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Category Learning in Older Adulthood: Understanding and Reducing Age-Related Deficits

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Abstract

Executive functions are important for learning rule-based (RB) categories, as well as non-rule-based (NRB) categories (e.g., categories learned implicitly, without a verbal rule). However, executive functioning is known to decline with age, leading to age-related deficits in category learning. The current thesis examines RB and NRB category learning in older adults using category sets that vary in difficulty (e.g., rule complexity, number of stimulus dimensions, salience of stimulus dimensions). In Chapter 2, older adults and younger adults completed three category sets (simple single-dimensional RB, disjunctive RB, and NRB). Older adults learned the simple, single-dimensional rules quite well. In contrast to younger adults, older adults found complex disjunctive RB categories harder to learn than NRB categories because of the executive functioning demands associated with complex rule learning. In Chapter 3, I introduced a pre-training procedure prior to the disjunctive RB and NRB categorization task used in Chapter 2. This was done in an effort to reduce task demands, as to minimize age-related categorization deficits. Both RB and NRB category learning improved among older adults following pre-training, but the improvements to RB learning were more drastic, suggesting that executive functioning plays a heavier role in RB learning. In Study 1 of Chapter 4 I used a difficult, single-dimensional RB category set (i.e., the correct rule is based on the less salient stimulus dimension) and a NRB category set to further examine category learning in normal aging and to better understand the types of strategies used by older adults. Relative to younger adults, older adults struggled with learning both the RB and NRB category set because they used suboptimal rules during the RB task and a RB strategy during the NRB task. In Study 2 of Chapter 4, I used a pre-training procedure to familiarize older adults with the stimulus dimensions of the RB category set, reducing the executive function demands of the task. Pre-training improved RB accuracy and the consistency with which older adults applied the rule. Across all studies, executive functioning abilities were associated with RB and NRB category learning. Overall, the results from this thesis help to better understand the locus of age-related categorization deficits and offer a method of reducing these deficits.

Keywords

Category learning; Executive function; Aging; Explicit learning; Implicit learning

Co-Authorship Statement

The research for this doctoral thesis was conducted in collaboration and under the supervision of my advisor Dr. John Paul Minda. The research presented in Chapter 2 has been published elsewhere and authorship is shared with Dr. Minda, however I was the first author of the paper. Brittany Ammendolia assisted with data collection for Chapter 2. Chapters 3 and 4 are entirely my own work. They have been written in preparation for publication, authored by Rahel Rabi and John Paul Minda. Celina DeLancey, Letty Peng, Lorena Cevallos Salinas, and Victoria Wiebe assisted in data collection for Chapters 3 and 4. I designed, assisted with data collection, analyzed, and interpreted data in all of the studies in this thesis. As my thesis advisor, Dr. Minda provided assistance with regard to the revision of the experimental papers and general introduction and discussion of this thesis.

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List of Abbreviations

AIC …..……………………………………………………… Akaike information criterion

BCST …………………………………………………..…………….. Berg Card Sorting Test

COVIS ...………………………………… Competition between Verbal and Implicit System

fMRI .... Functional Magnetic Resonance Imaging

FR ……………………………………………………………………….. Family resemblance

FrACT …………………………………………….. Freiburg Visual Acuity and Contrast Test

II ……………………………………………………………………... Information integration

IQ .... Intelligence Quotient

NRB …………………………………………………………………..…… Non-rule-based

PEBL ……………………………………...…. Psychology Experiment Building Language

PFC ……………………………………………………………………………. Prefrontal cortex

RB ……………………………………………………………………………………… Rule-based

WASI ……………………………...…………. Wechsler Abbreviated Scale of Intelligence

WCST .... Wisconsin Card Sorting Test

Chapter 1

1 General Introduction

The ability to distinguish between objects we encounter on daily basis and categorize them into meaningful groups is a fundamental cognitive process. A number of categories are acquired during childhood (e.g., shapes, animals, vegetables) but we continue to learn and acquire new categories throughout our lifetime. During adulthood, category learning plays an important role in both our professional and personal lives. For example, physicians may rely on categories to diagnose patients and engineers may rely on categories to determine whether a building is structurally sound. Likewise, we depend on categories when sorting laundry or filing bills and papers at home. Given the importance of category learning across our lifetime, it is important to understand how this cognitive process changes with age.

