi's performance on the tasks in the first 120 trials $\chi^2(2) = 27.250$, $p < .001$. Planned pairwise comparisons shows that Obi's proportion correct in the irrelevant task is significantly better than in the second relevant task (*cp* < .001) and the first relevant task (*cp* = .007). There was no significant difference between the two relevant tasks (*cp* = .091).

The McNemar's test showed a significant difference in performance between A and B categories in the irrelevant task, $p < .001$, indicating Obi learned Category B significantly better than Category A. There was no significant difference in Category A and Category B performance in the first relevant task, *p* = .059, or the second relevant task, *p* = .396.

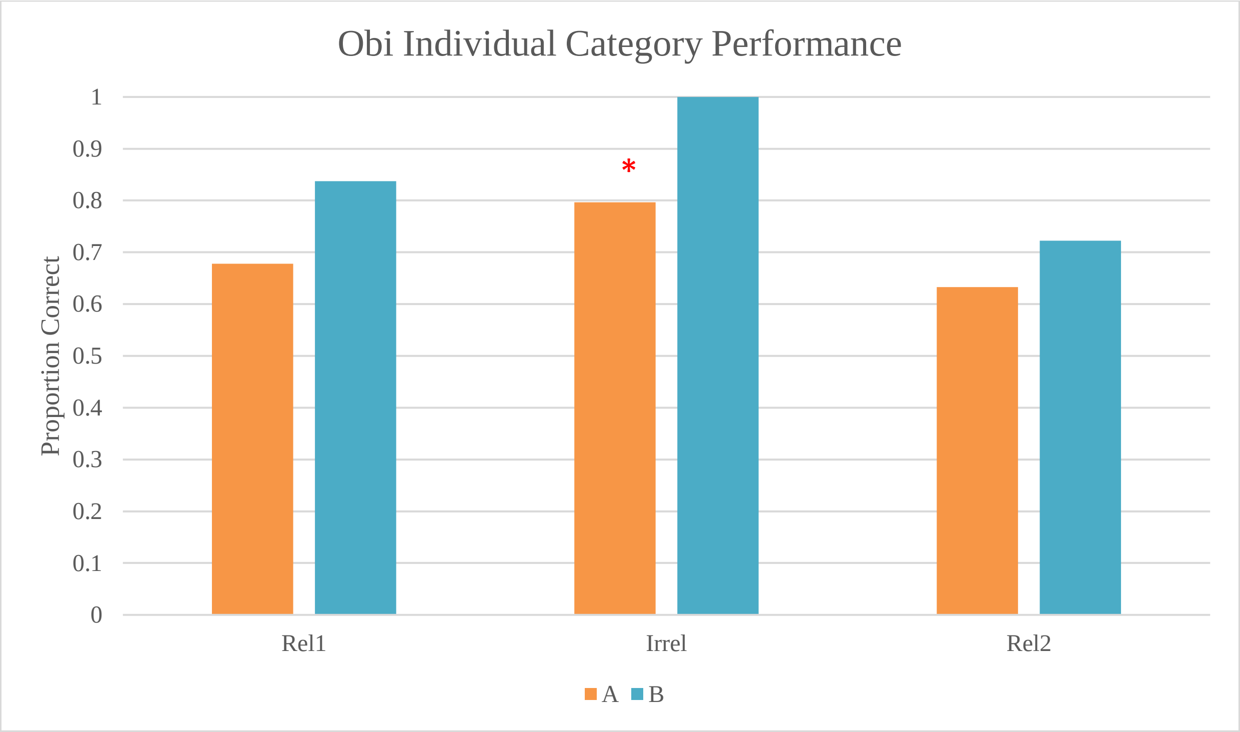
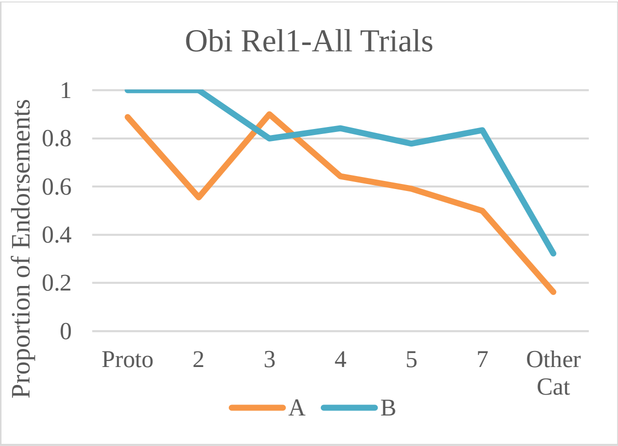
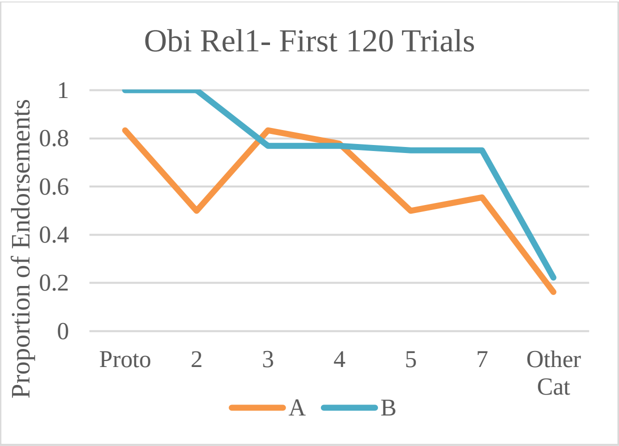


