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Investigating Exposure Learning of Family-Resemblance Categories

Brooke Jackson

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by

Brooke N. Jackson

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ABSTRACT

One important type of category follows a family-resemblance structure. Family-resemblance category members share an overall similarity, but no criterial attributes define all members of the category. Many of the world's natural categories follow a family-resemblance category structure (e.g., Rosch & Mervis, 1975). We can learn a single family-resemblance category merely by being perceptually exposed to members of the category even when there is no discussion of their category membership (e.g., Homa & Cultice 1984; Palmeri & Flanery 1999; Zabberoni et al., 2021). Research has shown that pre-exposure to category members benefits learning two family-resemblance categories simultaneously (Jackson et al., 2023), suggesting a role for perceptual learning in family-resemblance category learning. However, it is still unclear exactly what underlying mechanism generates this perceptual learning. Therefore, in these studies, I tested the MKM (McLaren, Kate, & Mackintosh) latent inhibition mode, attentional spotlighting, attentional weighting, and representational theories of perceptual learning as explanations of learning family-resemblance categories from exposure in four experiments. I hypothesized that exposure to relevant category members provides benefit to family-resemblance category learning because exposure allows participants to build cortical representations of the prototypes. This is consistent with representational models of perceptual learning.

INDEX WORDS: Perceptual learning, Exposure learning, Categorization, Family-resemblance categories

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by

Brooke N. Jackson

Committee Chair: Michael Beran

Committee: J. David Smith

Heather Offutt

Sarah Barber

Electronic Version Approved:

Office of Graduate Services

College of Arts and Sciences

Georgia State University

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DEDICATION

This dissertation 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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1 THEORETICAL FRAMEWORK

The ability to organize knowledge, events, and objects is important because it allows us to more efficiently and safely navigate the world around us. Categorization has been explored by cognitive scientists and neuroscientists for several decades. This research has sparked a great deal of debate, and theories about how we learn perceptual categories continue to develop (e.g., Ashby & Maddox, 2005; Smith & Church, 2018; Smith & Minda, 1998; Smith et al., 2016; Squire & Knowlton, 1995; Vogels et al., 2002; Zaki et al., 2003). One of the debates in the categorization literature is whether we have a single system for category learning (Bruner et al., 1956; Hull, 1920; Levine, 1975; Restle, 1962) or multiple systems that are better suited to learning different types of categories (e.g., Ashby et al., 2011; Minda & Smith, 2001; Nosofsky et al., 1994; Smith & Church, 2018; Smith et al., 2016). Many multiple-systems theorists have also tried to understand how different brain systems might facilitate these different types of category learning (Ashby & Spierling, 2004; Nosofsky & Zaki, 1998).

One important type of category follows a family-resemblance category structure. Family-resemblance category members share an overall similarity, but no criterial attributes define all members of the category. Many of the world's natural categories follow a family-resemblance category structure (e.g., birds, fruit, trees; Rosch & Mervis, 1975). Unlike some other types of categories, humans (even those with memory impairment) can learn a single family-resemblance category merely by being perceptually exposed to members of the category even when there is no discussion of their category membership (e.g., Homa & Cultice, 1984; Palmeri & Flanery, 1999; Reed et al.,1999, Zabberoni et al., 2021). Recently, Jackson et al. (2023) showed that pre-exposure to category members benefits learning two family-resemblance categories simultaneously, suggesting a role for perceptual learning in family-resemblance category learning. However, it is still unclear exactly what the underlying mechanism is of this perceptual learning. Therefore, in these current studies, I will test different theories of perceptual learning as explanations of learning family-resemblance categories from exposure. The theories I will be testing are MKM's (McLaren, Kate, & Mackintosh) latent inhibition model, attentional spotlighting, attentional weighting, and representational theories. These specific theories have been chosen as they are the theories predominantly used to explain an array of phenomena in the perceptual learning literature.

These studies could make important contributions to both the categorization and perceptual learning literature because they could help resolve how these two processes (category learning and perceptual learning) interact. I hypothesize that exposure to relevant category members provides benefit to family-resemblance category learning because exposure allows participants to build cortical representations of the prototypes. This is consistent with representational models of perceptual learning. In the sections that follow, I will begin by detailing the theories of category learning and present evidence of mixed models. Next, I will discuss the theories of perceptual learning, and compare and contrast evidence for each. I will then describe a recent study that shows exposure to relevant category members from multiple family-resemblance categories provides benefit in a later categorization test. Finally, I will describe a series of experiments designed to rule out MKM's latent inhibition model, attentional spotlighting, and attentional weighting theories of perceptual learning as the underlying mechanisms allowing individuals to learn multiple family-resemblance categories from exposure.

1.1 Theories of Category Learning

Although category learning has been studied for several decades, theorists do not all agree about how we categorize objects and events. The major hypothesized categorization processes are learning defining criteria, prototype comparison, exemplar comparison, and associative learning (e.g., Bruner et al., 1956; Medin & Schaffer, 1978; Pavlov, 1927; Rosch, 1973).

Initially, researchers believed that the only way to learn categories was by discovering defining criteria (category rules; Bruner et al., 1956; Hull, 1920; Levine, 1975; Restle, 1962). Defining criterial attributes theory suggests that humans define perceptual categories by focusing their attention on particular stimulus features and explicitly finding the features that could correctly define the stimulus into a category. For example, the features of four sides of equal length with equal angles sufficiently describe the “square” category because every entity with these attributes is a square (Ashby & Maddox, 1998). It was assumed that participants relied on working memory (Fuster, 1989) and executive functions (Posner & Peterson, 1990) as they evaluated these featural hypotheses when presented with a stimulus. Although many researchers have concluded that rule learning plays an important 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 banana in the berry 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 whether they belong to the category or not. This theory gained a lot of traction as it could easily explain many categorization phenomena (e.g., 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 (e.g., a peanut in the legume category).

In response to prototype comparison theories' shortcomings, exemplar-comparison theory emerged with a new explanation of categorization (e.g., Medin & Schaffer, 1978). Exemplar-comparison theory assumes that people categorize objects by comparing their similarity to the memory representations of all previous exemplars from each relevant category (e.g., Hintzman, 1986; Medin & Schaffer, 1978; Nosofsky, 1987). Therefore, no single member is more representative of the category than other members. Instead of having just one prototype representation of a dog, people have different representations of all of the dogs they have seen, and they can compare new experiences with dogs (or non-dogs) to all these representations to determine overall similarity. The overall similarity to many exemplars determines how quickly or accurately a category decision can be made (the typicality effect; e.g., Rosch, 1973, 1975), while still allowing atypical members to be learned over time because of the similarity to prior exemplars (e.g., Nosofsky, 1987). However, exemplar-comparison theory has been criticized for its unrealistic view of memory storage and retrieval (e.g., Smith & Minda, 1998, 2001; for review, see Smith, 2014).

More recently, some researchers have suggested we have multiple systems for category learning (e.g., Ashby et al., 2011; Minda & Smith, 2001; Nosofsky et al., 1994; Smith & Church, 2018; Smith et al., 2016). These multiple-systems theorists have tried to fully understand how different brain systems might facilitate different types of category learning. This has sparked a great deal of debate. Some single theorists have tried 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 which categorization processes to include. For example, some mixed model researchers theorize that we can switch between comparing possible category members to a prototype or a limited number of exemplars in memory (e.g., Minda & Smith, 2001). There is evidence showing that participants 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). This suggests that we can use either approach depending on the situation, thus supporting this mixed model view of categorization.

On the other hand, Nosofsky et al. (1994) created a multiple-systems model known as the rule-plus-exception model (RULEX). According to the RULEX model, categories are learned by creating and testing simple logical rules and then memorizing the occasional exception to the rules (Nosofsky et al., 1994). The few rules are then stored along with their exceptions as an exemplar. These rules are learned slowly, on a trial-by-trial basis (Nosofsky et al., 1994). In a categorization task, the participant would search for a consistent single-dimensional rule, and once found, they 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 multiple systems model is COVIS (Competition between Verbal and Implicit Systems). This model has been supported by cognitive and neuroscience findings (for review, see Ashby et al., 2011). According to this model, learning can take place using the explicit-declarative system, or the implicit-procedural system. The explicit-declarative system supports category learning through rule learning. Rule learning focuses on features of stimuli that are predictive of their category. Rules are conscious and verbalizable. The implicit-procedural system supports associative learning processes. These occur by associating responses to whole stimuli and generalizing based on similarity. The associations made are not conscious to the participant and typically are not verbalizable. Evidence of two systems comes from the cognitive behavioral literature showing dissociations between them (for review, see Ashby & Valentin, 2005, 2017). For example, delayed (Maddox et al., 2003; Maddox & Ing, 2005) and deferred feedback (Smith et al., 2014) negatively affect information-integration category learning, which is supported by implicit-procedural learning, but they do not affect rule-based category learning, which is supported by the explicit-declarative system. On the other hand, concurrent working memory load has more of a negative impact on rule-based category learning than information-information category learning (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006).

1.2 Categorization in Patients with Brain Damage: Support for Mixed Models

To better understand the role of exemplar memory in categorization, a number of researchers have studied patients with anterograde amnesia to see what abilities are still intact when explicit memory for exemplars is absent. For example, Knowlton et al. (1992) investigated whether the ability to classify based on a complex rules system can be learned without explicit memory for the specific instances to teach the rules. The researchers tested patients with amnesia as well as control participants using an artificial grammar task. For the artificial grammar task, the participants were first presented with letter strings. Later, they were told the strings they saw were governed by a complex set of rules and then were presented with new strings that had to be classified as conforming to the rules or not conforming to the rules. For the next phase of the task, the participants reviewed the strings five minutes later and were tested on their recognition memory. Both populations were able to classify the letter strings that had been generated according to the artificial grammar (Knowlton et al., 1992). The patients with amnesia were only impaired in their ability to explicitly recognize the exemplars that had been used to teach the rules. Knowlton et al. concluded that implicit classification does not require intact explicit memory.

To follow up, Squire and Knowlton (1995) presented E.P., a patient with amnesia, with 40 dot distortion patterns and later asked him to categorize the patterns as belonging to the category or not and tested his ability to recognize the viewed patterns in a recognition memory task. E.P. successfully classified novel dot patterns according to whether they belonged to the same category as the training patterns or not. This intact ability to acquire category-level information occurred despite his failure to recognize the previously presented dot patterns. The researchers suggested that these results were due to E.P.'s ability to abstract and retain a single prototype after training, even though he could not remember the particular exemplars. These studies were interpreted as disconfirmation of a unitary exemplar comparison theory because the ability to acquire rules and category-level information was still intact despite the failure of exemplar memory. However, it is not clear whether the participants in Knowlton et al.'s (1992) artificial grammar study actually learned the rules or if they simply learned to classify on the basis of similarity to a prototype string (Servan-Schreiber & Anderson, 1990). If the latter is true, it would suggest that only prototype learning may survive deficits in explicit memory.

Kolodny (1994) provided further evidence for intact prototype formation in patients with amnesia. He tested category learning and recognition memory in amnesic patients and controls using dot patterns. The participants were told that the patterns could be divided into three distinct categories. They were trained by being shown dot patterns along with their category label (A, B, C). Later the participants were informed that they would see old and new patterns, but the same categories still applied, and they were to circle A, B, or C on a sheet of paper to categorize the patterns. This study was then repeated using artwork from three artists with varying styles. In the study using dot patterns, the patients with amnesia were able to learn at the same rate as the controls and showed equivalent transfer. However, in the study using artwork, the patients with amnesia were not able to categorize based on style, unlike the controls who could successfully do so. During a recognition test, the control participants were significantly more accurate at recognizing old items with both dot patterns and paintings than the patients with amnesia. The patients were able to learn categories and their labels for the dot patterns even when explicit memory was absent. Kolodny suggested that the patients with amnesia were successful with the dot patterns and not the artwork because there was no systematic perceptual relationship between the category and the paintings, therefore, the classification of the paintings could not depend on simple perceptual features like the dot patterns (Kolodny, 1994). Also, the paintings may have engrained richer encoding because they contained meaningful objects such as scenery and people.

Reed et al. (1999) investigated whether patients with amnesia could learn category information independently of declarative memory using stimuli that have discrete features as well as easy-to-describe features. To do so, they tested patients' category knowledge about stimuli that had easily verbalizable discrete features using a mere exposure phase and then a categorization test phase. If exposed items were more distinct and easier to label, the participants could acquire category knowledge declaratively, that is, explicitly as propositional knowledge about the regularities among the training items (Reed et al., 1999). The patients with amnesia successfully categorized based on discrete features as accurately as the controls, suggesting that even verbalizable rule-like category knowledge can be obtained without explicit memory. Other researchers have replicated these results testing typical and atypical populations (i.e., Sinha, 1999; Zaki et al., 2003).

To provide additional evidence that learning of new perceptual categories can occur without the contribution of explicit memory, Zabberoni et al. (2021) created a new paradigm for testing prototype learning in patients with memory deficits. These researchers attempted to demonstrate spared prototype extraction in a memory-impaired population by testing patients with Alzheimer's disease and healthy controls in prototype distortion tasks using morphed faces (prototype A, prototype B, and a neutral prototype). Patients with Alzheimer's disease performed similarly to the controls in the face prototype learning task, suggesting that participants with severe memory deficits can learn new visual prototypes.