1.1 Multiple Systems in Category Learning

A large array of research on the cognitive processes involved in category learning has provided evidence that there are at least two separate category-learning systems. The COVIS model (Competition between Verbal and Implicit Systems) is a well-known version of these multiple systems theories (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Maddox & Ashby, 2004; Miles & Minda, 2011; Minda & Miles, 2010), which assumes that categories are learned by an explicit *verbal system* and an implicit, *nonverbal system* (see Figure 1.1). The verbal system is considered to be the default learning system, which individuals use to place objects into categories for which there is a verbal rule (i.e., rule-based, or RB categories). For example, given a group of objects consisting of squares and circles, one could quickly master this category set by applying the verbal rule: "Category A items are square". According to COVIS, the verbal system is mediated by the prefrontal cortex, the medial temporal cortex, the anterior cingulate cortex, and the head of the caudate (Zeithamova & Maddox, 2006). This system relies on

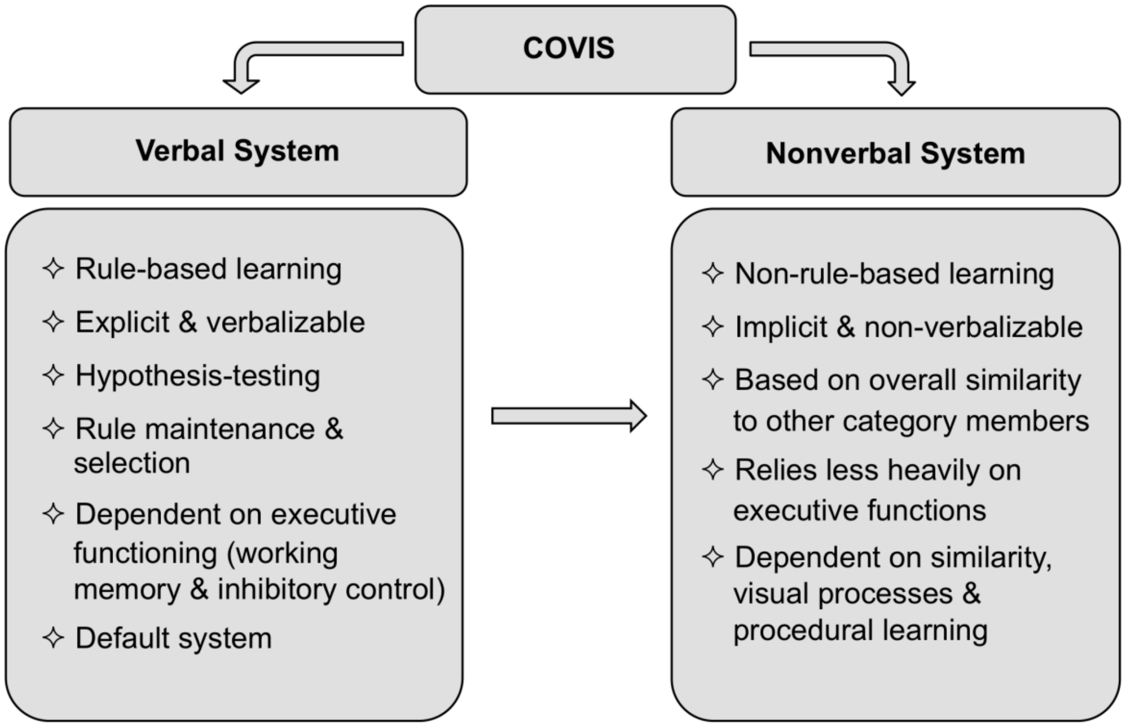

Figure 1.1: The key components of the COVIS theory of category learning.

sufficient cognitive resources (e.g., executive functioning abilities: working memory and inhibitory control) to search for a rule, inhibit inappropriate rules, store rules, and apply them.