Figure 12.4 Obi's Category Performance





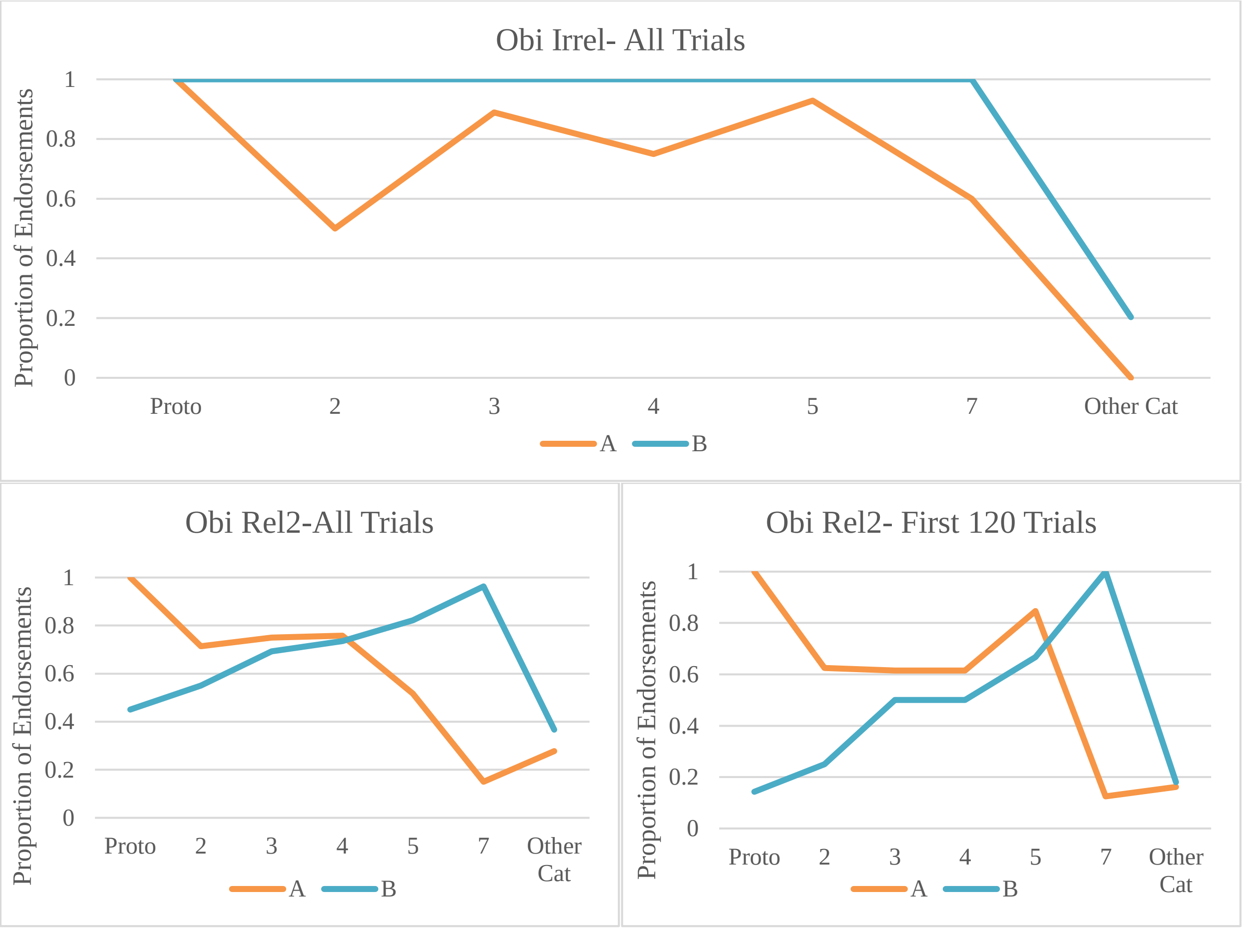


Figure 12.5 Obi's Proportion of Endorsements

Figure 12.7 depicts Lou’s category endorsements for the first 120 and all trials. Early in the first relevant task, Lou was performing well with the Category B prototype (88%) but was at chance with the Category A prototype. By the end of the task, his performance with each category was similar. In the irrelevant task, early performance again shows that he learned one category (Category B) better than the other, but by the end, performance with the two categories was similar. In the second relevant task, Lou’s early performance with Category B exemplars was better than performance with Category A members. By the end of the session, he was still endorsing the Category B prototype accurately, but was at chance with the Category A prototype, his performance was similar with the other distortion levels.

The Fisher's Exact test found no overall significant difference in Lou's performance in the relevant and irrelevant tasks, $\chi^2(1) = .443$, p = .511. The Cochran's Q test also found no significant differences between the tasks in the first 120 trials, $\chi^2(2)$ = .575, p = .750.

McNemar's test shows there were no significant differences in Category A or Category B performance in the first relevant task (p = 1.00), the irrelevant task (p = .422), or the second relevant task (p = .464), suggesting he always learned the categories relatively equally.