There is also evidence from patient research that classification can depend on implicit-procedural processes. For example, Knowlton et al. (1994) examined probabilistic classification learning in patients with amnesia and controls using the weather prediction task. The weather prediction task is a probabilistic classification task that requires participants to predict the weather based on different combinations of tarot-like cards. Participants were instructed that they would see one, two, or three cues with geometric symbols on each trial and that they should decide whether the cards predicted sunshine or rain. In the first experiment, the amnesic patients learned gradually to associate the cues with the appropriate outcome at the same rate as control subjects. Because the cue-outcome associations were probabilistic, declarative memory for the outcomes of specific trials was not as useful for performance as the information gradually accrued across trials. It was also demonstrated that performance on the probabilistic classification task was not the result of holding knowledge of cue outcome associations in short-term memory, because both control subjects and amnesic patients demonstrated significant savings when testing was interrupted by a 5-rain delay. This result suggested that classification is dependent on a more long-term, nondeclarative process.

Furthermore, 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).

Overall, these studies show that it is possible to acquire category information about complex stimuli without having conscious memory for exemplars or rules, even with deficits in associative learning (e.g., Knowlton et al.,1992; Lewicki et al.,1988; Reber & Allen 1978). Together this supports the idea that multiple-category learning systems support different types of 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.

1.3 Perceptual Learning Theories

To better understand how perceptual learning may be involved in family-resemblance category learning, it is important to understand the theories behind perceptual learning. Although perceptual learning has been studied for over a century, research into the cognitive and neural mechanisms underlying perceptual learning remains ongoing and inconclusive.

How the world appears to us depends on more than just the objects we experience or their features, it also depends on prior learning or experience with those objects or features. There are several different definitions of perceptual learning in the literature, but the most widely used definition comes from Gibson (1963, p. 29) who defined perceptual learning as "a relatively permanent and consistent change in the perception of a stimulus array, following practice or experience with this array." The literatures on perceptual learning and categorization have developed separately. However, they both describe ways of perceptually structuring our environment and therefore, it is important to understand their interaction (Carvalho & Goldstone, 2016). An example of this comes from color wheels which are made up of various shades of color. If we perceived it directly, we would simply see a continuous set of shades. However, what we actually experience is a variety of colors that can be labeled and defined. This example demonstrates how our perception can be influenced by our knowledge of categories. Categorization not only provides organization to a complex world but also works to adapt the perceptual features used to perceive this world. Thus, categorization is the result of perceptual experience and is simultaneously a pervasive influence on that same perceptual experience (e.g., Goldstone, 2000; Goldstone et al., 2000; Schyns et al., 1998; Schyns & Murphy, 1994). In this dissertation, I hope to provide a bridge between the perceptual and category learning literatures. In the next few sections, I will review theories of perceptual learning, which historically have fallen into four main categories. Then I will discuss the evidence supporting the theories in the following section.

1.3.1 Representational Theories

Goldstone (1998) first defined representational theories of perceptual learning when he introduced the ideas of unitization and differentiation as the foundations of perceptual learning. Both of these mechanisms involve the creation of new perceptual units (representations) through learning.

Differentiation involves an enhanced ability to discriminate between dimensions or stimuli that were psychologically fused together (Carvalho & Goldstone, 2016). This process allows us to discriminate between percepts that were at one point indistinguishable from one another. Differentiation can happen with whole stimuli as well as parts within stimuli. This can happen even through simple pre-exposure to stimuli, meaning no feedback is required. For example, Gibson and Gibson (1955) showed that even when no feedback is provided to participants, practice identifying visual scribbles increased their discriminability of the scribbles. Research has shown that it is very difficult, if not impossible, to separate saturation and brightness in perception because the overall experience of color causes them to be fused together (Garner, 1976). However, after training, participants can improve their differentiation abilities, and learn to ignore one dimension and selectively perceive the other (Burns & Shepp, 1988; Goldstone, 1994; Goldstone & Steyvers, 2001).

Unitization works in a manner opposite to differentiation. Here, learning causes the person to perceive the stimulus as a single object as opposed to perceiving it as multiple objects with distinct properties. Goldstone and Byrge (2015) liken this to the chunking phenomenon in memory. 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, which allows us to overcome some capacity limitations of short-term memory. Likewise, there is clear evidence that we can learn to perceptually group features into a single unit, as when we learn to perceive patterns. For example, fluent readers perceive familiar words as a single item, rather than distinct individual letters. Shiffrin and Lightfoot (1997) demonstrated that even novel separated line segments could become unitized following prolonged practice with the materials. Unitization is also thought to account for why perceptual pattern recognition training can help doctors and residents improve their diagnostic skills (Guerlain et al., 2004; Krasne et al., 2013). For example, Krasne et al. (2013) demonstrated improved accuracy in diagnosing disease patterns among medical residents who completed a computer-based perceptual training module. This computer-based training module works by presenting the learner with images of disease processes that are clearly present and representative of the disease category, and over time presents exemplars that are less representative of the disease category. Instead of analyzing each piece of information separately, these experienced medical professionals learn to perceive the disease categories more holistically.

Representational views of perceptual learning assume that pre-exposure and training actually change the way that stimuli are perceptually represented, and those representations are thought to be more unitized and/or more differentiated from other representations than representations that have not been pre-exposed (Church et al., 2013). Therefore, one relevant role for perceptual learning processes in category learning could be the unitization of a prototype representation. I hypothesize that exposure to relevant category members provides benefit to family-resemblance category learning because exposure allows participants to build cortical representations of the prototypes.

1.3.2 Elemental-Associative Theories

Another dominant explanation of perceptual learning comes from associative theories (e.g., McLaren et al., 1989; Pashler, 2013). These theories posit that perceptual learning occurs through the modification of elemental associative neural connections in the brain. The classic gradient interaction theory suggests that positive excitatory gradients of generalization develop around reinforced stimuli, while negative inhibitory gradients surround nonreinforced stimuli; therefore, our ability to discriminate is determined by the summation of these gradients (Spence, 1937). If reinforced and non-reinforced stimulus gradients overlap and are difficult to discriminate, they will negate each other, leading to slower learning. On the other hand, this theory suggests that if the gradients are overlapping but more distinct, their summation will create a more noticeable difference between reinforced and non-reinforced stimuli, which can generalize to new stimuli (see McLaren et al., 1989; McLaren & Mackintosh, 2000).

The most relevant elemental associative theory to the current topic is the MKM model, named after its authors McLaren, Kate, and Mackintosh. This theory proposes that perceptual learning requires associations between perceptual inputs and responses (McLaren et al., 1989). The MKM model proposes that stimuli are made up of a combination of elements or microfeatures, some of which are similar or more common to other stimuli, and some of which are relatively unique. The authors of this model assume that when stimuli share elements there will be a reduction in the salience of those elements because they will be presented more often.

This reduction in salience due to repeated exposure to the features is known as latent inhibition. For instance, two stimuli, AX and BX, will have unique elements (A and B elements) but will share some features in common (X). These X elements are the basis for any generalization between them. Therefore, if BX is pre-exposed 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. The X elements will then be overshadowed by the A elements that have not been inhibited, as the A elements will acquire more associative strength to the unconditioned stimulus, leaving less strength to accrue to the X elements and hence generalize to BX (McLaren & Mackintosh, 2000). Put into an example, in the two flavor compounds, saline-lemon (AX) and sucrose-lemon (BX), the unique elements are saline (A) and sucrose (B), and the shared element is lemon (X). If the sucrose-lemon solution is pre-exposed, before the saline-lemon solution is paired with a solution that will make the rat sick (e.g., lithium chloride), less conditioning will generalize to sucrose-lemon in comparison to a control group that did not receive pre-exposure because the lemon flavor will be latently inhibited by pre-exposure. The lemon elements will be overshadowed by the saline flavor that has not been inhibited, as the saline flavor will acquire more associative strength to the lithium chloride, leaving less strength to accrue to the lemon flavor and therefore generalize to sucrose-lemon.

One of the principal effects of pre-exposure according to this model is a faster reduction in salience to the elements that are shared more often than to elements that are shared less often (Milton et al., 2019). The unique elements that discriminate stimuli will then tend to be higher in salience than the common elements that both stimuli share, because the common elements will have been presented more frequently, and they are adequate predictors of one another. According to MKM theory this preferential processing of the unique elements, that discriminate between items, compared with the common elements, that do not discriminate, is what leads to the increased differentiation of stimuli after pre-exposure (e.g., McLaren et al., 1989; Milton et al., 2019).

1.3.3 Attentional Theories

Attentional theories have predominantly been used to explain perceptual learning phenomena, especially in the visual domain. There are two primary kinds of attentional theories of perceptual learning: attentional spotlighting and attentional weighting theories. Importantly, although they are both attention-based theories, their assumptions are very different.

Attentional spotlighting assumes participants actively search to find the unique aspects of the percept so they can pay more attention to those particular aspects and not others (Pashler & Mozer, 2013). Participants direct their attention to the various stimulus dimensions until the most relevant is identified. This search is intentional and happens suddenly through insightful explicit discovery. Once the most relevant dimension has been identified, it is perceived more minutely, altering the perception of the dimension permanently.

On the other hand, attentional weighting requires processes that are more associative and unconscious in nature. Attentional weighting suggests perception adapts to tasks and environments by elevating attention towards crucial perceptual aspects and reducing attention towards irrelevant dimensions and features. This adjustment allows individuals to emphasize what is important and discard what is not necessary for the given task or context. Improvements in perceptual discriminations are caused by the development of more efficient connections between higher-level sensory signals or responses and feature representations lower in the perceptual pathway. Attentional weighting models use simulated visual cortical neurons with predefined response characteristics as inputs for artificial networks based on associative learning. These models are built on the idea that the weights in these networks symbolize the focus of attention (e.g., Lu et al., 2011). Participants can perform successfully in tasks as their attentional weights gradually learn which of the visual features are shared across different events or objects and which features are unique to each event/object (e.g., Petrov et al., 2005). Over time, the unique elements or features become more strongly associated with the output. When a novel event activates these elements to a greater degree than a trained stimulus, the individual will respond more to the novel event (e.g., Lu et al., 2011). The input of sensory representations relevant to a decision should be strengthened, while the irrelevant inputs are down-weighted in the decision (e.g., Dosher & Lu, 2009).

1.3.4 Evidence for Perceptual Learning Theories

Next, I will compare and contrast the evidence supporting the perceptual learning theories just discussed. Much of the evidence in support of attentional weighting and spotlighting comes from the visual domain using simple stimuli with basic visual features (for discussion see Song et al., 2005). Because the stimuli are quite easy to discriminate, it sometimes becomes difficult to know how much true learning is happening in these experiments. Within this context, numerous studies have demonstrated examples of perceptual learning that are highly specific to the original training situation (e.g., Ball & Sekuler, 1982; Fiorentini & Berardi, 1980; Karni & Sagi, 1991; Poggio et al., 1992). For instance, studies have shown that participants' enhanced discriminability produced by exposure was restricted to the stimulus orientation and retinal position used in training and did not transfer to conditions during which these were changed (Dwyer & Mundy, 2016). This high degree of specificity is observed with simple stimuli because it is differentiated early in the visual system where the neurons with the requisite location and orientation specificity are found (Dwyer & Mundy, 2016). This supports the attentional theories of perceptual learning and has led to the assumption that perceptual learning cannot involve actual representational change but only attentional change because these early visual areas are thought to be fixed and relatively unchanging after early development.

However, there is evidence that if more complex stimuli are used, perceptual learning is not as basic as previously believed. For example, Song et al. (2005) tested participants in two experiments using event-related potentials to see if using stimuli that varied in complexity involved different levels of visual cortical processing. In the studies, the participants completed three consecutive training sessions in which they discriminated between simple stimuli made of line segments or complex stimuli made of compound shapes. Song et al. found learning effects were focused over the occipital cortex for simpler stimuli and were focused over the central/parietal cortices for more complex stimuli. This suggests that perceptual learning can operate at different levels of visual cortical processing depending on the complexity of the stimulus. Furthermore, Dolan et al. (1997) tested participants using PET scans and showed that complex visual stimuli enhanced the activity of inferior temporal regions. Once again, this shows that perceptual learning does not occur only early in the visual system as once suggested by some attentional-weighting theorists.

Theories of perceptual learning have been tested by studies investigating easy-to-hard effects. In this phenomenon, perceptual learning is more efficient and effective when training begins with stimuli that are easier to discriminate, and then gradually progresses toward more difficult discriminations. Research has shown that the easy-to-hard effect is a robust phenomenon across a variety of perceptual learning tasks (Church et al., 2013; Liu et al., 2008; Orduña et al., 2012; Suret & McLaren, 2003). Attentional spotlighting theorists suggested that the easy-to-hard phenomenon occurs because the initial easy trials direct learners' attention to task-relevant dimensions, and then the learner can disregard the irrelevant dimensions. One study found that simply telling participants which feature to attend to in a visual categorization task produced equal performance to giving initial easy trials, seeming to support this attentional spotlighting (Pashler & Mozer, 2013). However, other studies suggest that the easy-to-hard effect may not simply be due to identifying the relevant feature as suggested by attentional spotlighting theories. For example, a study using complex auditory information found easy-to-hard effects even after instructing participants about the relevant feature (Church et al., 2013; Liu et al., 2008).

Other studies have also provided evidence that attentional spotlighting cannot fully explain the easy-to-hard phenomenon. For example, Wisniewski et al. (2017) conducted two experiments in which participants were trained to discriminate periodic, frequency-modulated (FM) tones in two separate frequency ranges (300–600 Hz or 3000–6000 Hz). In one frequency range, training was easy-to-hard discriminations. In the other, stimulus similarity was constant throughout training. Attentional spotlighting views propose that the benefits of easy-to-hard arise from simplifying the explicit search process used to identify the relevant dimensions. Therefore, any advantage of progressive similarity should extend to the same critical dimension in a new frequency space in an auditory task (Pashler & Mozer, 2013). However, after training, participants showed better performance in their progressively trained (easy-to-hard) frequency range, even though the discrimination-relevant dimension across ranges was the same. Theories of perceptual learning that propose changes in stimulus representations or associative changes at early levels of perception depending on experience (like attentional reweighting) predict this specificity of easy-to-hard effects (Wisniewski et al., 2017).