COVIS also assumes that an implicit/nonverbal system learns non-rule-based (NRB) categories, also referred to as information integration (II) categories, which are categories for which no easily verbalizable rule exists. For example, consider a category in which most of the objects are large, most are round, and most are black. These objects share an overall similarity with each other, but there is no single feature to act as the rule. These types of categories may be learned by integrating two or more aspects of the stimulus at a pre-decisional stage (Ashby & Ell, 2001). Categorization responses are computed using overall similarity, visual processes, and procedural learning (Ashby, Maddox, & Bohil, 2002; Miles & Minda, 2011). The system is mediated by sub-cortical structures in the tail of the caudate nucleus, it relies on a dopamine-mediated reward signal to learn, and it does not depend as heavily on verbal working memory and controlled attention (Maddox, Ashby, & Bohil, 2003).

In general, COVIS assumes that the two systems compete during learning. However, the system with the more successful strategy will eventually dominate performance (Ashby et al., 1998). For example, while adults are initially biased toward the verbal system, for some types of categories (e.g., information integration categories), a nonverbal based strategy may be more appropriate. In such a case, the nonverbal system would result in better categorization performance, and so would take over. That is, an individual would eventually switch from the verbal to nonverbal system. Maddox, Filoteo, Hejl, and Ing (2004) provided evidence for this verbal system dominance, showing that for a NRB category set (cannot simply be learned by applying a straight-forward rule), participants tended to use a RB strategy early in learning. However, as learning progressed, they eventually switched to a NRB strategy. Additional evidence for separate category learning systems, comes from research showing that NRB category learning is impaired when feedback is delayed (Maddox, Ashby, & Bohil, 2003; Maddox & Ing, 2005) or when no feedback is given (Ashby, Maddox, & Bohil, 2002), whereas RB performance is not affected. These findings highlight how the availability and timing of dopamine release is important for NRB category learning. In contrast, RB category learning is impaired when participants are asked to learn RB categories while performing a concurrent task that interferes with verbal working memory (e.g., digit span task) or executive functioning. This results in impaired learning by the verbal system but intact learning by the nonverbal system (Miles & Minda, 2011; Minda, Desroches, & Church, 2008; Zeithamova & Maddox, 2006).

It is clear, that COVIS has provided strong support for the idea of multiple learning systems, helping to explain the factors that can differentially impact RB and NRB category learning. While developmental differences in category learning have been examined in early and middle childhood (Huang-Pollock et al., 2011; Minda et al., 2008; Rabi & Minda, 2014), category learning abilities have been extensively studied in younger adults. At the opposite end of the age spectrum, category learning abilities in older adulthood have only recently begun to receive attention. Quick and accurate categorization is just as important later in life as it is earlier in life, and it is important to examine if and why age-related declines in category learning may appear in older adulthood. That being said, the current thesis will investigate how older adults learn categories, specifically focusing on how executive functions may impact RB and NRB category learning.