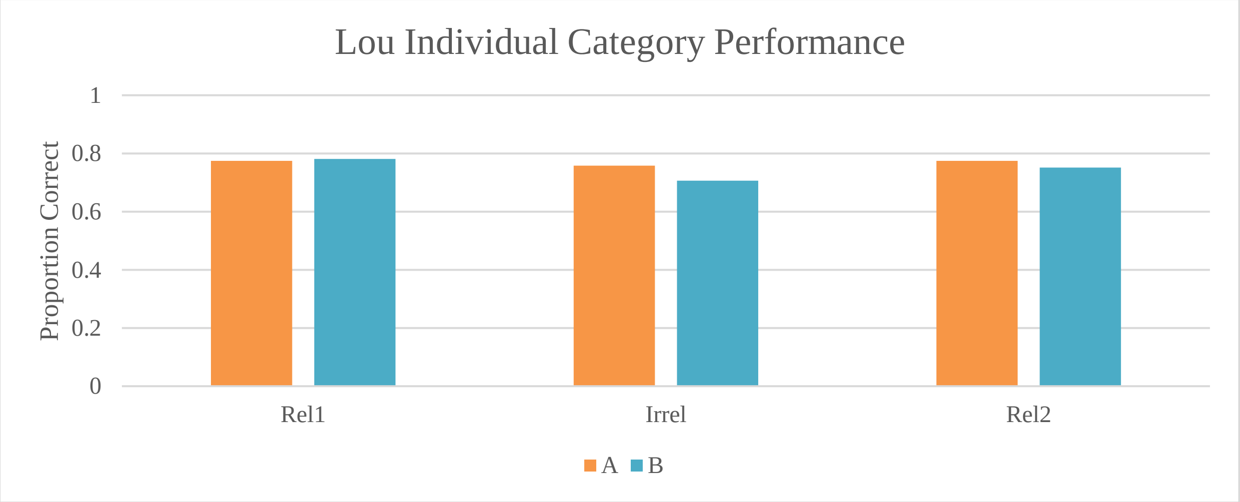


Figure 12.6 Lou's Category Performance

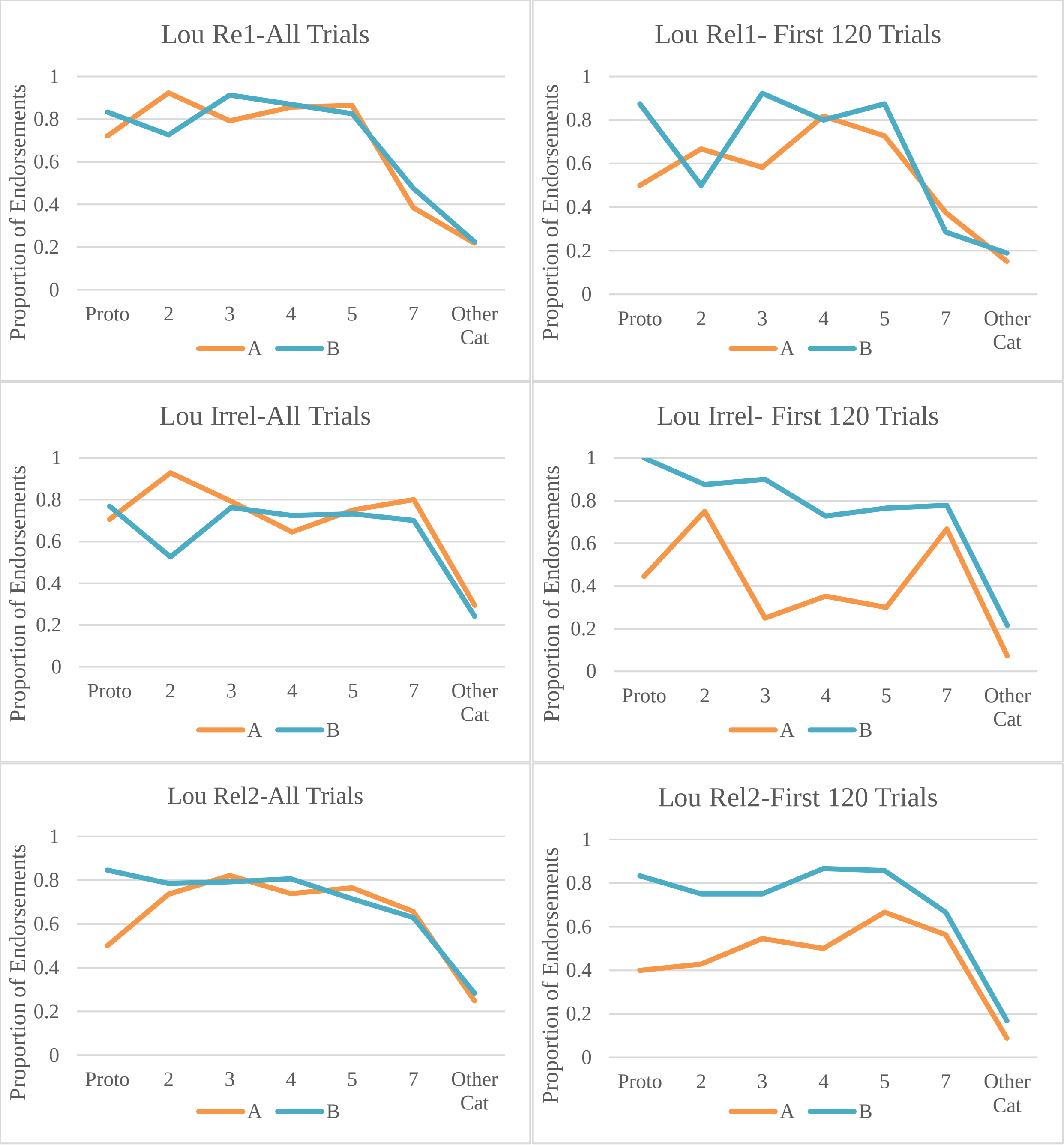


Figure 12.7 Lou's Proportion of Endorsements

12.3 Prototype Modeling

Table 12.4 shows the criterion, sensitivity and fit for each category in each task across all trials and the first 120 trials. Looking at early performance (first 120 trials), Murph’s fit for both Category A and B was relatively good in both of his relevant tasks, however the fit for both categories in his irrelevant tasks was not good. Looking at all trials, Murph had really good fits for both categories in both relevant tasks, but still did not have a good fit for both categories in the irrelevant task. In Obi's first 120 trials and overall trials, he only had a decent fit for both categories in his first relevant task (B presented first). In Lou's first 120 trials, he only had a good fit for both categories in his second relevant task (A presented first). Looking at all trials, Lou still had a really good fit for both categories in his second relevant task, but also in his irrelevant task.

Table 12.4 Prototype Modeling

Murph	Overall Criterion	Overall Sensitivity	Overall Fit	120 Criterion	120 Sensitivity	120 Fit
A_Irrel	0.3762	0.0001	0.2459	0.4247	0.0001	0.2584
B_Irrel	0.0027	1.7979	0.0018	0.0111	1.1211	0.0058
A_AB	0.3081	0.2608	0.0633	0.7506	0.0001	0.1656
B_AB	0.4545	0.0001	0.0341	0.7518	0.0001	0.0999
A_BA	0.09	0.6963	0.0356	0.1074	0.6071	0.0928
B_BA	0.4712	0.0001	0.1053	0.5866	0.0001	0.1847
Obi	Overall Criterion	Overall Sensitivity	Overall Fit	120 Criterion	120 Sensitivity	120 Fit
A_Irrel	0.2351	0.0001	0.2363	0.2351	0.0001	0.2363
B_Irrel	0.0005	2.1512	0.0006	0.0005	2.1512	0.0006
A_AB	0.3035	0.5021	0.3426	0.3828	0.247	0.4532
B_AB	0.4447	0.0001	0.1743	0.7498	0.0001	0.5519
A_BA	0.3964	0.0614	0.1695	0.447	0.0001	0.1608
B_BA	0.084	0.6226	0.0325	0.1312	0.3838	0.0575
Lou	Overall Criterion	Overall Sensitivity	Overall Fit	120 Criterion	120 Sensitivity	120 Fit
A_Irrel	0.2772	0.1105	0.0481	0.7497	0.0001	0.4091
B_Irrel	0.408	0.0001	0.043	0.1362	0.3393	0.0383
A_AB	0.4081	0.0001	0.0656	0.743	0.0001	0.1812
B_AB	0.2381	0.2684	0.0168	0.2516	0.03	0.0322
A_BA	0.2276	0.2854	0.1737	0.5723	0.0001	0.153
B_BA	0.2088	0.293	0.1086	0.2909	0.2643	0.3175

Note. Below .1 is a good fit, between .1 and .2 is an okay fit, and .2 and above is a bad fit. A_Irrel represents Category A after irrelevant exposure. B_Irrel represents Category B after irrelevant exposure. A_AB represents Category A after relevant exposure when the Category A members were presented first after intermixing both categories. B_AB represents Category B after relevant exposure when the Category A members were presented first after intermixing both categories. A_BA represents Category A after relevant exposure when the Category B members were presented first after intermixing both categories. B_BA represents Category B after relevant exposure when the Category B members were presented first after intermixing both categories.