Attentional spotlighting predicts that when participants' attention is explicitly drawn to the relevant dimension early in the training phase (e.g., by the presentation of an easy contrast in that dimension, called anchoring), then they should not show benefits of further progressive training as they have already learned the relevant dimension to succeed in a later discrimination task (e.g., Pashler & Mozer, 2013). However, Wisniewski et al. (2017) showed that training with stimuli that progressively became more difficult increased learning more than simply presenting easy “anchor” contrasts at the beginning of training.

Representational modification and reweighting/associative learning mechanisms (e.g., Saksida, 1999) can both account for the specificity of easy-to-hard effects and the advantage of progressive training over anchoring alone. Wisniewski et al. (2019) further pitted the predictions of attentional spotlighting theories against representational and reweighting/associative learning theories by testing how easy the initial trials should be to see easy-to-hard effects. Attentional spotlighting predicts that as long as the relevant dimension is made obvious to the participant, easy trials should always facilitate their performance. Whereas representational and reweighting theories predict that if the easy trials are *too* easy, it is less likely that representations/weights will be modified enough to aid discrimination on a harder version of the task. The results showed that when initial training blocks were too easy or too difficult there was less benefit than when the blocks had an intermediate difficulty. This result was observed for two different acoustic dimensions and was predicted by representational and reweighting accounts of learning, but not the attentional spotlighting model.

Church et al. (2013) tested the predictions made by representational theories against associative models like MKM or reweighting. They examined sequencing in an auditory discrimination task with incidental (no feedback) versus intentional (with feedback) training. The results showed that pre-exposure to a progressive sequencing of auditory stimuli, in comparison to equally variable training in either a random or an anti-progressive order, led to higher performance with the difficult contrasts and greater generalization to new contrasts. This remained true even when the progressively sequenced stimuli were only pre-exposed in an incidental learning task that did not involve any direct training or feedback. These results suggested that the advantages shown by progressive training cannot be fully explained by direct associations between stimulus features and the corresponding responses. The progressive training advantage cannot be explained by elemental-associative or incremental attentional reweighting theories that assume that the advantage is caused by learning task-relevant features. Overall, associative and attentional theories are not able to fully explain all of the phenomena seen in the literature. This may be because perceptual learning often reflects actual representational change producing differentiation or unitization of perceptual representations.

2 FAMILY-RESEMBLANCE CATEGORIES

Many natural categories follow a family-resemblance category structure (e.g., Rosch & Mervis, 1975). In family-resemblance category structures, category members share an overall similarity, meaning that they share several features with other members of the category. However, there is not a single feature common to all category members that defines the category. In tasks involving family-resemblance categories, the optimal strategy is to make decisions based on the overall similarity and not on a single feature.

In the categorization literature, participants are typically provided feedback to learn the categories (e.g., Reed et al.,1999). However, research in perceptual learning has investigated whether we can learn family-resemblance categories through mere exposure. Mere exposure means that participants are not given any information about the categories, they are simply presented with category members in an unrelated task. These studies often use an A, not A paradigm. In an A, not A task, there is a single Category A and participants are presented with members belonging to Category A and with random stimuli that do not belong to the category. Participants need to decide if the stimulus presented belongs to Category A or not.

Few studies have investigated exposure learning of multiple family-resemblance categories to see if exposure is still beneficial. One study examined the effect of exposure on learning multiple family-resemblance categories in a free classification task (Milton et al., 2019). These researchers looked at how we naturally form categories without feedback. Participants were assigned to one of two groups: same-stimuli exposure or unrelated-stimuli exposure. In the same-stimuli condition, participants were exposed to the exact stimuli that they would later categorize. In the unrelated-stimuli condition, participants were exposed to different stimuli than those used for classification. Participants were exposed to all stimuli and then later they were told to classify the stimuli however they saw fit. No feedback was provided. 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). This study indicates that participants experience ease of family-resemblance comparison after exposure to the exact exemplars they later categorized. However, Milton et al. (2019) did not test whether this advantage generalizes to novel category members.

Jackson et al. (2023) investigated whether participants can transfer knowledge to novel category members in an A-B task (two family-resemblance categories) after exposure learning. Participants completed two tasks. In one task, they were exposed to members from the same categories (relevant information) that they would later be tested with. In the other task, they were exposed to members from different categories (irrelevant information) than they would be later tested with. After the exposure phase, participants completed a categorization task during which they were presented with new Category A and B members as well as random shapes. They pressed A, B, or N on their keyboard to call a shape a member of Category A, Category B, or a nonmember. The results showed that participants' category performance was significantly better after receiving relevant exposure to category members than irrelevant exposure. This shows that exposure is beneficial when learning multiple family-resemblance categories simultaneously. This is the first study to investigate learning multiple family-resemblance categories simultaneously through exposure and then testing never-before-seen members.

This study is important as a predominant theory of categorization does not predict that learning multiple family-resemblance categories simultaneously through exposure is possible.

COVIS predicts that exposure can only be beneficial for learning a single-family-resemblance category at a time because exposure learning can produce perceptual fluency (Ashby & Maddox, 2005). Fluency happens when a previous experience induces a graded pattern of activation in the visual cortex causing 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/familiarity 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. The results from Jackson et al. (2023) show that exposure is beneficial when learning multiple family-resemblance categories simultaneously, which shows that fluency is not the only mechanism for learning from exposure.

Theories of perceptual learning would allow learning of multiple family-resemblance categories simultaneously through exposure. However, it is still unclear exactly what the underlying mechanism is that allows this learning. Therefore, in the current studies, I tested the predominant theories of perceptual learning to better understand how we learn family-resemblance categories from exposure.

2.1 MKM Latent Inhibition Theory

In my first experiment, I tested the MKM elemental-associative theory of latent inhibition in exposure learning. The MKM theory assumes that when stimuli share elements/features, there is a reduction in the salience of these elements (latent inhibition; McLaren et al., 1989). One of the principal effects of pre-exposure is that elements that frequently occur simultaneously are reduced in salience more than elements that rarely occur together. 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 (e.g., McLaren et al., 1989; Milton et al., 2014). This effect is likely to be greater for items that are perceptually similar to each other because they share many common elements and therefore latent inhibition will be more pronounced than for items that are very different (i.e., that have few common elements). If perceptual learning is more marked for perceptually similar items than perceptually different items as the MKM model proposes, then one prediction that follows is that pre-exposure will lead to better family-resemblance sorting for perceptually similar stimuli compared to perceptually different stimuli.

Milton and colleagues (2014) tested this prediction in a free classification task. They created four stimulus sets using five binary-valued dimensions. The stimuli were organized around two prototypes, each representative of one category. The rest of the stimuli were mild distortions of the two prototypes in that they had four features characteristic of their category and one atypical feature more characteristic of the other category. In total, there were 12 stimuli in each set. The two pairs of stimulus sets were identical except that in one of the sets the binary values for each dimension were perceptually easier to distinguish and for the other set the differences were perceptually more difficult to distinguish. Participants were either given relevant exposure or irrelevant exposure and then a free classification task. For the free classification phase, a match-to-standards procedure was used. The two category prototypes were presented at the top of the screen and below the prototypes was one of the twelve stimuli in the set. Participants sorted the stimulus into Category A or Category B with no feedback. Each of the stimuli in the set appeared once in each block in random order. In total, there were six blocks of twelve stimuli. The results showed that relevant exposure increased family-resemblance sorting for the perceptually easy (easier to distinguish) stimuli but not for the perceptually difficult (difficult to distinguish) stimuli. Contrary to the latent inhibition mechanism of MKM theory (but consistent with unitization; Goldstone, 1999), there was no benefit of exposure to perceptually relevant stimuli in comparison to irrelevant stimuli for the perceptually difficult stimuli, and the participants did not learn to sort these stimuli based on family resemblance (Milton et al., 2014).

Milton et al. (2014) noted several limitations of this study. First, while the match-to-standards procedure of displaying the prototype as a reference on every trial is often used in free classification/sorting tasks, it is more restrictive than other procedures which do not present the prototypes and do not specify the number of categories that can be created (e.g., Pothos & Close, 2008). Therefore, it would be informative to determine if the results would be replicated using other procedures. Second, the stimulus sets used in the study were very small, containing only twelve unique stimuli. It would be beneficial to examine whether having a greater number of unique stimuli influences the results and would allow tests for generalization. The results were not predicted by the MKM latent inhibition model. However, the results could be explained by unitization. The authors concluded that they were not fully able to rule out the MKM theory because of the study's limitations. For my first experiment, I plan to retest the role of latent inhibition in exposure learning of family-resemblance categories by addressing the limitations of Milton et al. (2014).

Rather than presenting the prototypes on the screen during every trial, the prototypes were presented as examples of each category on the instruction screen once. Afterward, there were no examples of category members presented to the participants. I also created larger stimulus sets and ensured that the same stimuli from exposure did not repeat in the free classification task, that way the participant never saw the same stimulus twice, allowing me to test generalization. The MKM theory of latent inhibition predicts that relevant pre-exposure will lead to a greater family-resemblance sorting for perceptually difficult categories. Representational theories predict that exposure will not be beneficial if the category prototypes are too similar. During the exposure phase, separate category representations may not form, or the representations may be too similar making it difficult (if not impossible) to subsequently differentiate between the perceptually similar categories.

2.2 Attentional Spotlighting

In Experiment 2, I investigated the attentional spotlighting theory of perceptual learning. Attentional spotlighting theory suggests that the effects of perceptual learning occur because of increased dimensional salience. Researchers who advocate for attentional spotlighting argue that progressive training (easy-to-hard progression) causes an attention-related "stretching" of dimensions by finding the most relevant dimension (Carvalho & Goldstone, 2016). Alternately, representation-based learning theories explain the easy-to-hard effect with mechanisms that involve gradual, experience-dependent changes to stimulus representations themselves.

Wisniewski et al. (2017) tested the attentional spotlighting and representational theories in the auditory domain. In Experiment 1, participants were simultaneously trained in progressive and constantly difficult training conditions to categorize frequency-modulated sweep trains with different rates of frequency modulation as 'Fast' or 'Slow.' Participants were assigned randomly to either receive progressive training in the 'low' or the 'high' frequency range, with constant training assigned to the opposite range. The sweep trains consisted of five upwardly directed frequency-modulated sweeps spanning frequencies from 300–600 Hz ('low' frequency range) or 3000–6000 Hz ('high' frequency range). For the progressive training, the Fast/Slow contrasts started with a large differences (very Fast and very Slow) but progressively become more difficult (somewhat Fast and somewhat Slow). In the constant difficulty training, contrasts started difficult to differentiate and remain difficult throughout training. For example, if participants received the low frequency range in progressive training, and the high frequency range in constant training, the first block of training would consist of easy-to-discriminate trains in the ‘low’ frequency range, but hard-to-discriminate trains in the ‘high’ frequency range. Over the course of trial blocks, the ‘low' frequency range included progressively more difficult contrasts until reaching the same frequency modulation rate contrast as the ‘high’ frequency range. Meanwhile, the ‘high’ frequency range remained at a fixed level of difficulty throughout the training phase.

For training, participants were told the sounds would differ in speed. On each trial, participants had to decide if the stimulus presented was “Slow” or “Fast.” Half of the trials presented a “Slow” sweep train (< = 8.4 octaves per second) and the other half presented “Fast” sweep trains (> = 9.4 octaves per second). After training, participants completed a test phase containing high- and low-frequency range sweep trains at the hardest contrast (8.4 vs. 9.4 octaves per second). On each trial they had to categorize the stimulus as Fast or Slow. No feedback was given during the test phase.

The results showed that participants performed more accurately after progressive training than constant difficulty training. This suggests that learning goes beyond dimensional spotlighting because it predicts that the effects of spotlighting the relevant dimension (speed) should transfer across frequency ranges. Representational theories, on the other hand, predict that benefits are restricted to the trained sounds, explaining the specificity of the results.

In a second experiment, Wisniewski et al. (2017) tested generalizability of their findings. They investigated whether there was a progressive advantage when participants were tested in a task that was not previously trained. Participants completed training similar to Experiment 1 and then were tested on their ability to discriminate between rates in the progressive and constantly difficult trained frequency ranges. The stimulus contrasts were also made to be more difficult in the testing phase than the training phase by shortening the sweep trains in testing. The results replicated those of Experiment 1, showing a progressive training advantage.

Wisniewski et al. (2017) used auditory stimuli in both experiments, whereas most researchers that argue for attentional spotlighting models use visual stimuli. Because processing in the visual and auditory systems is distinct, it is important to see if this effect generalizes to the visual modality. Wisniewski et al. (2017) also used direct training with feedback. Therefore, for my second experiment, I will investigate easy-to-hard effects using visual stimuli and instead of receiving direct training, participants will receive mere exposure. These are important modifications that will allow me to directly test two theories in a different modality to see how mere exposure (rather than direct training) affects family-resemblance categories.

In my second experiment, participants were divided into one of two exposure conditions: progressive (starting with easy contrasts that become more difficult over time), and anchoring (a small number of easy contrasts to spotlight relevant features followed by mostly difficult contrasts). Participants were exposed to two categories. The categories were related to one another, making some of the exemplars difficult to differentiate. To create separate but related categories, prototype A was created, and then prototype B was a high-level distortion of a low-level Category A member. Representational theories of perceptual learning predict that easy-to-hard exposure will benefit differentiation of these related categories. Whereas if the exposure phase contains mostly difficult contrasts, participants will not learn to differentiate difficult contrasts in a later task. Attentional spotlighting predicts that both types of training will be equally beneficial because the relevant category features are equally spotlighted in the anchoring condition (Pashler & Mozer, 2013).