1.2 Age-Related Changes in Strategy Selection

Before reviewing the literature relevant to category learning in older adulthood, it is important to discuss how the decision strategies of older adults differ from those of younger adults because appropriate strategy use is crucial for successful category learning to occur. Previous research suggests that older adults prefer simpler, less cognitively demanding strategies over complex strategies in a range of tasks (e.g., Gigerenzer, 2003; Sanfey & Hastie, 1999). Thevenot, Castel, Danjon, Fanget, and Fayol (2013) demonstrated that older adults rely on retrieval strategies more frequently than calculation strategies when solving addition problems. Thevenot et al. suggested that older adults' reliance on simpler strategies may reflect less efficient working memory processes, since active maintenance and application of complex strategies are more resource demanding. In addition to mental arithmetic, older adults have demonstrated a preference for simpler strategies in decision-making tasks (Chen & Sun, 2003; Gigerenzer, 2003; Johnson, 1990; Mata, Schooler, & Rieskamp, 2007; Sanfey & Hastie, 1999), as well as in memory tasks (Dunlosky & Hertzog, 1998, 2000). Generally, age differences in strategy selection are associated with limitations in executive functions, like working memory and inhibition, which may influence which types of strategies can be applied. Given that older adults struggle with maintaining information in working memory and inhibiting irrelevant information, it follows that older adults may rely on simpler categorization strategies, relative to their younger counterparts. Category learning is a particularly useful cognitive process to study in order to gain more insight regarding the role of aging on strategy preference, because executive functions are important for learning certain types of categories.

1.3 Age-Related Changes in Executive Functioning

Prior research has suggested that executive functioning may influence the types of strategies older adults can formulate and apply, which has important implications for category learning. Executive function can be thought of as a set of cognitive abilities, predominantly supported by the prefrontal cortex, which are responsible for goal-directed beahviour (Banich, 2009). The Miyake and Friedman model of executive functioning specifies that there are three core components of executive functioning: working memory updating, inhibitory control, and set-shifting (Miyake, Friedman, Emerson, Witzki, Howerter, & Wager, 2000). The relationship between age and executive function is best depicted by an inverted U-shaped curve (see Figure 1.2). Executive functioning increases across childhood, peaks in late adolescence or young adulthood, and decreases across older adulthood (Craik & Bialystok, 2006; Jurado & Rosselli, 2007; Zelazo, Craik, & Booth, 2004). Age-related changes in executive function have been attributed to frontal lobe function. This brain region is the last region to mature during childhood and among the first region to deteriorate during older adulthood (Brown & Park, 2003; Duncan, 1995; Prull, Gabrieli, & Bunge, 2000; Raz et al., 2005; West, 1996; Zelazo et al., 2004). Behavioural research has also demonstrated age-related declines across the three key components of executive functioning. Older adults struggle with inhibiting responses, reflecting deficits in inhibitory control, where irrelevant information interferes with task relevant goals (Chao & Knight, 1997; Connelly & Hasher, 1993; Milham et al. 2002; Zacks et al., 2000). Another consequence of inefficient inhibitory processes is that irrelevant information enters working memory, creating interference (Hasher, Lustig, & Zacks, 2007; Hasher & Zacks, 1988). In addition to inhibitory control, age-related declines in working memory have also been associated with reduced processing speed (Salthouse, 1993, 1996), as well as an overall decrease in processing resources (working memory capacity) (Oberauer, Wendland, & Kliegl, 2003). The last key component of executive function, set-shifting, has also been shown to decline in older adulthood, reflecting difficulty switching between tasks or cognitive sets (Gunning-Dixon, & Raz, 2003; Head, Kennedy, Rodrigue, & Raz, 2009; Rhodes, 2004).

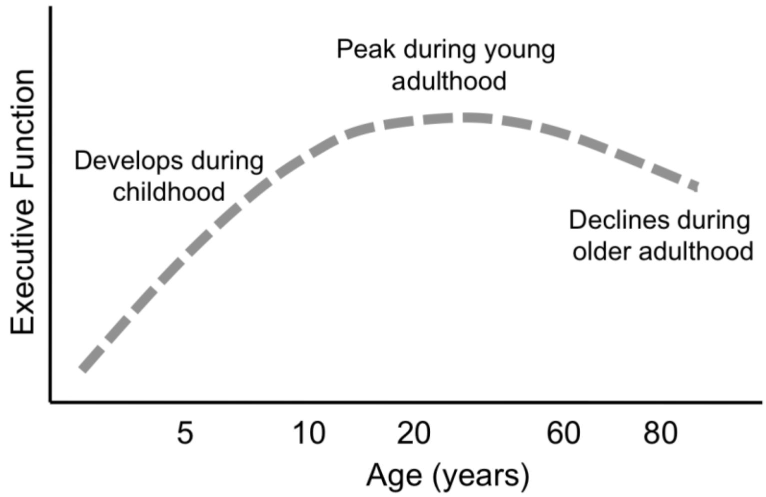

Figure 1.2: Executive functioning across the lifespan. Based on research from Zelazo, Craik, and Booth, 2004; Craik and Bialystok, 2006; Jurado and Rosselli, 2007.