13 GENERAL DISCUSSION

Multiple-systems theorists have tried to understand how different brain systems facilitate different types of category learning. One model, COVIS, assumes that category learning takes place either through associative learning or by discovering defining criteria (rule learning). Associative learning is thought to be supported by the implicit-procedural system, which learns by associating responses to whole stimuli and generalizing based on similarity. Rule learning is thought to be supported by the explicit-declarative system, which focuses on features of stimuli that are predictive of its category and are typically verbalizable. This classic COVIS theory assumes that family resemblance (overall similarity) information is learned implicitly, whereas single atypical exemplars are learned explicitly through memorization. However, the classic COVIS theory has some difficulty with the finding that some family-resemblance based categorization tasks can be learned without feedback or reinforcement. To explain this finding, it has been suggested that we are able to learn family-resemblance categories without feedback due to fluency (Ashby & Maddox, 2005). Fluency happens when a previous experience that induces a graded pattern of activation in the visual cortex causes that group of cells to fire more rapidly to the presentation of similar patterns in the future (Ashby & Maddox, 2005). In other words, during exposure to category members, cells common to category members repeatedly fire causing an enhanced visual response, then, during the transfer phase, participants can use the feeling of fluency to decide which stimuli belong to the category. This presents problems if you are trying to learn more than one category simultaneously without feedback, as stimuli from both categories will feel fluent and cannot be differentially categorized.

In this paper, I questioned whether fluency was the only option for explaining learning without feedback in family-resemblance categorization tasks, or if actual unitized prototype representation in the visual cortex through perceptual learning could better explain these findings. Representational perceptual learning theories predict that as we have perceptual experience with stimuli, the way they are represented changes, and they become more unitized and more distinguished from other representations. Instead of the cortical activation during exposure simply creating *faster* future activation (fluency), it may create a unitized representation of the prototypes (representational theories of perceptual learning). Therefore, exposure should aid in single and multiple family-resemblance category learning. I proposed a COVIS plus theory, which still assumes separate implicit and explicit systems. However, it also assumes that the visual perceptual system feeding inputs into both these systems can build cortical representations of prototypes through perceptual learning that can later aid either type of category learning allowing sorting or quick mapping onto multiple categories as well as single categories. Therefore, family-resemblance learning from exposure does not have to be based simply on fluency. With clear visual representations of the prototypes, one would be able to more quickly map stimuli that share similarity with those prototype representations to categories. This view predicts that initial exposure to category members creates representations that should aid family-resemblance category learning in both single category learning (A-not-A tasks) and in discriminating between two categories (A-B tasks).

Previous research has shown that humans, including amnesic patients, are able to learn single category tasks through mere exposure (e.g., Reed et al.,1999), and rhesus macaques are able to learn single category tasks (A-not-A) and are able to transfer their prototype knowledge to novel stimuli (Smith et al., 2008). However, this was the first time that rhesus macaques were tested to see if they could learn this single category task (A-not-A) through mere exposure. My goal through these studies was to answer that question and determine (for the first time in humans or monkeys) if the macaques can also show a benefit in a two-category discrimination task (A-B) after exposure.

13.1 Findings

In the pilot study, macaques were exposed to a single category and random shapes, and then were tested in a one category A-not-A task. The macaques met criterion significantly faster after receiving relevant exposure to category members. When learning one category, all of the macaques had a significantly higher proportion correct in one of the relevant conditions than the irrelevant condition, and two macaques had a significantly higher proportion correct in both relevant conditions. When the proportion of endorsements for each item type was analyzed using standard prototype modeling, results showed that all but one of the monkeys' best fit was in one of the relevant conditions.

In Experiment 1, when trying to learn two categories simultaneously, there were no consistent significant differences in the number of trials it took to meet criterion between the relevant and irrelevant tasks. Therefore, the original COVIS plus theory prediction was not confirmed. However, two of the three monkeys actually had significantly higher proportions correct in the irrelevant task than the relevant tasks, suggesting that exposure was having some type of effect. These two monkeys also learned one category significantly better than the other category in the irrelevant condition. This may suggest that exposure to two categories produced learning (or fluency) about both categories but being able to fixate on a single category and ignore the other led to better performance. When looking to see whether both categories had good fits in the different conditions, all monkeys had relatively good fits for both categories in at least one of the relevant conditions, but fits were only good for one category in the irrelevant conditions (exception for Lou). In the pilot study and Experiment 1, the best fits to the predicted model were almost always in the relevant conditions, suggesting that exposure was somehow helping prototype comparison. The better fits in the relevant tasks than the irrelevant tasks are consistent with the hypothesis that exposure helps to build representations of prototypes.

The original alternative prediction assumed by the classic COVIS theory was that there would be no effect of exposure at all in a two-category task. The results of Experiment 1 are not consistent with this prediction either. It is not that there is no effect of exposure, as predicted by classic COVIS, and it is not clearly beneficial as initially predicted by representational views. Instead, it seems exposure to two categories may actually be harmful to the speed of learning and proportion correct. However, the macaques typically showed better prototype comparison fits for *both* categories after relevant exposure. This may suggest that the monkeys are indeed building two prototypes during exposure, but it is not making it faster for them to do the mapping. Instead, it may be easier for monkeys to map responses when they focus on and learn one category and can easily ignore the other.

13.2 Intra-study Issues

The current study succeeded in showing that relevant exposure affected the monkeys' categorization decisions. It allowed the monkeys to create two separate representations, as shown by the similar performance and prototype-like comparisons of *both* categories after relevant exposure, but not after irrelevant exposure. This also suggests that the prototype representations were still accessible to the monkeys even when reinforcement was present, and that the visual representations and the reinforcement-based system were not competing with each other to guide categorization decisions. Though both classic COVIS and COVIS plus assume that any changes (in activation or representation) in the visual perceptual system would feed as inputs to the implicit system, an alternative theory might assume that these visual representations comprise a third independent system that might compete to control the decision process. As noted above, this data clearly does not support this alternative.

However, this study has failed to clearly distinguish between classic COVIS and COVIS plus. It is possible that slower learning is the result of the difficulty mapping two representations to category responses when the task (without pesky pre-representation) can be learned simply mapping one. It is also possible that fluency due to exposure is making it harder to distinguish A's and B's. The current methodology of only having two categorization options during the test phase does not allow me to distinguish between these alternatives.

13.3 Future Study

To further investigate this issue, I plan to test macaques as well as humans in a categorization task similar to Experiment 1. However, instead of only including Category A and B, I would add random shapes to the test phase and have a third categorization option (N for nonmember). Adding this third non-category response will help distinguish whether the participants have created two category representations and are having trouble mapping them to the category symbols, or if everything is just fluent or not.

In order to help participants distinguish between the two categories they are learning about, I plan to use only an intermixed exposure schedule. Blocked exposure can be beneficial when trying to learn similarities within a category (Dwyer & Mundy, 2016). This may be why it was beneficial in the pilot study, as the category members shared overall similarity and the random shapes did not. If the goal is to discriminate two categories from each other, and to create two separate representations, an intermixed exposure schedule may be more beneficial.

Research on exposure schedules suggests that intermixing categories is significantly better for discriminating between categories than blocked exposure for both humans (Dwyer et al., 2004; Lavis & Mitchell, 2006) and animals (Symonds & Hall, 1995).