2.3 Representational Theory

For my third experiment, I explored unitization and differentiation mechanisms in exposure learning. While representational theories suggest unitization and differentiation both occur and are important mechanisms, little is known about their role during exposure learning and whether one mechanism is predominant, or if they work together. Differentiation enhances our ability to discriminate between dimensions or stimuli that were originally psychologically fused together, allowing us to discriminate between percepts that were previously indistinguishable from one another. Unitization allows us to perceive a stimulus as a single property as opposed to perceiving its distinct properties, similar to the chunking phenomenon in memory. It is possible that these processes change participants' perceived similarity of category members.

Previous work has shown that after a categorization test, participants rate category members as being more similar to each other (Ashby et al., 2020; Goldstone et al., 2001; Livingston et al., 1998; Pérez-Gay Juárez et al., 2019), and they rate stimuli as being more dissimilar to members from other categories (Goldstone et al., 2001; Gureckis & Goldstone, 2008; Pérez-Gay Juárez et al., 2019). This research typically uses feedback to teach the participants which stimuli belong to each category and uses small stimulus sets, showing participants the same category members multiple times and asking participants to rate the members they were exposed to.

In my third experiment, I assessed how participants' perceived similarity of Category A and B members changed after mere exposure. Unlike previous studies, participants did not see the same stimulus more than once, they were only asked to rate new members, not ones they were previously trained on. Participants were asked to rate stimuli similarity, some from the same category and some from another category, after trial blocks of exposure. It is important to test this with mere exposure as opposed to direct training because we often learn family-resemblance categories without any feedback in the real world. The experiment allows me to explore if participants perceive within-category members more similarly after exposure and if they perceive between-category members as more dissimilar than each other, as seen in experiments that use training with feedback before similarity ratings (Goldstone et al., 2001). These changes in perception may be due to changes in prototype representations created during exposure.

2.4 Attentional Weighting

In Experiment 4, I investigated attentional weighting theory of perceptual learning. Attentional weighting theories suggest that perception adapts to tasks by increasing attention toward crucial perceptual aspects and reducing attention toward irrelevant dimensions or features. Improvements in perceptual discriminations are caused by the development of more efficient connections between higher-level sensory signals or responses and feature representations lower in the perceptual pathway.

Support for attentional weighting theory comes from research using simple stimuli with basic visual features (see Song et al., 2005) and suggests that perceptual learning occurs early in the visual cortex. Research on attentional weighting has shown that some examples of perceptual learning are specific to their original training situation (e.g., Ball & Sekuler, 1982; Fiorentini &

Berardi, 1980; Karni & Sagi, 1991; Poggio et al., 1992). For example, studies have shown that the enhanced discriminability participants display was restricted to the stimulus orientation and retinal position used in training and did not transfer to conditions during which these were changed (Dwyer & Mundy, 2016). This high degree of specificity is observed with simple stimuli because it is differentiated early in the visual system where the neurons with the requisite location and orientation specificity are found (Dwyer & Mundy, 2016). This has been taken as support for the attentional weighting theories of perceptual learning because these early visual areas are thought to be fixed and relatively unchanging after early development. Therefore, there is an assumption that perceptual learning cannot involve actual representational change, but only attentional change.

Studies using more complex stimuli have shown that perceptual learning is not as basic a process as previously believed (Dolan et al., 1997; Song et al., 2005). In addition, Coutinho et al. (2010) examined whether prototype formation occurred in the early visual cortex or if it was more complex. Studies show that in the early areas of the visual cortex, the neurons represent topographically and respond differently to different-sized stimuli. Shape selectivity does not endure through changes in size; stimuli with similar features but varying in size elicit distinct patterns of activity (Engel et al., 1997; Vuilleumier et al., 2002). Research has differentiated between retinotopic and non-retinotopic regions of the visual cortex by employing a stimulus that produced traveling wave responses (Engle et al., 1997). They measured these responses using functional magnetic resonance imaging (fMRI) and established that the primary, secondary, and tertiary visual cortices (V1, V2, and V3) exhibited a retinotopic organization. Vuilleumier et al. (2002) examined repetitive exposure to stimuli of different sizes and found that repeated exposure was accompanied by decreases in visual-cortical activity. However, size variability disrupted these activity decreases in early visual areas. If category learning is occurring in early visual areas, size variability should weaken it and undermine the process of prototype formation. To examine whether prototype formation occurred in the early visual cortex, they tested participants in an A, not A categorization task and manipulated the sizes of stimuli to see if categorization performance is robust to stimuli of different sizes. Participants were randomly assigned to the size-variable or size-constant condition. During training, participants were presented with high-level distortions of the category prototype all in the medium size and told that all members belonged to the same category. For testing, participants were presented with high- and low-level distortions of the category prototype, and random shapes not belonging to a category. For participants in the size-constant condition, all test shapes were medium in size. For participants in the size-variable condition, the test stimuli were of five sizes ranging from much smaller to much larger than those used in the size-constant condition. Participants received feedback after every trial. The results showed no difference in participants' categorization accuracy between the conditions. The results also showed that in both conditions, participants showed steep typicality gradients (a large change in category endorsement level from prototypes to low-level distortions to high-level distortions). These steep typicality gradients suggested that there is an underlying prototype representation; as the exemplar becomes more dissimilar to the prototype, category endorsement should also go down.

In a second experiment, half of the participants received the same training instructions as Experiment 1, explicitly stating that the shapes presented belong to the same category. The other half of participants received training instructions that simply told them they would see polygon shapes and needed to move their cursor to touch the shape. Therefore, they were not aware that the shapes were related. The results showed that for both instruction conditions, there was no difference between participants' categorization performance in the size-constant and size-variable conditions. Participants still showed steep typicality gradients regardless of size condition or feedback condition. If prototype formation occurs in the early visual cortex, stimulus-size variability should lessen prototype effects, however, they were the same in both conditions (size-constant vs size-variable), even when they had no prior knowledge that the shapes belonged to the same category. Low-level visual areas, featuring retinotopic perceptual representations, would not support category learning. These results provide support for representational theories of perceptual learning, but not attentional weighting theories.

In the current experiment, I investigated whether early visual cortex areas mediate learning of multiple family-resemblance categories after mere exposure. To do so, participants were randomly assigned to the Constant Size or Variable Size condition. For training, participants were not told any information about the two categories, and all category members were medium sized. For the categorization test, participants in the Constant Size condition were presented with shapes in the medium size. In the Variable Size condition, the stimuli varied in size (tiny, small, medium, large, huge). Attentional weighting theories suggest that participants' performance in the task will be better in the Constant Size condition, as learning is occurring in the early visual cortex. Representational views suggest participants will learn in both conditions.

3 METHODS

3.1 Experiment 1

Experiment 1 tested the MKM elemental-associative theory of latent inhibition in exposure learning. Milton et al. (2014) showed that relevant exposure increased family-resemblance classification for the perceptually easy stimuli but not the perceptually difficult stimuli. This result is not predicted by the latent inhibition mechanism of MKM theory, as this theory predicts that the perceptually difficult-to-distinguish stimuli should benefit more from relevant exposure than perceptually easier-to-distinguish stimuli. However, this result is predicted by the representational theories of perceptual learning because it predicts exposure will not be beneficial if the category prototypes are too similar. This is because, during the exposure phase, separate category representations may not form, or the representations may be too similar making it difficult to differentiate between perceptually-similar categories.

Milton et al. (2014) listed several limitations to their study and therefore the authors were not fully able to rule out the MKM theory as an explanation. The current study addressed these limitations by using different procedures, as well as testing generalization. Experiment 1 retested the role of latent inhibition in exposure learning of family-resemblance categories. Instead of using a small stimulus set (12 stimuli), the current experiment never repeated stimuli to test whether participants could categorize never-before-seen stimuli, and it presented the prototypes only once, instead of on every trial.

Table 3.1 Research Question and Prediction for Experiment 1

Question	Predictions
Does pre-exposure to relevant category members provide benefit in a later categorization task for both Perceptually Easy and Perceptually Difficult categories?	Representational theory: Pre-exposure to relevant category members will only benefit categorization of the Perceptually Easy condition, not the Difficult condition. MKM Latent Inhibition theory: Pre-exposure to relevant category members will only benefit categorization of the Perceptually Difficult condition, not the Easy condition.

3.1.1 Power analysis and participants

An *a priori* power analysis was conducted using G*Power version 3.1.9.7 (Faul et al., 2007) to determine the required sample size for a mixed-factor general linear model test with an alpha level of 0.05. The power analysis indicated that a minimum of 36 participants was required to achieve 80% statistical power to detect a medium effect size, as measured by $n_p^2 = .06$.

A total of 63 undergraduates (with an approximate gender distribution of 76% female, 20% male, and 3% preferred not to answer) at Georgia State University participated for partial fulfillment of a course requirement. Participants' ages ranged from 18 to 58 years ($M = 20.92$). Participants who did not complete all trials ($N = 1$) or showed significant bias (selecting one of the choices more than 50% of the time; $N = 12$) were not included in the analyses. Therefore, 50 participants were included in the analyses.

3.1.2 Stimuli

Stimuli were created using Turbo Pascal 7.0 programming. Prototype shapes were created by randomly selecting nine points in a 50 X 50 grid and connecting successively selected points by lines. Once prototypes were established, the distortions were produced by applying a series of probabilities that determined whether each dot kept the same position it had in the prototype and, if not, how far it was displaced. The dot 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. Different levels of distortion were created by adjusting the probabilities that dots would make small or large movements away from their original position (for specific algorithms, see Smith et al., 2008). Higher levels of distortion were generated by moving the dots farther away from their original position.

Each pixel position in the distortion algorithm was mapped to a 3 x 3-pixel square on the screen, and the dot was placed in the center of the appropriate 9-pixel cell on the screen. Doing this magnified the stimulus pattern threefold from being drawn in a virtual 50 x 50 coordinate space to being shown in an actual 150 x 150-pixel space 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 (e.g., Homa et al., 1973, 1981).

Two base stimulus sets were created. For each stimulus set a Category A prototype was created as well as a perceptually “difficult” to discriminate Category B prototype, and a perceptually “easier” to discriminate Category B prototype. To create a Prototype B that was perceptually more similar to Prototype A (difficult to distinguish), a level-3 distortion of Prototype A was created, and then a level-3 distortion of that shape was used as Prototype B. To create a Prototype B that was perceptually more different from Prototype A (easier to distinguish), a level-3 distortion was created of Prototype A, and then a level-7 distortion of that shape was used as Prototype B. For exposure trials, 10 level 3, 10 level 5, and 10 level 7 distortions were created for each prototype. For the free sorting task, 5 prototypes, 5 level 2, 10 level 3, 10 level 4, 10 level 5, and 10 level 7 shapes were created from each prototype, providing

50 total members for each category. An additional set of exposure stimuli was created from new prototypes to create irrelevant exposure categories. Figure 3.1 presents the prototypes for each category as well as some of the stimuli from each distortion level.

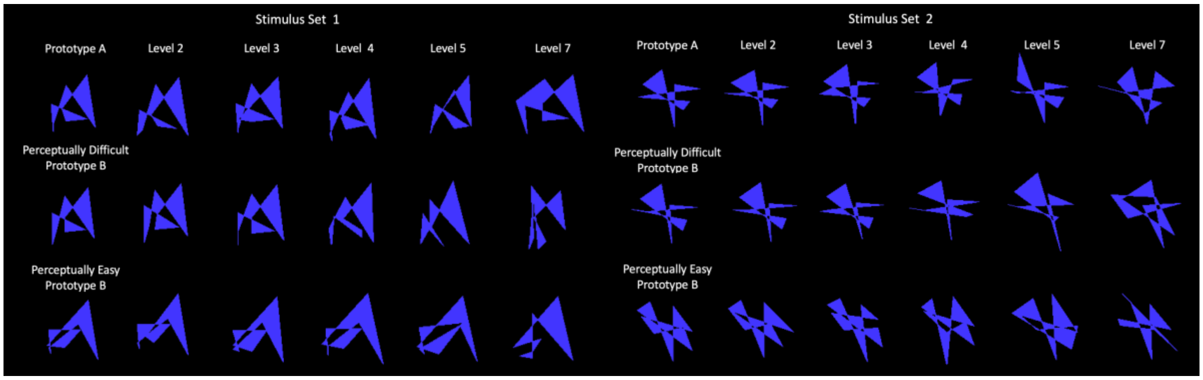

Figure 3.1 Prototypes and Sample Distortion Levels for each Stimulus Set

3.1.3 Design and Materials

This experiment used a 2 x 2 mixed factorial design with categorization accuracy as the dependent measure. The between-participants variable was perceptual difficulty (Perceptually Difficult or Perceptually Easy), and the within-participant variable was exposure type (Relevant and Irrelevant).

Each participant completed two tasks, one with Relevant exposure and one with Irrelevant exposure. Participants were randomly assigned to either the Perceptually Difficult or Perceptually Easy conditions. Each task had an initial exposure phase, followed by a categorization test phase. The order of the tasks was counterbalanced across participants. Half of the participants completed the Irrelevant task first, and half the Relevant task first. Half of the participants were randomly assigned to the Perceptually Difficult task (prototypes A and B more similar), and half to the Perceptually Easy task (prototypes A and B more different). The stimulus sets were counterbalanced so half of the participants received Set 1 first and the other half received Set 2 first.