1.4 The Role of Executive Function in Category Learning

Given the abundance of literature demonstrating that executive functioning declines with age, it follows that category learning which relies on executive functioning should also decline with age. The role of executive functions in category learning has been examined in a number of studies, involving populations other than older adults. In younger adults, research has shown that introducing a secondary concurrent task that taxes executive functioning interferes more with RB than NRB category learning (Filoteo, Lauritzen, & Maddox, 2010; Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). This suggests that the verbal system depends on executive functioning more heavily than the nonverbal system. Similarly, Minda and Rabi (2015) determined that temporarily reducing younger adults' executive functioning via a cognitive resource depletion manipulation impaired RB learning but not NRB learning. Together, these studies demonstrate that executive functions are used by the verbal system during RB category learning. While executive functions are particularly important for RB learning because they assist with the hypothesis testing process, research has demonstrated that executive functions may also be important for NRB learning, but for different reasons. In order to succeed in NRB learning, one must inhibit the dominant verbal system, and switch to the nonverbal system. While the NRB system does not rely on executive functioning to learn NRB categories, executive functioning may help to mediate the transition from the verbal to nonverbal system. In line with this hypothesis, a series of studies have demonstrated that executive functions may also be important for the operation of the nonverbal system. Studying populations with known executive functioning deficits, allowed researchers to test this hypothesis. Participants with frontal lobe damage were significantly less accurate than controls on both RB and NRB category learning and patients performed significantly worse on the Wisconsin Card Sorting Test, suggesting that these patients may have struggled with rule formation and the ability to switch between category learning systems (Schnyer et al., 2009). Additionally, children and sleep-deprived individuals have decreased executive function abilities and they also performed more poorly on RB and NRB categories relative to age-matched controls (Huang-Pollock et al., 2011; Maddox, Glass, Wolosin, Savarie, Bowen, & Matthews, 2009; Rabi, Miles, & Minda, 2015; Rabi & Minda, 2014).

1.5 Category Learning in Older Adulthood

Extensive research has been conducted involving category learning in childhood and young adulthood. However, relatively little research has been conducted involving category learning in older adulthood. Racine and colleagues (2006) were among the first to study RB category learning in older adulthood using a novel RB category set, finding that older adults performed more poorly than younger adults when complex rules were required to arrive at the correct categorization judgment. Davis, Love, and Maddox (2012) examined the ability of older adults to learn a rule-plus-exception category set, showing that older adults learned and applied the rule-following items quite well, but struggled with the exception items. This finding again suggests that task complexity impeded the ability of older adults to learn a RB category set at the same level as younger adults. Maddox, Pacheco, Reeves, Zhu, and Schnyer (2010) also demonstrated that older adults struggled with learning a complex, conjunctive RB task, where participants were required to categorize stimuli into one of four categories. However, given that there were four category groups, it is difficult to determine whether older adults struggled due to the complex nature of the conjunctive RB category set, to difficulty keeping track of the four category options, or a combination of both. Although studies involving NRB learning are rather limited, prior research has also shown that older adults struggle with NRB category learning (Filoteo & Maddox, 2004; Maddox et al., 2010). Difficulties with NRB learning have been attributed to older adults struggling with consistently applying the task appropriate NRB strategy.

1.6 Overview of Present Research

The main goal of the present research is to examine changes in RB and NRB category learning that occur during older adulthood. Given that strategy use and executive functioning changes with age, these factors will also be considered in relation to category learning performance. Age-related category learning deficits have been reported in prior literature. For this reason, I will not only focus on better understanding why these deficits occur, but I will also focus on methods of reducing these deficits so that older adults can perform more like younger adults.