I will change the criterion to 80% correct with *both* categories in the last 120 trials, as opposed to just 85% overall correct in the last 120 trials. This way the participants have to learn both categories to the same criterion, and I can measure how quickly they are able to learn to map both categories in the relevant and irrelevant conditions.

13.4 Importance of Multiple Systems

The research with patients with amnesia demonstrates the benefit of having multiple systems. For example, it has been shown that patients with amnesia are able to learn rules even when they cannot recognize the exemplars that had been used to teach them, demonstrating that rule learning does not require intact episodic memory (Knowlton et al., 1992). Kolodny (1994) and Reed et al. (1999) showed that patients with amnesia were able to learn categories and their labels through training, even when explicit memory was absent. Conversely, Knowlton et al. (1994) showed that categorization by patients with amnesia in the weather prediction task was not dependent on short-term memory, but instead depended on a more long-term, nondeclarative process. In addition, a variety of patient groups are known to have deficits in both rule-based learning and tasks thought to require associative learning, yet they show normal prototype distortion learning when asked to decide whether items belong to the category or not (Ashby & Maddox, 2005). This includes patients with Parkinson’s disease (Reber & Squire, 1999), schizophrenia (Kéri et al., 2001), and Alzheimer’s disease (Sinha, 1999). The failure or absence of one system does not mean all categorization abilities are lost. Patients are still able to learn and thrive.

Having multiple systems can also be beneficial in cognitive aging. As we age, it becomes more difficult to learn exceptional items, but our categorization performance of prototypical stimuli remains intact (Schenk et al., 2016) allowing for most categorization items to be correctly classified. This suggests that there is a decline in explicit category learning (Glass et al., 2012), but implicit categorization (e.g., A-not-A prototype learning) remains intact (Casale & Ashby, 2008; Heindel et al., 2013). Cognitive decline can also be compensated for by enhanced perceptual processing and a broader selective attention to individual stimulus features (Lighthall et al., 2014; Madden, 2007).

Having multiple systems available for category learning is beneficial. When one system fails us, we have a backup system. We have the implicit-associative system that requires no conscious awareness and produces stable performance and behavior. However, this system fails without immediate reinforcement and repetition. The explicit-declarative system complements the implicit-associative system working almost as an opposite. This system works through rule learning which is fast, conscious, can be abstracted, and does not require immediate reinforcement and repetition. The perceptual representation systems (different ones for different modalities) feed information to the implicit-associative and explicit-declarative systems. However little research has been done before now to investigate how perceptual learning and representation affects category learning. Though the current results are not conclusive, it is possible that through perceptual learning, we are able to take in information and create cortical representations which can then be used by the implicit-associative and explicit-declarative systems to help inform categorization decisions. This seems to be the case when learning a single category, but its role in learning multiple categories is less clear. Hopefully, this will be answered through future research.

REFERENCES

Ahn, W., & Medin, D. L. (1992). A two-stage model of category construction. *Cognitive Science*, *16*(1), 81–121. https://doi.org/10.1207/s15516709cog1601_3

Ashby, F. G., & Ell, S. W. (2001). The neurobiology of human category learning. *Trends in Cognitive Sciences*, *5*(5), 204–210. https://doi.org/10.1016/S1364-6613(00)01624-7

Ashby, F. G., & Maddox, W. T. (1998). Stimulus categorization. In M. H. Birnbaum (Ed.), *Measurement, judgment, and decision making.* (pp. 251–301). Academic Press. https://doi.org/10.1016/B978-012099975-0.50006-3

Ashby, F. G., & Maddox, W. T. (2005). Human category learning. *Annual Review of Psychology*, *56*, 149–178. https://doi.org/10.1146/annurev.psych.56.091103.070217

Ashby, F. G., Paul, E. J., & Maddox, W. T. (2011). COVIS. In E. M. Pothos & A. J. Wills (Eds.), *Formal approaches in categorization.* (pp. 65–87). Cambridge University Press. https://doi.org/10.1017/CBO9780511921322.004

Ashby, F. G., Queller, S., & Berretty, P. M. (1999). On the dominance of unidimensional rules in unsupervised categorization. *Perception & Psychophysics*, *61*, 1178–1199. http://dx.doi.org/10.3758/BF03207622

Ashby, F. G., & Valentin, V. V. (2005). Multiple systems of perceptual category learning: Theory and cognitive tests. *Handbook of Categorization in Cognitive Science*, 547–572. https://doi.org/10.1016/B978-008044612-7/50080-9

Ashby, F. G., & Valentin, V. V. (2017). Multiple systems of perceptual category learning: Theory and cognitive tests. In H. Cohen & C. Lefebvre (Eds.), *Handbook of categorization in cognitive science., 2nd ed.* (pp. 157–188). Elsevier Academic Press. https://doi.org/10.1016/B978-0-08-101107-2.00007-5

Ball, K., & Sekuler, R. (1982). A specific and enduring improvement in visual motion discrimination. *Science*, *218*(4573), 697–698. https://doi.org/10.1126/science.7134968

Bruner, J. S., Goodnow, J. J., & Austin, G. A. (1956). *A study of thinking*. John Wiley and Sons.

Carvalho, P. F., & Goldstone, R. L. (2016). Human perceptual learning and categorization. In R. A. Murphy & R. C. Honey (Eds.), *The Wiley handbook on the cognitive neuroscience of learning.* (pp. 223–248). Wiley-Blackwell. https://doi.org/10.1002/9781118650813.ch10

Casale, M. B., & Ashby, F. G. (2008). A role for the perceptual representation memory system in category learning. *Perception & Psychophysics*, *70*(6), 983–999. https://doi.org/10.3758/PP.70.6.983

Church, B. A., Mercado, E. Wisniewski, M.G., & Liu, E. H. (2013). Temporal dynamics in auditory perceptual learning: Impact of sequencing and incidental learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition,* 39, 270–76. https://doi.org/10.1037/a0028647

Czerwinski, M., Lightfoot, N., & Shiffrin, R. M. (1992). Automatization and training in visual search. *The American Journal of Psychology*, *105*(2), 271–315. https://doi.org/10.2307/1423030

Dolan, R. J., Fink, G. R., Rolls, E., Booth, M., Holmes, A., Frackowiak, R. S. J., & Friston, K. J. (1997). How the brain learns to see objects and faces in an impoverished context. *Nature*, *389*(6651), 596–599. https://doi.org/10.1038/39309

Dosher, B. A., & Lu, Z. L. (2009). Hebbian reweighting on stable representations in perceptual learning. *Learning & Perception*, *1*, 37–58. https://doi.org/10.1556/LP.1.2009.1.4

Dwyer, D. M., Hodder, K. I., & Honey, R. C. (2004). Perceptual learning in humans: Roles of preexposure schedule, feedback, and discrimination assay. *Quarterly Journal of*

Experimental Psychology: Section B, *57*(3), 245–259. https://doi.org/10.1080/02724990344000114