Tasks used Psychopy programming and were posted online through Pavlovia. PsychoPy is a free cross-platform package used for creating experiments (Pierce et al., 2019). Pavlovia is an experiment server for running and uploading studies. PsychoPy and Pavlovia are created and supported by Open Science Tools Ltd (https://opensciencetools.org/). Participants first completed consent and demographics information through Qualtrics, and after consenting they were transferred to Pavlovia.

3.1.4 Procedures

In the Irrelevant task, participants were exposed to a stimulus set derived from different prototypes than those used in the categorization task. In the Relevant task, participants were exposed to members of the same categories they would classify in the categorization task (derived from the same prototypes). In the exposure phase, participants were instructed to decide if they would remember the shape if they saw it again the next day, that there was no right or wrong answer, that they would not be asked again tomorrow, and that the investigators just wanted to know what they think. On each trial, a shape appeared on the screen, and the words "Yes" and "No" appeared below the shape. The participant responded Yes by pressing Y on their keyboard, or No by pressing N on their keyboard. Exposure shapes consisted of 10 level-3, 10 level-5, and 10 level-7 distortions of each category (30 per category).

After responding to all 60 exposure shapes, participants then moved directly to the categorization task instructions. The participants were informed that the complex shape on each trial belonged to one of two categories. To put a shape into Category 1, they pressed the 1 key, for Category 2, they pressed the 2 key. On the instruction page, there was an example of a Category 1 shape and a Category 2 shape. Unbeknownst to the participant the examples were the category prototypes. They were also informed that they would be presented with an equal number of Category 1 and 2 members. On each trial, a shape appeared in the middle of the screen, with a 1 and 2 below. No feedback was provided. Once the participant made a decision, they moved directly to the next trial. For the categorization task, there were 5 prototypes, 5 level-2, 10 level-3, 10 level-4, 10 level-5, and 10 level-7 exemplars presented from each prototype in random order. After completing the categorization task, participants moved on to the next exposure and then categorization tasks (i.e., Set 2 stimuli). After participants completed the study, they returned to Qualtrics to read the debriefing form.

3.1.5 Experiment 1 Results

Analyses examined how exposure affects accuracy for the Perceptually Difficult and Perceptually Easy conditions. All statistical comparisons were two-tailed and used an α of .05. Bonferroni corrections were applied to all pairwise comparisons. A 2 x (2) general linear model (GLM) with perceptual difficulty (Difficult or Easy) as the between-subjects variable, exposure type (Relevant or Irrelevant) as the within-subject variable, and categorization accuracy as the dependent measure was conducted.

There was a significant main effect of exposure, $F(1, 48) = 8.315$, $p = .006$, $n_p^2 = .148$, showing that participants were significantly more accurate after Relevant exposure ($M = .63$, $SD = .147$) than after Irrelevant exposure ($M = .57$, $SD = .167$). There was a significant main effect of perceptual difficulty, $F(1) = 17.421$, $p < .001$, $n_p^2 = .266$, showing that participants were significantly more accurate with the Perceptually Easy ($M = .67$, $SD = .182$) categories than the Perceptually Difficult ($M = .53$, $SD = .092$) categories.

There was also a significant interaction between exposure type and perceptual difficulty, $F(1, 48) = 5.805$, $p = .020$, $n_p^2 = .108$. Pairwise comparisons show that for the Perceptually Easy condition, participants were significantly more accurate after Relevant exposure ($M = .724$, $SD =$

.141) than Irrelevant exposure (*M* = .612, *SD* = .203; $p < .001$), but for the Perceptually Difficult condition, there was no significant difference in accuracy between Relevant (*M* = .533, *SD* = .076) or Irrelevant exposure (*M* = .523, *SD* = .107; $p = .739$). This shows that when the categories were less difficult to tell apart (Perceptually Easy), relevant exposure was beneficial to later learning to categorize accurately. However, relevant exposure was not beneficial when the categories were perceptually more difficult to tell apart. The categorization accuracy for each condition is presented in Figure 3.2.

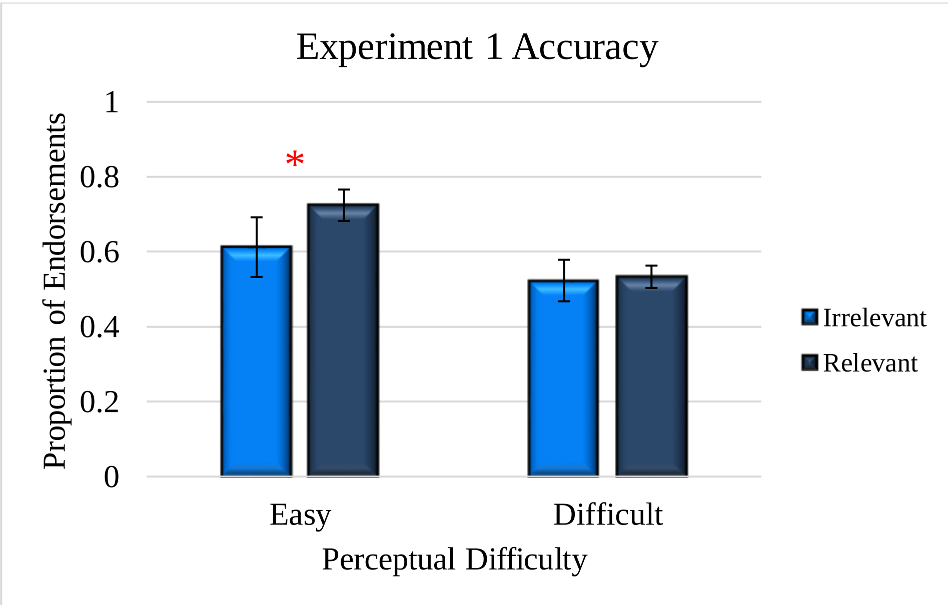

Figure 3.2 Proportion of Endorsements in Each Condition
Note. Error bars represent 95% confidence intervals.

The MKM theory of latent inhibition predicts that relevant exposure should increase performance in both Perceptually Difficult and Perceptually Easy conditions, and performance should be better in the Perceptually Difficult condition. On the other hand, representational theories predict that relevant exposure will not be beneficial if the category prototypes are too similar (Perceptually Difficult condition) as separate category representations are unlikely to form. The results suggest that Relevant exposure is beneficial for the Perceptually Easy condition and not the Perceptually Difficult condition. This is in line with the predictions of the representational theory, not the MKM model.

3.2 Experiment 2

Experiment 2 investigated the attentional spotlighting theory of perceptual learning. Wisniewski et al. (2017) showed that participants' performance was better in their progressively trained frequency range than in their constantly difficult trained range, even though the relevant dimension across ranges was the same suggesting that if it was spotlighted in one it should be spotlighted in both. This result suggested that learning goes beyond dimensional spotlighting because it predicts that the effects of spotlighting the relevant dimension should transfer across frequency ranges. On the other hand, representational theories predict that benefits should be restricted to the trained sounds, explaining the specificity of the results.

Most researchers that support attentional spotlighting models use visual stimuli; however, Wisniewski et al. (2017) used auditory stimuli. Given the distinct characteristics of visual and auditory processing, it is important to investigate whether attentional spotlighting also fails to predict progressive effects in the visual domain. Therefore, for my second experiment, I investigated easy-to-hard effects with visual stimuli. Wisniewski et al. (2017) also provided participants feedback during training to learn the contrasts, however, for the current experiment, I was interested in whether participants could learn the categories through mere exposure. These are important changes that will allow me to test attentional spotlighting and representational theories in the visual domain without direct feedback using family-resemblance categories.

Representational theories of perceptual learning predict that easy-to-hard exposure will benefit the differentiation of related categories compared to training using mostly difficult contrasts with only a few easy anchoring examples. Attentional spotlighting predicts that anchoring should be equally beneficial as the relevant category features are equally spotlighted in the anchoring condition (Pashler & Mozer, 2013).

Table 3.2 Research Question and Prediction for Experiment 2

Question	Predictions
Do participants benefit in a differentiation task after the Easy-to-Hard order and Anchoring (mostly difficult with a few easy contrasts) conditions?	Representation theory: Participants will benefit from Easy-to-Hard exposure but not Anchoring exposure. Attentional spotlighting theory: Participants will benefit from both Easy-to-Hard and Anchoring exposure.

3.2.1 Power analysis and participants

An *a priori* power analysis was conducted using G*Power version 3.1.9.7 (Faul et al., 2007) to determine the required sample size for a t-test with an alpha level of 0.05. The power analysis indicated that a minimum of 128 participants were required to achieve 80% statistical power to detect a medium effect size, as measured by d = 0.5.

One hundred and fifty-one undergraduates (with an approximate gender distribution of 76% female, 21% male, and 2% preferred not to answer) at Georgia State University participated for either partial fulfillment of course requirements (N = 130) or for extra credit in a course (N = 21). Participants' ages ranged from 18 to 59 (M = 19.92). Participants who did not complete all trials (N = 5), showed significant bias (selecting one of the choices more than 50% of the time; N = 14), or failed the attention checks (N = 2) were not included in the analyses. Therefore, 130 participants were included in the analyses.

3.2.2 Stimuli

Stimuli were created using the same method as Experiment 1, described in section 3.1.2. For this study, prototype A was created, and to create a related perceptually different prototype B, a level-7 distortion was created from a level-3 distortion of prototype A. Because prototype B was derived from prototype A, and exemplars could distort towards the opposite prototype, the stimuli were pre-rated by twenty participants and then classified as easy, medium, and difficult. For each category, 15 easy, 25 medium, and 70 difficult stimuli from each category were chosen.

Figure 3.3 presents the prototypes for each category as well as some of the stimuli from each distortion level. As described in Experiment 1, stimuli were compiled into tasks using Psychopy programming and posted online through Pavlovia.

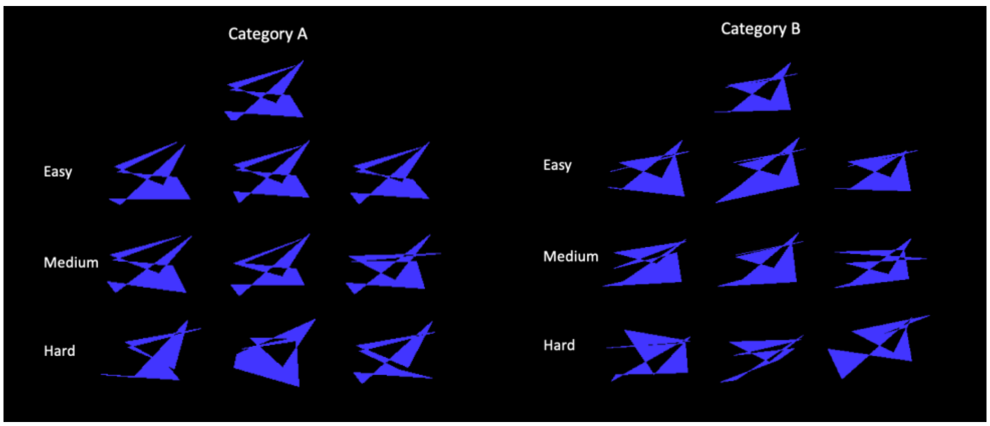

Figure 3.3 Prototypes and Sample Distortion Levels for each Stimulus Set

3.2.3 Design and Materials

The between-subjects variable was exposure condition (Easy-to-hard or Anchoring), and the dependent variable was categorization accuracy. Participants were randomly assigned to either the Easy-to-Hard condition or the Anchoring exposure condition. Participants completed two phases: an exposure phase, and a categorization test phase.

After completing consent and demographic forms online through Qualtrics, participants were directed to the online testing platform Pavlovia to complete the study. Mobile phone and tablet testing was disabled. Therefore, testing had to be completed on a desktop or laptop computer.

3.2.4 Procedures

For the Easy-to-Hard condition, participants were presented with 15 easy contrasts, followed by 15 medium contrasts, and then 15 hard contrasts of each category. For the Anchoring condition, participants were presented with 5 easy and then 40 difficult contrasts from each category. Category A and B members were intermixed in both conditions. For both exposure conditions, participants were told that they needed to decide if they would remember the shape if they saw it again the next day, there was no right or wrong answer, they would not be asked again tomorrow, and the experimenter just wanted to know what they think. On each trial, a shape appeared on the screen, and the words “Yes” and “No” appeared below the shape. The participants responded Yes by pressing Y on their keyboard or No by pressing N on their keyboard. After completing the exposure phase, participants moved to the categorization test instructions.

For the categorization test, participants were informed that they would see a complex shape on each trial that belonged to one of two categories. To put a shape into Category A, they needed to press the A key, and for Category B, they needed to press the B key. They were informed that they would be presented with an equal number of Category A and B members. On each trial, a shape appeared in the middle of the screen, with an A and B below. After each response participants were presented with “Correct” in green for a correct response, or “Incorrect” in red for an incorrect response. The categorization test consisted of 30 hard and 10 medium shape trials from each category. The entire experiment took approximately 40 minutes to complete. After participants completed the study, they returned to Qualtrics to read the debriefing form.

3.2.5 Experiment 2 Results and Conclusions

To investigate whether there was a difference in participants' overall accuracy in the test phase between the Easy-to-Hard and Anchoring conditions, an independent t-test was conducted with the exposure condition as the between-subjects variable and the proportion of correct responses as the dependent measure. Participants' categorization accuracy for each condition can be seen in Figure 3.4.