The study presented in Chapter 2 examined category learning on three categorization tasks: one where a single-dimensional rule governed category membership, one where a multi-dimensional rule defined category membership, and one with a non-rule-based structure. The three category sets used were adapted from the Shepard, Hovland, and Jenkins' (1961) classification tasks, which is a standardized category set that has been used in a number of studies across many different population types (e.g., younger adults, children, depressed individuals, monkeys). However, this widely accepted, well-studied category set has yet to be examined in older adults. Prior category learning studies involving older adults have typically included novel or less well-studied category sets, making it somewhat difficult to draw strong conclusions regarding the effects of healthy aging on category learning, due to possible confounds (e.g., feature salience, prior knowledge, unclear instructions, etc.) that come along with using novel category sets.

Additionally, prior research involving older adults has generally focused on examining either RB or NRB category learning alone, rather than in conjunction with one another, making it difficult to draw conclusions regarding the functioning of both category learning systems. Since executive functioning is thought to play an important role in both RB and NRB category learning, I will investigate the relationship between category learning performance and executive functioning (based on a series of measures tapping into working memory, inhibitory control, and set-shifting). This will provide additional insights regarding RB and NRB category learning deficits. By examining the executive functioning abilities within each age group separately, I will be able to determine whether individual differences in executive functioning help with learning RB and NRB categories. Based on prior literature demonstrating age-related declines in executive functioning (Gunning-Dixon, & Raz, 2003; Hasher, Lustig, & Zacks, 2007; Rhodes, 2004; Zelazo, Craik, & Booth, 2004), it is hypothesized that older adults will struggle with complex RB learning and NRB learning, but not struggle with easy RB category learning. The single-dimensional RB category set in Chapter 2 is relatively straightforward and places minimal demands on executive functioning resources. Additionally, developmental research has demonstrated that children can learn easy, single-dimensional rules quite well. For these reasons, I expect that as rule complexity increases, the categorization performance of older adults will decrease relative to younger adults. Older adults may also struggle with learning the NRB category set, because it too requires executive functioning abilities to inhibit the verbal system and switch to the nonverbal system. Furthermore, stronger executive functioning abilities should be associated with better category learning performance.

The study presented in Chapter 3 will be the first of its kind to examine a method of reducing category learning deficits in older adults through the use of a pre-training procedure which reduces the executive function demands of the categorization task. Older and younger adults will complete the hard RB task and the NRB task from Chapter 2, with or without pre-training. By familiarizing participants with the stimulus dimensions in the category set, I expect that the cognitive deficits associated with normal aging can be minimized, if not overcome. More specifically, I expect that pre-training will improve both RB and NRB category learning in both older adults and younger adults, but the benefits to RB learning may be more substantial. The reasoning behind this prediction is that RB learning heavily depends on executive functioning to take part in the hypothesis-testing process. On the contrary, executive functions are needed to transition to the nonverbal system, but are not central to actually learning NRB categories. In addition, pre-training involves describing the stimulus dimensions, which naturally promotes awareness of potential categorization rules, encouraging individuals to take part in RB category learning, more so than NRB category learning that is more implicit in nature and not dependent on verbalizable rules. Similar to the Chapter 2 study, I expect that stronger executive functioning abilities should be associated with better category learning performance.

The goal of Study 1 presented in Chapter 4 is to determine how older adults will perform when learning a more complex single-dimensional RB category set, relative to a NRB category set. Simple, single-dimensional rules (e.g., circles belong in Category A) do not place must strain on executive functioning resources, and older adults can learn these rules quite well. I designed an experiment to determine whether increasing the complexity of the single-dimensional rule structure would impact the ability of older adults to learn the category set. If older adults struggle with learning the complex single-dimensional RB category set, this would suggest that increasing RB task complexity influences performance. However, if older adults perform well on this category set, this may suggest that older adults can learn single-dimensional rules well (regardless of task complexity), but struggle to learn multi-dimensional rules which require binding features together into a complex rule (e.g., big circles and small squares belong in Category A). This might imply that older adults struggle particularly with binding information regarding stimulus dimensions together and maintaining this information in working memory.