Dwyer, R. A., & Mundy, R. C (2016). Perceptual learning: Representations and their development. In R. A. Murphy & R. C. Honey (Eds.), *The Wiley handbook on the cognitive neuroscience of learning.* (pp. 202–222). Wiley-Blackwell. https://doi.org/10.1002/9781118650813.ch10

Fahle, M., & Edelman, S. (1993). Long-term learning in vernier acuity: Effects of stimulus orientation, range and of feedback. *Vision Research*, *33*(3), 397–412. https://doi.org/10.1016/0042-6989(93)90094-D

Fahle, M., Edelman, S., & Poggio, T. (1995). Fast perceptual learning in hyperacuity. *Vision Research*, *35*(21), 3003–3013. https://doi.org/10.1016/0042-6989(95)00044-Z

Fiorentini, A., & Berardi, N. (1980). Perceptual learning specific for orientation and spatial frequency. *Nature, 287*(5777), 43–44. https://doi.org/10.1038/287043a0

Fuster, J. M. (1989). *The prefrontal cortex,* (2nd ed.). Lippincott-Raven.

Gibson, E. J. (1963). Perceptual learning. *Annual Review of Psychology, 14,* 29–56.

Gibson, J. J., & Gibson, E. J. (1955). Perceptual learning: Differentiation or enrichment? *Psychological Review*, *62*(1), 32–41. https://doi.org/10.1037/h0048826

Glass, B. D., Chotibut, T., Pacheco, J., Schnyer, D. M., & Maddox, W. T. (2012). Normal aging and the dissociable prototype learning systems. *Psychology and Aging*, *27*(1), 120–128. https://doi.org/10.1037/a0024971

Goldstone, R. L. (1998). Perceptual learning. *Annual Review Psychology, 49,* 585-612.

Goldstone, R. L. (2000). Unitization during category learning. *Journal of Experimental Psychology: Human Perception and Performance*, *26*(1), 86–112. https://doi.org/10.1037/0096-1523.26.1.86

Goldstone, R. L., Steyvers, M., Spencer-Smith, J., & Kersten, A. (2000). Interactions between perceptual and conceptual learning. In E. Dietrich & A. B. Markman (Eds.), *Cognitive dynamics: Conceptual and representational change in humans and machines.* (pp. 191–228). Lawrence Erlbaum Associates Publishers.

Heindel, W. C., Festa, E. K., Ott, B. R., Landy, K. M., & Salmon, D. P. (2013). Prototype learning and dissociable categorization systems in Alzheimer's disease. *Neuropsychologia*, *51*(9), 1699–1708. https://doi.org/10.1016/j.neuropsychologia.2013.06.001

Hintzman, D. L. (1986). "Schema abstraction" in a multiple-trace memory model. *Psychological Review*, *93*(4), 411–428. https://doi.org/10.1037/0033-295X.93.4.411

Homa, D., Cross, J., Cornell, D., Goldman, D., & Shwartz, S. (1973). Prototype abstraction and classification of new instances as a function of number of instances defining the prototype. *Journal of Experimental Psychology*, *101*(1), 116–122. https://doi.org/10.1037/h0035772

Homa, D., Sterling, S., & Trepel, L. (1981). Limitations of exemplar-based generalization and the abstraction of categorical information. *Journal of Experimental Psychology: Human Learning and Memory*, *7*(6), 418–439. https://doi.org/10.1037/0278-7393.7.6.418

Hull, C. L. (1920). Quantitative aspects of evolution of concepts: An experimental study. *Psychological Monographs*, *28*(1), i-86. https://doi.org/10.1037/h0093130

Imai, S., & Garner, W. R. (1965). Discriminability and preference for attributes in free and constrained classification. *Journal of Experimental Psychology, 69*, 596–608. http://dx.doi.org/10.1037/h0021980

Karni, A., & Sagi, D. (1991). Where practice makes perfect in texture discrimination: Evidence for primary visual cortex plasticity. *Proceedings of the National Academy of Sciences of the United States of America*, *88*(11), 4966.

Kéri, S., Kelemen, O., Benedek, G., & Janka, Z. (2001). Intact prototype learning in schizophrenia, *Schizophrenia Research*, *52*(3), 261–264. https://doi.org/10.1016/S0920-9964(00)00092-X

Knowlton, B. J., Ramus, S. J., & Squire, L. R. (1992). Intact artificial grammar learning in amnesia: Dissociation of classification learning and explicit memory for specific instances. *Psychological Science*, *3*(3), 172–179. https://doi.org/10.1111/j.1467-9280.1992.tb00021.x

Knowlton, B. J., Squire, L. R., & Gluck, M. A. (1994). Probabilistic classification learning in amnesia. *Learning & Memory*, *1*(2), 106–120.

Kolodny, J. A. (1994). Memory processes in classification learning: An investigation of amnesic performance in categorization of dot patterns and artistic styles. *Psychological Science*, *5*(3), 164–169. https://doi.org/10.1111/j.1467-9280.1994.tb00654.x

Lavis, Y., & Mitchell, C. (2006). Effects of preexposure on stimulus discrimination: an investigation of the mechanisms responsible for human perceptual learning. *Quarterly Journal of Experimental Psychology*, *59*(12), 2083–2101. https://doi.org/10.1080/17470210600705198

Le Pelley, M. E. (2014). Primate polemic: Commentary on Smith, Couchman, and Beran (2014). *Journal of Comparative Psychology*, *128*(2), 132–134. https://doi.org/10.1037/a0034227

Le Pelley, M. E., Newell, B. R., & Nosofsky, R. M. (2019). Deferred feedback does not dissociate implicit and explicit category-learning systems: Commentary on Smith et al (2014). *Psychological Science*, *30*(9), 1403–1409. https://doi.org/10.1177/0956797619841264

Levine, M. (1975). *A cognitive theory of learning: Research on hypothesis testing*. Lawrence Erlbaum.

Lewicki, P., Hill, T., & Bizot, E. (1988). Acquisition of procedural knowledge about a pattern of stimuli that cannot be articulated. *Cognitive Psychology*, *20*(1), 24–37. https://doi.org/10.1016/0010-0285(88)90023-0

Lighthall, N. R., Huettel, S. A., & Cabeza, R. (2014). Functional compensation in the ventromedial prefrontal cortex improves memory-dependent decisions in older adults. *The Journal of Neuroscience*, *34*(47), 15648–15657. https://doi.org/10.1523/JNEUROSCI.2888-14.2014

Lu, Z.-L., Hua, T., Huang, C.-B., Zhou, Y., & Dosher, B. A. (2011). Visual perceptual learning. *Neurobiology of Learning and Memory*, *95*(2), 145–151. https://doi.org/10.1016/j.nlm.2010.09.010

Madden, D. J. (2007). Aging and visual attention. *Current Directions in Psychological Science*, *16*(2), 70–74. https://doi.org/10.1111/j.1467-8721.2007.00478.x

McLaren, I. P. L., Kaye, H., & Mackintosh, N. J. (1989). An associative theory of the representation of stimuli: Applications to perceptual learning and latent inhibition. In R.