Participants in the Easy-to-Hard condition (*M* = .60, *SD* = .091) were significantly more accurate in their categorization responses than participants in the Anchoring condition (*M* = .55, *SD* = .074), *t*(128) = 2.995, *p* = .003, *d* = .525.

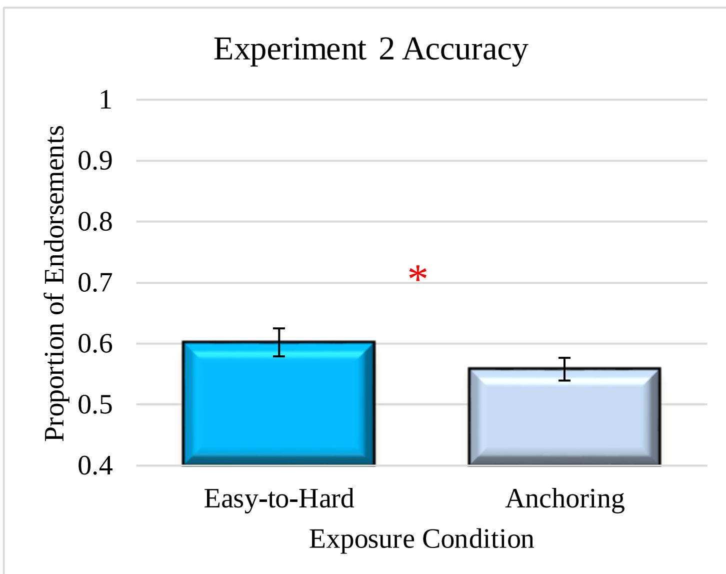

Figure 3.4 Proportion of Endorsement in Each Condition
Note. Error bars represent 95% confidence intervals.

Participants performed significantly better in the Easy-to-Hard condition than in the Anchoring condition. This suggests that participants were better able to differentiate the two categories when exposure began with easy contrasts, then progressed to medium contrasts, and then hard contrasts rather than when exposure only presented a few easy contrasts and mostly hard contrasts. The results support representational theories of perceptual learning, but not the attentional spotlighting theory. Representational theories predict that easy-to-hard exposure will benefit the differentiation of these related categories, whereas if the exposure phase contains mostly difficult contrasts, participants will not learn to differentiate difficult contrasts in a later task. Attentional spotlighting predicts that both types of training will be equally beneficial because the relevant category features are equally spotlighted in the anchoring condition (Pashler & Mozer, 2013).

3.3 Experiment 3

Experiment 3 was a first attempt to see how participants actually perceived and rated members of two categories after exposure. Previous work looking at how training with feedback affects participants' similarity ratings of category members has shown that participants rate category members as being more similar to each other (Ashby et al., 2020; Goldstone et al., 2001; Livingston et al., 1998; Pérez-Gay Juárez et al., 2019), and participants rate stimuli as being more dissimilar to members from other categories (Goldstone et al., 2001; Gureckis & Goldstone, 2008; Pérez-Gay Juárez et al., 2019) after training. The current study will look at how participants' similarity ratings change after mere exposure to stimuli from two categories and will also look at how this may change over time (multiple blocks of exposure) rather than just before and after training. In one condition, participants received exposure to the category members before every rating block, in order to see how initial exposure affected ratings. In a second condition, there was no exposure before the first rating block.

Table 3.3 Research Question and Prediction for Experiment 3

Question	Predictions
Does exposure to two categories change participants' perceived similarity of with- and between-category members?	Participants will rate within-category members as more similar and between-category members as more different with more exposure.

3.3.1 Power analysis and participants

An *a priori* power analysis for a mixed effect 2 x (2 x 5) ANOVA was conducted using G*Power version 3.1.9.7 (Faul et al., 2007) to determine the minimum sample size necessary for this experiment. Results indicated the minimum sample size needed to achieve 80% power for detecting a medium effect at a significance criterion of $\alpha = .05$ is $N = 20$.

A total of 76 participants were recruited (with an approximate gender distribution of 67% female, 29% male, and 3% preferred not to answer). Participants' ages ranged from 18-35 (M = 21.4). Fifty-five participants were Georgia State University undergraduates who completed the study for partial fulfillment of course credit, and 21 participants were recruited from Prolific and received $6 as compensation for completing the experiment. Prolific participants were required to be from the United States and no older than 35 years old. Participants who did not complete all trials (N = 15) or failed the attention checks (N = 1) were not included in the analyses. Therefore, 60 participants were included in the analyses.

3.3.2 Stimuli

Stimuli were created using the methods described in section 3.1.2. Two prototypes were created. From each prototype, 75 level-3, level-5, and level-7 distortions were created to make the exposure block shapes. Then 35 level-2, level-3, level-5, and level-7 distortions from each prototype were created for the similarity rating blocks from each prototype.

The exposure stimuli were divided into 5 sets so that each set had 15 level-3, level-5, and level-7 distortions of each prototype. The similarity rating task stimuli were divided into 5 stimulus sets, each containing both category prototypes, and 7 each of level-2, level-3, level-5, and level-7 distortions from each prototype.

3.3.3 Design and Materials

This experiment used a 2 x (2 x 5) mixed factors design with similarity ratings as the dependent measure. The between-participants variable was exposure before the first rating block or not, and the within-participant variable was comparison type (within- and between-category) and block (1-5).

After completing consent and demographic forms through Qualtrics, participants were directed to Pavlovia to complete the study. Mobile phone and tablet testing was disabled. Therefore, testing had to be completed on a desktop or laptop computer.

3.3.4 Procedures

Half of the participants alternated 5 exposure blocks and 5 rating blocks starting with an exposure block. Half of the participants alternated 4 exposure blocks and 5 rating blocks starting with a rating block. One stimulus set was used for each block. The stimulus set order was randomized for each participant. The exposure and rating blocks alternated back and forth.

Exposure blocks consisted of 15 Category A and 15 Category B members (5 level-3, 5 level-5, and 5 level-7 distortions from each prototype) in a randomized order. Each exposure block used different category members, so participants were never presented with the same stimulus more than once. On each trial, a shape appeared on the screen, and the words “Yes” and “No” appeared below the shape. Participants were told that they needed to decide if they would remember the shape if they saw it again tomorrow, that there was no right or wrong answer, they would not be asked again tomorrow, and the investigators just wanted to know what they thought. The participants responded Yes by pressing the Y on their keyboard, or No by pressing the N on their keyboard.

Similarity rating blocks consisted of 64 trials each. Thirty-two of the trials presented two shapes from the same category (within-category). On half of these trials, both shapes were Category A members, and on half of the trials, both shapes were Category B members. Thirty-two of the trials presented a shape from each category (between-category) for comparison. Each block presented all pairwise combinations (16) for Category A and Category B. In each block, all pairwise combinations were presented for the between-category comparisons (17). On each trial, participants were presented with two stimuli presented side by side. The shapes were randomly selected to appear on the left or right side. Below the stimuli was the question "How similar are these two shapes?" Then below this question was a scale of 0 to 6, with the label "No Difference" below 0 and "Big Difference" below 6. Participants used their mouse to select a rating. Once a rating was selected the trial ended; no feedback was given. Trials were self-paced and the entire study took approximately 30 minutes to complete. After participants completed the study, they returned to Qualtrics to read the debriefing form. An example of a similarity rating trial can be seen in Figure 3.5.

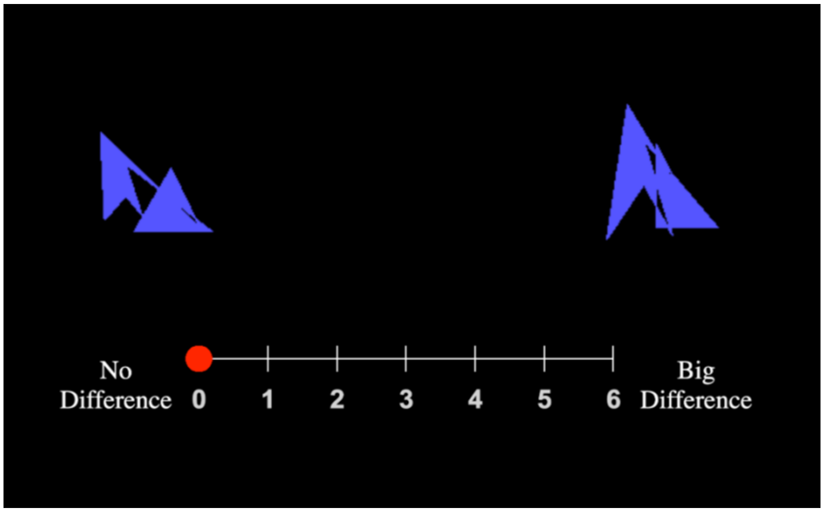

Figure 3.5 A Sample of a Similarity Rating Trial

3.3.5 *Experiment 3 Results and Conclusions*

Analyses were conducted to look at how participants' similarity ratings of Category A and B exemplars changed over time. All statistical comparisons were two-tailed and used an α of .05. Bonferroni corrections were applied to all pairwise comparisons. Participant ratings can be seen in Figure 3.6.

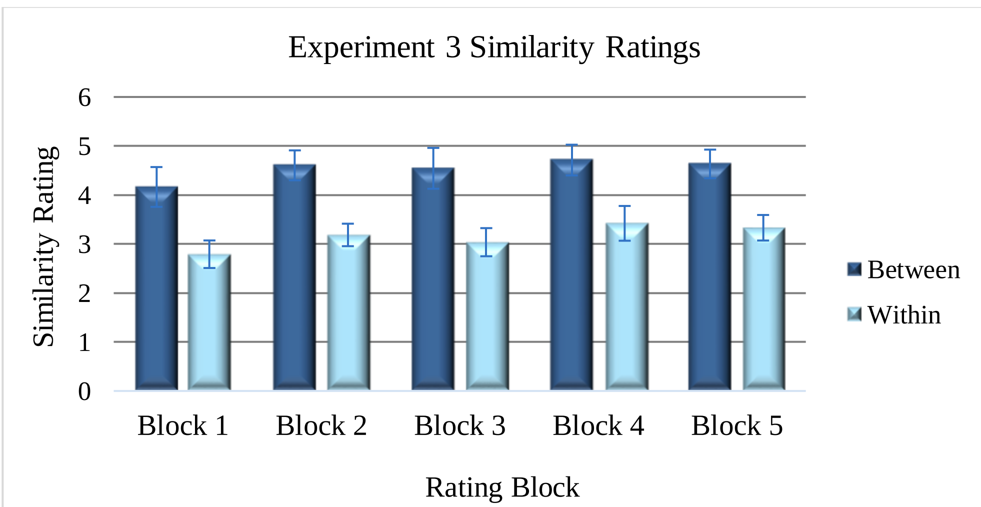

Figure 3.6 Rating for Between- and Within-Categories in each Block
Note. Error bars represent 95% confidence intervals.

A 2 x (2 x 5) GLM was conducted with similarity rating (0-6) as the dependent variable, Block 1 exposure condition (exposure vs no exposure) as the between-subjects variable, and comparison type (within-category vs between-category) and block (1-5) as the within-subject variables. There was a significant main effect of block, $F(4, 55) = 4.778$, $p = .002$, $n_p^2 = .258$, suggesting that participants ratings changed over time. Pairwise comparisons show that Block 1 ratings were significantly lower than Block 2 ($p = .042$), Block 3 ($p = .003$), Block 4 ($p = .025$), and Block 5 ($p = .004$). There was a significant main effect of comparison type, $F(1, 58) = 306.898$, $p < .001$, $n_p^2 = .841$, showing that participants rated within-category members lower (more similarly) than between-category members. There was no significant main effect of exposure condition, $F(1) = .034$, $p = .855$, $n_p^2 = .001$, showing that overall participants did not rate items differently if they received exposure before Block 1 or not.

There was no significant interaction between block and condition, $F(4, 55) = 1.582$, $p = .192$, $n_p^2 = .103$, suggesting that changes in ratings across blocks did not depend on receiving exposure before the first block or not. There was no significant interaction between comparison type and exposure condition, $F(4, 55) = 3.067$, $p = .085$, $n_p^2 = .050$, suggesting that within-category members were rated lower than between-category members regardless of exposure before the first block. There was no significant interaction between comparison type and block, $F(4, 55) = 1.911$, $p = .121$, $n_p^2 = .122$, showing that within-category members were consistently rated lower than between-category members across blocks. There was no 3-way interaction between block, comparison type, and exposure condition, $F(4, 55) = .893$, $p = .474$, $n_p^2 = .061$, suggesting that within-category members were rated as more similar than between-category members for both exposure conditions across blocks.

To better understand exposure's effect on the participants' initial perceived similarity of the categories, I compared Block 1 ratings for the participants who received exposure before Block 1 and those who did not receive exposure before Block 1. Means and standard deviations can be found in Table 3.4.

A 2 x (2) GLM was conducted with similarity rating (0-6) as the dependent variable, condition (with exposure vs no exposure) as the between-subjects variable, and comparison type (within-category vs between-category) as the within-subjects variable. There was a significant main effect of comparison type, $F(1, 58) = 273.672$, $p < .001$, $n_p^2 = .825$, showing that participants consistently rated within-category members lower (more similar) than between-category members. There was no significant main effect of condition, $F(1) = 2.025$, $p = .160$, $n_p^2 = .034$, showing that exposure before Block 1 did not affect participants ratings. There was no significant interaction between comparison type and condition, $F(1, 58) = 1.942$, $p = .169$, $n_p^2 = .032$, suggesting that within-category and between-category member ratings were similar with or without exposure before Block 1.

Table 3.4 Means and standard deviations for Experiment 3

Comparison Type	Block	All Exposure	No Exposure Block 1
		M(SD)	*M(SD)*
Within			
	Block 1	2.79(.786)	2.96(.641)
	Block 2	3.18(.641)	2.92(.662)
	Block 3	3.04(.803)	3.01(.704)
	Block 4	3.42(.992)	3.19(.783)
	Block 5	3.33(.728)	3.19(.783)
Between			
	Block 1	4.16(1.13)	4.58(.826)
	Block 2	4.60(.854)	4.72(.950)
	Block 3	4.54(.1.16)	4.73(.902)
	Block 4	4.71(.875)	4.79(.936)
	Block 5	4.63(.818)	4.76(.9360

Taken together, these results suggest that there was no significant change in participants' perceived similarity ratings either within- or between-categories after mere exposure. This result may seem surprising given previous findings showing that participants’ ratings change for within-category members as being more similar after training (Ashby et al., 2020; Goldstone et al., 2001; Livingston et al., 1998; Pérez-Gay Juárez et al., 2019) and between-category members as being less similar (Goldstone et al., 2001; Gureckis & Goldstone, 2008; Pérez-Gay Juárez et al., 2019) after training. However, those experiments used direct categorization training with feedback and this study used mere exposure. This may suggest that training effects on perceptions of within and between-category similarity may require the involvement of feedback-dependent striatal-mediated learning.

3.4 Experiment 4

In Experiment 4, I investigated attentional weighting and representational theories of perceptual learning. Attentional weighting theories suggest that perception adapts to tasks by incrementally increasing attention toward crucial features and by slowly reducing attention toward irrelevant features. Improvements in perceptual discriminations are caused by the development of more efficient connections between higher-level sensory signals or responses and feature representations lower in the perceptual pathway. Evidence for attentional weighting theory comes from research using simple stimuli with basic visual features suggesting that perceptual learning occurs early in the visual cortex (see Song et al., 2005). Research supporting attentional weighting has shown that some examples of perceptual learning are specific to their original training situation (e.g., Ball & Sekuler, 1982; Fiorentini & Berardi, 1980; Karni & Sagi, 1991; Poggio et al., 1992).

To investigate whether early visual cortex mediates learning multiple family-resemblance categories after mere exposure, I had participants complete an exposure phase and a categorization test phase, during which some participants were presented with stimuli varying in size from the exposure phase. Participants were randomly assigned to the Constant Size or Variable Size condition. For training, participants were not told any information about the two categories, and all category members were medium-sized. For the categorization test, participants in the Constant Size condition were presented with shapes in the medium size. In the Variable Size condition, the stimuli varied in size. Attentional weighting theories predict that participants' performance in the task will be better in the Constant Size condition, as learning is occurring in the early visual cortex. Representational views predict that participants can learn in both conditions because representational change affecting categorization is likely taking place at higher levels of visual cortex with object-level representations.

Table 3.5 Research Question and Prediction for Experiment 4

Question	Prediction
Can high-level areas in the visual cortex contribute to prototype formation under conditions that would make it difficult for low-level areas to do so?	Representational theory: There will be no differences between the Variable Size and Constant Size conditions. Attentional weighting theory: Participants will have better categorization accuracy in the Constant Size condition than the Variable Size condition.

3.4.1 Power analysis and participants

An *a priori* power analysis was conducted using G*Power version 3.1.9.7 (Faul et al., 2007) to determine the required sample size for a mixed-factor general linear model test with an alpha level of 0.05. The power analysis indicated that a minimum of 24 participants were required to achieve 80% statistical power to detect a medium effect size, as measured by n_p^2 = .06.

A total of 33 participants were recruited (approximate gender distribution of 55% female, 42% male, and 3% preferred not to answer). Participants' ages ranged from 18-34 (*M* = 24.3). Thirteen participants were Georgia State University undergraduates who completed the study for partial fulfillment of course credit. Twenty participants were recruited from Prolific and received $6 as compensation for completing the experiment. They were required to be from the United States and no older than 35 years old. Participants who did not complete all trials (*N* = 2), or showed significant bias (selecting one of the choices more than 75% of the time; *N* = 1) were not included in the analyses. Therefore, 30 participants were included in the analyses.

3.4.2 Stimuli

Stimuli were created using the methods described in Section 3.1.2. For this study, prototype A and prototype B were first created. For each category, 15 level-3, -5, and -7 distortions were created from each prototype as exposure stimuli. For the test stimuli, 30 level-2, -3, -5, and -7 distortions were created from each prototype. The stimuli were arranged into 12 blocks. Half of the blocks contained 18 stimuli, 9 from each category, with 1 prototype A and 1 prototype B, then 2 of each level-2, -3, -5, and -7 distortions from each category. The other half of the blocks did not include the prototypes but consisted of 2 of each level-2, -3, -5, and -7 distortions from each category.

The blocks were presented in a randomized order. All stimuli were created in the same Medium size. For the Variable Size condition, the program was set up so that each level would appear in each size approximately 4 to 5 times to ensure all crosswise comparisons were presented. The Large size was a 10% width and height increase to the Medium size, and the

Huge was a 10% increase of the Large size. The Small size was a 10% decrease in size from the Medium size, and Tiny was a 10% decrease from the Small size. Figure 3.7 presents the category prototypes in varying sizes. As described in Experiment 1, stimuli were compiled into tasks using Psychopy programming and posted online through Pavlovia.

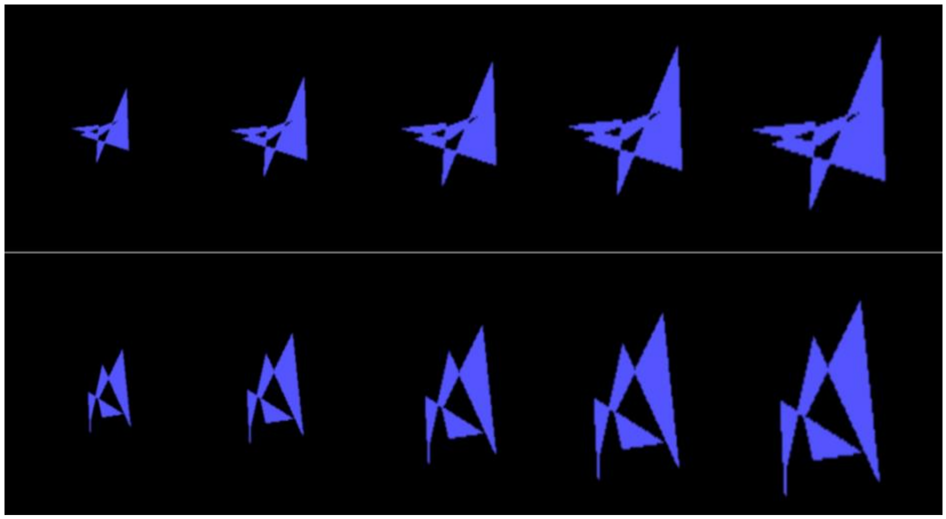

Figure 3.7 Category Prototypes in each Size
Note. The top row shows the Category A prototype, the bottom row shows the Category B prototype. From left to right the sizes are Tiny, Small, Medium, Large, and Huge.

3.4.3 Design and Materials

This experiment used a 2 x (5) mixed factorial design with categorization accuracy as the dependent measure. The between-participants variable was size condition (Constant Size, Variable Size), and the within-participant variable was item type (prototype, level-2, -3, -5, and -7 distortion).

Participants were randomly assigned to either the Constant Size or Variable Size conditions. Each task had an initial exposure phase, followed by a categorization task phase. Tasks used Psychopy programming and were posted online through Pavlovia. Participants first completed consent and demographics information through Qualtrics, after consenting, they were transferred to Pavlovia.

3.4.4 Procedures

In the Constant Size condition, participants were exposed and tested on only Medium-sized stimuli. In the Variable Size condition, participants were exposed to Medium size stimuli, and tested on stimuli that varied in size: Tiny, Small, Medium, Large, and Huge.

All participants started with the exposure phase. In the exposure phase, participants were instructed to decide if they would remember the shape if they saw it again the next day. They were told there was no wrong or right answer, and they would not be asked again tomorrow, and the investigators just wanted to know what they thought. On each trial, a Medium-sized shape appeared on the screen, and the words "Yes" and "No" appeared below the shape. The participant responded Yes by pressing Y on their keyboard, or No by pressing N on their keyboard. Exposure shapes consisted of 15 level-3, 15 level-5, and 15 level-7 distortions of each category.

After responding to the 90 exposure shapes, participants then moved to the categorization task instructions. The participants were informed that the complex shape on each trial belonged to one of two categories. To put a shape into Category A, they pressed the A key, for Category B, they pressed the B key. They were also informed that they would be presented with an equal number of Category A and B members. On each trial, a shape appeared in the middle of the screen, with an A and B below. After each response participants were presented with "Correct" in green for a correct response, or "Incorrect" in red for an incorrect response. The categorization task was a total of 204 trials. The experiment took approximately 30 minutes to complete. After participants completed the study, they returned to Qualtrics to read the debriefing form.

3.4.5 Experiment 4 Results and Conclusions

All statistical comparisons were two-tailed and used an α of .05. Bonferroni corrections were applied to all pairwise comparisons. Means and standard deviations are in Table 3.6. A 2 x (5) GLM was conducted with condition (Variable Size vs. Constant Size) as the between-subject variable, item type as the within-subjects variable (prototype, level-2, -3, -5, and -7 distortion), and categorization performance was the dependent variable.

Table 3.6 Means and standard deviations for Experiment 4

Item Type	Size Variable		Same Size	
	M	*SD*	*M*	*SD*
Prototype	0.92	0.099	0.9	0.114
Level-2	0.88	0.114	0.87	0.145
Level-3	0.88	0.125	0.88	0.132
Level-5	0.85	0.125	0.85	0.134
Level-7	0.76	0.135	0.73	1.28

There was a significant main effect of item type, $F(4, 28) = 22.903$, $p < .001$, $n_p^2 = .450$. Pairwise comparisons showed that categorization accuracy with the prototypes was significantly better than with the level-5 ($p = .010$) and level-7 ($p < .001$) distortions. But there was no significant difference between the prototype and level-2 ($p = .307$) or level-3 ($p = 1.000$) distortions. Categorization accuracy was significantly higher with the level-2 distortions than the level-7 distortions, but not the level-3 ($p = 1.000$) or level-5 ($p = .244$). Category accuracy was significantly higher for level-3 distortions than level-5 ($p = .026$) and level-7 ($p < .001$) distortions. Categorization accuracy was significantly higher with the level-5 distortions than the level-7 (p < .001) distortions. There was no significant main effect of condition, $F(1) = .090$, $p = .767$, $n_p^2 = .003$, showing that participants' categorization accuracy was not significantly better with either constant or variable stimuli size. There was no signification interaction of item type and condition, $F(1, 28) = .025$, $p = .875$, $n_p^2 = .001$. Participants' categorization accuracy for the

Variable Size condition can be found in Figure 3.8A and the Constant Size condition in Figure 3.8B.

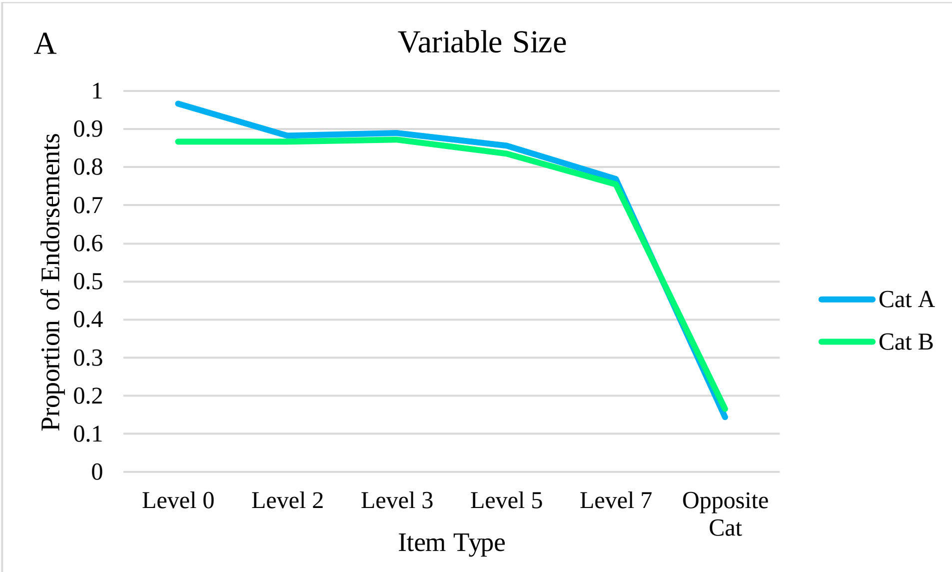

Figure 3.8 Proportion of Endorsements of each Condition

The categorization accuracy of the first 50 trials was also examined for each condition to see if learning occurred over time through trial-and-error, or if participants could successfully categorize the stimuli at different sizes early in the test phase after exposure. The independent t-test showed that there was no significant difference in early performance between Constant Size and Variable Size conditions, $t(28) = .183$, $p = .856$, $d = .067$.

A (5 x 5) GLM was conducted to see if participants in the Variable Size condition performed similarly with all size stimuli, or if they had higher accuracy for the Medium size, to which they had been exposed. The within-subject variables were size (Tiny, Small, Medium, Large, Huge), and item type (prototype, level-2, -3, -5, and -7 distortions). The dependent variable was categorization accuracy.