G. M. Morris (Ed.), *Parallel distributed processing: Implications for psychology and neurobiology*. (pp. 102–130). Clarendon Press/Oxford University Press.

McLaren, I. P. L., & Mackintosh, N. J. (2000). An elemental model of associative learning: I Latent inhibition and perceptual learning. *Animal Learning & Behavior*, *28*(3), 211–246. https://doi.org/10.3758/BF03200258

Medin, D. L., & Schaffer, M. M. (1978). Context theory of classification learning. *Psychological Review, 85*, 207–238. http://dx.doi.org/10.1037/0033-295X.85.3.207

Medin, D. L., Wattenmaker, W. D., & Hampson, S. E. (1987). Family resemblance, conceptual cohesiveness, and category construction. *Cognitive Psychology, 19*, 242–279. http://dx.doi.org/10.1016/0010-0285(87)90012-0

Milton, F., McLaren, I. P. L., Copestake, E., Satherley, D., & Wills, A. J. (2019). The effect of preexposure on overall similarity categorization. *Journal of Experimental Psychology: Animal Learning and Cognition*. http://dx.doi.org/10.1037/xan0000226

Milton, F., & Wills, A. J. (2004). The influence of stimulus properties on category construction. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 30*, 407–415. http://dx.doi.org/10.1037/0278-7393.30.2.407

Minda, J. P., & Smith, J. D. (2001). Prototypes in category learning: The effects of category size, category structure, and stimulus complexity. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *27*(3), 775–799. https://doi.org/10.1037/0278-7393.27.3.775

Minda, J. P., & Smith, J. D. (2002). Comparing prototype-based and exemplar-based accounts of category learning and attentional allocation. *Journal of Experimental Psychology:*

Learning, Memory, and Cognition, *28*(2), 275–292. https://doi.org/10.1037/0278-7393.28.2.275

Mitchell, C., & Hall, G. (2014). Can theories of animal discrimination explain perceptual learning in humans? *Psychological Bulletin*, *140*(1), 283–307. https://doi.org/10.1037/a0032765

Newell, B. R., Dunn, J. C., & Kalish, M. (2010). The dimensionality of perceptual category learning: A state-trace analysis. *Memory & Cognition*, *38*(5), 563–581. https://doi.org/10.3758/MC.38.5.563

Nosofsky, R. M. (1987). Attention and learning processes in the identification and categorization of integral stimuli. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *13*(1), 87–108. https://doi.org/10.1037/0278-7393.13.1.87

Nosofsky, R. M., Palmeri, T. J., & McKinley, S. C. (1994). Rule-plus-exception model of classification learning. *Psychological Review*, *101*(1), 53–79. https://doi.org/10.1037/0033-295X.101.1.53

Palmeri, T. J. (2014). An exemplar of model-based cognitive neuroscience. *Trends in Cognitive Sciences*, *18*(2), 67–69. https://doi.org/10.1016/j.tics.2013.10.014

Pashler, H., & Mozer, M. C. (2013). When does fading enhance perceptual category learning? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *39*(4), 1162–1173. https://doi.org/10.1037/a0031679

Pavlov, I. P. (1927). *Conditioned reflexes: An investigation of the physiological activity of the cerebral cortex*. Oxford University Press.

Petrov, A. A., Dosher, B. A., & Lu, Z.-L. (2005). The dynamics of perceptual learning: An incremental reweighting model. *Psychological Review*, *112*(4), 715–743. https://doi.org/10.1037/0033-295X.112.4.715

Poggio, T., Fahle, M., & Edelman, S. (1992). Fast perceptual learning in visual hyperacuity. *Science*, *256*(5059), 1018–1021. https://doi.org/10.1126/science.1589770

Posner, M. I., & Keele, S. W. (1968). On the genesis of abstract ideas. *Journal of Experimental Psychology, 77*(3, Pt.1), 353–363. https://doi.org/10.1037/h0025953

Posner, M. I., & Keele, S. W. (1970). Retention of abstract ideas. *Journal of Experimental Psychology*, *83*(2, Pt.1), 304–308. https://doi.org/10.1037/h0028558

Posner, M. I., & Petersen, S. E. (1990). The attention system of the human brain. *Annual Review of Neuroscience, 13*, 25–42. http://dx.doi.org/10.1146/annurev.ne.13.030190.000325

Reber, A. S. & Allen, R. (1978). Analogy and abstraction strategies in synthetic grammar learning: A functionalist interpretation. *Cognition, 6*, 189-221.

Reber, P. J., & Squire, L. R. (1999). Intact learning of artificial grammars and intact category learning by patients with Parkinson’s disease. *Behavioral Neuroscience*, *113*(2), 235–242. https://doi.org/10.1037/0735-7044.113.2.235

Reed, S. K. (1972). Pattern recognition and categorization. *Cognitive Psychology*, *3*(3), 382–407. https://doi.org/10.1016/0010-0285(72)90014-X

Reed, J. M., Squire, L. R., Patalano, A. L., Smith, E. E., & Jonides, J. (1999). Learning about categories that are defined by object-like stimuli despite impaired declarative memory. *Behavioral Neuroscience*, *113*(3), 411–419. https://doi.org/10.1037/0735-7044.113.3.411

Restle, F. (1962). The selection of strategies in cue learning. *Psychological Review, 69*(4), 329–343. https://doi.org/10.1037/h0044672

Rosch, E. H. (1973). Natural categories. *Cognitive Psychology*, *4*(3), 328–350. https://doi.org/10.1016/0010-0285(73)90017-0

Rosch, E. (1975). Cognitive reference points. *Cognitive Psychology*, *7*(4), 532–547. https://doi.org/10.1016/0010-0285(75)90021-3

Rosch, E. (1976). Classifications of objects in the real world: Origins and representations in cognition. *Bulletin de Psychologie*, *Special Annual*, 242–250.

Rosch, E., & Mervis, C. B. (1975). Family resemblances: Studies in the internal structure of categories. *Cognitive Psychology*, *7*(4), 573–605. https://doi.org/10.1016/0010-0285(75)90024-9

Saksida, L. M. (1999). Effects of similarity and experience on discrimination learning: A nonassociative connectionist model of perceptual learning. *Journal of Experimental Psychology: Animal Behavior Processes*, *25*(3), 308–323. https://doi.org/10.1037/0097-7403.25.3.308

Schenk, S., Minda, J. P., Lech, R. K., & Suchan, B. (2016). Out of sight, out of mind: Categorization learning and normal aging. *Neuropsychologia*, *91*, 222–233. https://doi.org/10.1016/j.neuropsychologia.2016.08.013

Schyns, P. G., Goldstone, R. L., & Thibaut, J.-P. (1998). The development of features in object concepts. *Behavioral and Brain Sciences*, *21*(1), 1–54. https://doi.org/10.1017/S0140525X98000107

Schyns, P. G., & Murphy, G. L. (1994). The ontogeny of part representation in object concepts. In D. L. Medin (Ed.), *The psychology of learning and motivation: Advances in research and theory, Vol. 31.* (pp. 305–349). Academic Press. https://doi.org/10.1016/S0079-7421(08)60413-2

Servan-Schreiber, E., & Anderson, J. R. (1990). Learning artificial grammars with competitive chunking. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *16*(4), 592–608. https://doi.org/10.1037/0278-7393.16.4.592

Shepard, R. N., Hovland, C. I., & Jenkins, H. M. (1961). Learning and memorization of classifications. *Psychological Monographs: General and Applied*, *75*(13), 1–42. https://doi.org/10.1037/h0093825

Shiffrin, R. M., & Lightfoot, N. (1997). Perceptual learning of alphanumeric-like characters. In R. L. Goldstone, D. L. Medin, & P. G. Schyns (Eds.), *Perceptual learning.* (pp. 45–81). Academic Press.

Shiu, L., & Pashler, H. Improvement in line orientation discrimination is retinally local but dependent on cognitive set. *Perception & Psychophysics*, 52, 582–588 (1992) doi:10.3758/BF03206720

Sinha, R. R. (1999). *Neuropsychological substrates of category learning (vision, memory)*. *Dissertation Abstracts International: Section B: The Sciences and Engineering*. ProQuest Information & Learning.

Smith, J. D. (2014). Prototypes, exemplars, and the natural history of categorization. *Psychonomic Bulletin & Review*, *21*(2), 312–331. https://doi.org/10.3758/s13423-013-0506-0

Smith, J. D., Beran, M. J., Crossley, M. J., Boomer, J., & Ashby, F. G. (2010). Implicit and explicit category learning by macaques (*Macaca mulatt*a) and humans (*Homo sapiens*). *Journal of Experimental Psychology: Animal Behavior Processes,* 36, 54-65. http://dx.doi.org/10.1037/a0015892

Smith, J. D., Berg, M. E., Cook, R. G., Murphy, M. S., Crossley, M. J., Boomer, J., Spiering, B., Beran, M. J., Church, B. A., Ashby, F. G., & Grace, R. C. (2012). Implicit and explicit categorization: A tale of four species. *Neuroscience and Biobehavioral Reviews*, *36*(10), 2355–2369. https://doi.org/10.1016/j.neubiorev.2012.09.003

Smith, J. D., & Church, B. A. (2018). Dissociable learning processes in comparative psychology. *Psychonomic Bulletin & Review*, *25*(5), 1565–1584. https://doi.org/10.3758/s13423-017-1353-1

Smith, J. D., & Minda, J. P. (1998). Prototypes in the mist: The early epochs of category learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *24*(6), 1411–1436. https://doi.org/10.1037/0278-7393.24.6.1411

Smith, J. D., & Minda, J. P. (2001). Journey to the center of the category: The dissociation in amnesia between categorization and recognition. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *27*(4), 984–1002. https://doi.org/10.1037//0278-7393.27.4.984

Smith, J. D., Redford, J. S., & Haas, S. M. (2008). Prototype abstraction by monkeys (*Macaca mulatta*). *Journal of Experimental Psychology: General*, *137*(2), 390–401. https://doi.org/10.1037/0096-3445.137.2.390

Smith, J. D., Zakrzewski, A. C., Johnson, J. M., Valleau, J. C., & Church, B. A. (2016). Categorization: The view from animal cognition. *Behavioral Sciences*, *6*(2), bs6020012. https://doi.org/10.3390/bs6020012

Song, Y., Ding, Y., Fan, S., Qu, Z., Xu, L., Lu, C., & Peng, D. (2005). Neural substrates of visual perceptual learning of simple and complex stimuli. *Clinical Neurophysiology*, *116*(3), 632–639. https://doi.org/10.1016/j.clinph.2004.09.019

Spence, K.W. (1937). The differential response in animals to stimuli varying within a single dimension. *Psychological Review, 44*, 430-444.

Squire, L. R., Knowlton, B. J. (1995). Learning about categories in the absence of memory. *Proceedings of the National Academy of Science, 92(26)*, 12470-12474. https://doi.org/10.1073/pnas.92.26.12470

Symonds, M., & Hall, G. (1995). Perceptual learning in flavor aversion conditioning: Roles of stimulus comparison and latent inhibition of common stimulus elements. *Learning and Motivation*, *26*(2), 203–219. https://doi.org/10.1016/0023-9690(95)90005-5

Vogels, R., Sary, G., Dupont, P., & Orban, G. A. (2002). Human brain regions involved in visual categorization. *NeuroImage*, *16*(2), 401–414. https://doi.org/10.1006/nimg.2002.1109

Washburn, D. A., & Rumbaugh, D. M. (1992). Testing primates with joystick-based automated apparatus: Lessons from the language research center's computerized test system. *Behavior Research Methods, Instruments, and Computers*, 24, 157–164. http://dx.doi.org/10.3758/BF03203490

Wisniewski, M. G., Church, B. A., Mercado, E., III, Radell, M. L., & Zakrzewski, A. C. (2019). Easy-to-hard effects in perceptual learning depend upon the degree to which initial trials are "easy." *Psychonomic Bulletin & Review*, *26*(6), 1889–1895. https://doi.org/10.3758/s13423-019-01627-4

Wisniewski, M. G., Radell, M. L., Church, B. A., Mercado, E. (2017). Benefits of fading in perceptual learning are driven by more than dimensional attention. *PLOS ONE*, *12,* https://doi.org/10.1371/journal.pone.0180959

Yagishita, S., Hayashi-Takagi, A., Ellis-Davies, G. C., Urakubo, H., Ishii, S., & Kasai, H. (2014). A critical time window for dopamine actions on the structural plasticity of dendritic spines. *Science, 345,* 1616–1620. http://dx.doi.org/10.1126/science.1255514

Yin, H. H., Ostlund, S. B., Knowlton, B. J., & Balleine, B. W. (2005). The role of the dorsomedial striatum in instrumental conditioning. *European Journal of Neuroscience*, *22*(2), 513–523. https://doi.org/10.1111/j.1460-9568.2005.04218.x

Zaki, S. R., Nosofsky, R. M., Jessup, N. M., & Unversagt, F. W. (2003). Categorization and recognition performance of a memory-impaired group: Evidence for single-system models. *Journal of the International Neuropsychological Society*, *9*(3), 394–406. https://doi.org/10.1017/S1355617703930050