There was a significant main effect of item type, $F(1, 12) = 10.597$, $p < .001$, $n_p^2 = .469$. Pairwise comparisons showed that accuracy with the level-7 distortions was significantly lower than the prototype ($p = .014$), and level-2 distortions ($p = .003$). There were no other significant differences between item types. This result suggested that participants found it more difficult to correctly categorize the high distortions (level 7) of the prototype in comparison to the prototypes and low-level distortions (level 2). There was no significant main effect of size, $F(4, 48) = .780$, $p = .538$, $n_p^2 = .062$, and no significant interaction between size and item type, $F(16, 192) = .912$, $p = .556$, $n_p^2 = .071$. This result showed that participants' accuracy was not better for the Medium size that they were exposed to; their performance was consistent across stimulus sizes. Category endorsements for each size can be found in Figure 3.9.

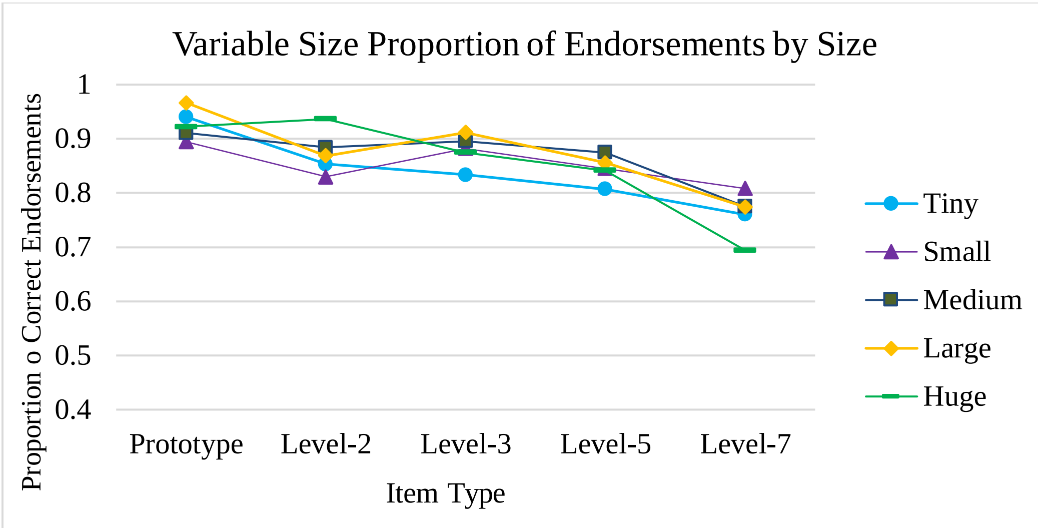

Figure 3.9 Proportion of Endorsements Correct for each Stimulus Size

Attentional weighting theory suggests that perceptual learning occurs early in the visual cortex (Song et al., 2005). If perceptual learning's enhancement of family-resemblance category learning occurs in the early visual cortex, stimulus-size variability should lessen exposure learning. However, category learning was similar in both conditions (Constant Size vs Variable Size). Participants in the Variable Size condition accurately categorized all size stimuli. Taken together, these results imply that perceptual learning's enhancement of categorization is not occurring early in the visual cortex as attentional weighting theorists suggest. These results provide support for representational theories of perceptual learning, but not attentional weighting theories.

4 GENERAL DISCUSSION

For decades multiple system theorists have tried to understand how different brain systems may facilitate different types of category learning. Many natural categories follow a family-resemblance category structure (e.g., Rosch & Mervis, 1975). Unlike other types of categories, humans (even those with memory impairments) can learn a single family-resemblance category merely by being perceptually exposed to members of the category even when there is no discussion of their category membership (e.g., Homa & Cultice 1984; Palmeri & Flanery 1999; Reed et al.,1999, Zabberoni et al., 2021). Jackson et al. (2023) recently showed that pre-exposure to category members also benefits learning two family-resemblance categories simultaneously, suggesting a role for perceptual learning in family-resemblance category learning. However, Jackson et al. (2023) did not pinpoint exactly what the underlying mechanism is of this perceptual learning is. Therefore, in the current studies, I tested different theories of perceptual learning as explanations of family-resemblance category learning from exposure. The theories I tested were MKM's latent inhibition model, attentional spotlighting, attentional weighting, and representational theory. These specific theories were chosen because they are the predominant theories trying to explain how perceptual learning occurs. I hypothesized that exposure to relevant category members provides benefit to family-resemblance category learning because exposure allows participants to build cortical representations of the prototypes. This is consistent with representational models of perceptual learning. Below I will outline the findings and any potential limitations to each experiment, and then discuss the theoretical interpretations.

4.1 Experiment 1 Findings

Experiment 1 investigated the MKM model and representational theories' predictions of perceptual learning in a categorization task without feedback to see how participants labeled category A and B members after being shown examples from the categories (the prototypes). Participants were assigned to either the Perceptually Difficult or the Perceptually Easy condition and then completed a relevant and irrelevant exposure task before completing a categorization task. In the Perceptually Difficult condition, the category prototypes were highly related to one another, making it difficult to tell them apart. In the Perceptually Easy condition, the category prototypes were less related, and easier to tell apart.

The MKM model predicted that relevant exposure to category members would increase performance in both Perceptually Difficult and Perceptually Easy conditions, and performance would be better in the Perceptually Difficult condition. This is because the MKM model suggests that when stimuli share elements, there will be a reduction in salience of those elements, and any unique elements to the stimuli will be higher in salience. This effect is likely to be greater for items that are perceptually similar to each other because they share many common elements and hence latent inhibition will be more pronounced than for items that are very different (i.e., that have few common elements; Milton et al., 2014). If perceptual learning is more marked for perceptually similar items than perceptually different items as the MKM model proposes, then one prediction that follows is that pre-exposure will lead to better family-resemblance sorting for perceptually similar stimuli (Perceptually Difficult condition) compared to perceptually different stimuli (Perceptually Easy condition). On the other hand, representational theories predict that relevant exposure will not be beneficial if the category prototypes are too similar (Perceptually Difficult condition) as separate category representations are unlikely to form. The results from this study suggest that relevant exposure is only beneficial for the Perceptually Easy condition. Representational theory is able to explain the results of Experiment 1, however, the MKM model cannot.

4.2 Experiment 2 Findings

In Experiment 2, I investigated the attentional spotlighting and representational theories of perceptual learning. Participants were randomly assigned to the Easy-to-Hard or Anchoring condition. In the Easy-to-Hard condition, exposure started with easy contrasts of the categories (exemplars rated similar to their prototype), and then moved to medium contrasts, and lastly hard contrasts (exemplars rated less similar to the prototypes). For the Anchoring condition, participants viewed just a few examples of easy contrasts during exposure, and the rest were difficult contrasts.

Attentional spotlighting suggests that easy-to-hard presentation of stimuli is beneficial because the initial easy trials direct participants' attention to category-relevant features, and once these features are identified, it is perceived more minutely, altering the perception of the dimension permanently. If this line of reasoning is correct, participants should perform similarly in the Easy-to-Hard and Anchoring conditions, as they both started with easy contrasts containing category relevant dimensions. However, representational theories predict that easy-to-hard exposure incrementally aids in differentiation of these related categories (A-B), whereas if the exposure phase contains mostly difficult contrasts, this representational differentiation cannot occur.

The results showed that participants performed significantly better in the Easy-to-Hard condition than in the Anchoring condition. The results suggest that participants are better at differentiating the two categories when exposure begins with easy contrasts, then medium contrasts, and then hard contrasts rather than when exposure only shows a few easy contrasts and then mostly hard contrasts. Once again, these results are predicted by representational theories, but not attentional spotlighting theories.

4.3 Experiment 3 Findings

Experiment 3 aimed to explore how participants perceive and rate members of two categories after mere exposure and how those ratings change over time. Previous work has investigated how training with feedback affects participants' similarity ratings of category members and has shown that participants rate category members as being more similar to each other (Ashby et al., 2020; Goldstone et al., 2001; Livingston et al., 1998; Pérez-Gay Juárez et al., 2019), and more dissimilar to members from other categories (Goldstone et al., 2001; Gureckis & Goldstone, 2008; Pérez-Gay Juárez et al., 2019) after training.

In one condition participants received exposure to the category members before every similarity rating block. In order to see how initial exposure affected ratings, there was a second condition in which there was no exposure before the first rating block. The results showed that there was not any change over time with further exposure and there was no initial change in participants' perceived similarity of the categories after the first exposure block. This may suggest that training effects on perceptions of within and between-category similarity may require the involvement of feedback-dependent striatal-mediated learning.

4.3.1 Experiment 3 Limitations

The results of Experiment 3 seem to contradict previous research that has looked at similarity ratings of categories after direct training. However, this study differs from others in that participants were not given any information or training about the categories, but instead they received mere exposure. To better understand why the exposure in this experiment did not alter participants' perception of category A and B members, it would be beneficial to conduct the same study with a training condition in which participants complete a categorization task with feedback instead of a mere exposure task. This would be more similar to how other studies have looked at similarity ratings. If ratings do not change in a task that uses direct training, it would suggest there are bigger methodological issues as direct training has been shown to change participants' similarity ratings in previous work (Goldstone et al., 2001). However, if there are effects after training that do not occur after exposure, this may suggest that the underlying mechanisms driving these changes in similarity may require the involvement of reinforcement-dependent learning systems like the basal ganglia.

4.4 Experiment 4 Findings

Experiment 4 investigated attentional weighting theory and representational theories of perceptual learning. Attentional weighting theory has suggested that perceptual learning is a low-level process that occurs early in the visual cortex (for discussion see Song et al., 2005). However, the research supporting this theory has used simple stimuli with basic features and has suggested that perceptual learning is specific to the original training situation (e.g., Ball & Sekuler, 1982; Fiorentini & Berardi, 1980; Karni & Sagi, 1991; Poggio et al., 1992). This has led attentional weighting theorists to assume that perceptual learning cannot involve actual representational change, but only attentional change because these early visual areas are thought to be fixed and relatively unchanging after early development.

To test these two theories, I investigated whether early visual cortex mediated learning multiple family-resemblance categories after mere exposure. To do so, participants were randomly assigned to the Constant Size or Variable Size condition. For training, participants were not told any information about the two categories, and all category members were medium sized. For the categorization test, participants in the Constant Size condition were presented with shapes in the medium size. In the Variable Size condition, the stimuli varied in size. Attentional weighting theories suggest that participants' performance in the task will be better in the Constant Size condition, as learning is occurring in the early visual cortex where there is no size constancy. Representational views suggest participants will learn in both conditions because representational change should be taking place at higher areas of visual cortex where size is constant. The results showed no differences in categorization performance between the two conditions, and participants in the Variable Size condition were able to learn all sizes equally well. These results suggest that early visual cortex may not mediate exposure learning in multiple family-resemblance categories as predicted by attentional weighting theory. The data again support representational views.

4.5 Theoretical Interpretations

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). The current studies make important contributions to both the perceptual and categorization learning literatures, as they shed light on how these two processes can interact in learning multiple family-resemblance categories through mere exposure.

Collectively, these experiments contribute insights to the perceptual learning literature by challenging the predominant theories of perceptual learning. Experiment 1 showed that contrary to the MKM model's predictions, relevant exposure only enhanced performance in the Perceptually Easy condition, aligning more closely with representational theories and not the MKM model's predictions. This discrepancy emphasizes the complexity of the relationship between exposure and category learning and shows that there are limitations to learning through mere exposure if categories are too similar. Experiment 2 not only provides further support for representational theories but also has meaningful implications for practical applications, particularly for training regimens and educational practices. The results highlight the importance of using easy-to-hard sequencing in optimizing perceptual learning through exposure. While previous studies indicated that training with feedback influenced participants' similarity ratings, Experiment 3, using mere exposure, revealed no significant changes in perceived similarity over time (blocks). The results prompt further investigation to better understand how exposure changes our perception of family-resemblance categories. Experiment 4 focused on attentional weighting theory and representational theories by investigating whether the early visual cortex mediated learning in multiple family-resemblance categories after mere exposure. The results indicated no significant differences between Constant Size and Variable Size conditions. This challenges attentional weighting theory and supports the idea that representational changes are occurring at higher levels of the visual cortex.

These studies also add to the multiple-systems view of category learning. A predominant theory of categorization, COVIS, predicts that we are able to learn through exposure due to fluency (Ashby & Maddox, 2005). Fluency happens when previous experience induces a graded pattern of activation in the visual cortex causing 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/familiarity to decide which stimuli belong to the category. Fluency would only be beneficial in learning a single-family-resemblance category through exposure and not multiple family-resemblance categories. This is because if we were exposed to two family-resemblance categories, the stimuli from both categories (A-B) would feel fluent and could not be differentially categorized. The results from Jackson et al. (2023) showed that exposure is beneficial when learning multiple family-resemblance categories simultaneously, which shows that fluency is not the only mechanism for learning from exposure. The current studies helped to pinpoint the mechanism for learning multiple family-resemblance categories through exposure, which Jackson et al. (2023) were not able to do.

These studies suggest that the ability to learn multiple family-resemblance categories through mere exposure is not reliant on the reduced salience of shared features between category stimuli as proposed by MKM model, is not reliant on an explicit search process for relevant dimensions as proposed by attentional spotlighting theories, and is not processed early in the visual cortex as suggested by attentional weighting theory. The current studies provide support for representational theories of perceptual learning, which suggest that exposure and training actually change the way that stimuli are perceptually represented. During exposure, the visual perceptual system can build cortical representations of prototypes through perceptual learning that can later aid category learning allowing sorting or quick mapping onto multiple categories.

Having multiple systems available for category learning is beneficial. When one system fails us, we have a backup system. We have an 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 system feeds information to the implicit-associative and explicit-declarative systems. These studies suggest 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.

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