I used a different standardized, well-studied category set (from what was used in Chapters 2 and 3) to examine complex single-dimensional RB category learning and NRB category learning in older adults and younger adults. The category set used consisted of Gabor patch stimuli (sine-wave gratings) varying in line frequency (number of bands within the Gabor patch) and orientation (spatial orientation/angle of the lines in the Gabor patch). In the RB category set, participants have to find a single-dimensional rule to correctly classify the stimuli on the basis of the frequency of the grating, while ignoring the more salient dimension of orientation. For the NRB category set, no easy to verbalize rule exists and instead the participant must combine information regarding both stimulus dimensions prior to the decision stage (reflecting implicit learning). This category set will be used because it is unfamiliar to participants. Unlike some prior category learning studies involving familiar stimuli, the current category set controlled for possible confounds introduced by extra knowledge participants have acquired. Additionally, this category set lends itself well to computational modeling of strategy use, providing a clearer picture of how older adults perform, beyond accuracy. Some of the category learning studies involving older adults conducted in the past have not included strategy analyses, making it difficult to truly determine how older adults solved a task. The current study will not only examine strategy differences between older adults and younger adults on a RB and NRB task, but will also examine individual differences in strategy selection, to better identify performance differences within the group of older adults. Based on the premise that older adults tend to rely on simpler, less complex strategies, I expect that older adults will struggle with both RB and NRB category learning because of difficulties identifying the correct strategy. That is, older adults may struggle with inhibiting the salient but irrelevant dimension in the RB category task, and they may struggle with switching to nonverbal strategy from the dominant, verbal system in the NRB category task. In line with prior studies in this thesis, I looked at executive functioning performance, to determine the relationship between executive functioning and category learning in older adulthood. I expected that stronger executive functioning abilities would be associated with both better RB and NRB category learning performance and strategy use.

As cognitive aging is associated with declines in executive functioning resources, I examined whether reducing executive function task demands would improve the complex, single-dimensional RB performance of older adults. As discussed earlier, since executive functions play a larger role in RB category learning and pre-training naturally promotes RB learning, I was particularly interested in examining the influence of pre-training on RB category learning. Aside from the pre-training study discussed in Chapter

3, this is the only other study to examine methods of reducing RB categorization deficits in older adults. In Study 2 of Chapter 4, I will investigate whether a new pre-training procedure will improve the RB accuracy and strategy use of both older adults and younger adults. Individuals (both older and younger adults) with higher executive functioning scores are expected to benefit more from pre-training, as they may be able to test hypotheses and rule out incorrect rules more easily.

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Chapter 2

2 Category Learning in Older Adulthood: A Study of the Shepard, Hovland, and Jenkins (1961) Tasks[1]

The ability to categorize is a key aspect of cognition, which we rely on to group like objects together so that they can later be treated equivalently. Starting from infancy and continuing to older adulthood, we make categorization decisions to help organize the world around us. That is, children may rely on categorization when deciding whether some types of objects are dangerously hot (e.g., stove) or not (e.g., fridge), whereas older adults might rely on categorization to decide which types of medications are dangerous or safe. This being said, a principal question to examine is whether category learning abilities vary with age, and which factors are responsible for these changes. Developmental differences in category learning have been examined in early and middle childhood (Huang-Pollock et al., 2011; Minda et al., 2008; Rabi & Minda, 2014), and category learning abilities have been extensively studied in university-aged adults. At the opposite end of the age spectrum, category learning abilities in older adulthood have only recently begun to receive attention. Given the fact that quick and accurate categorization is just as important later in life as it is earlier in life, it is important to examine if and why age-related changes in category learning may appear in older adulthood.

2.1 Parallels between Category Learning in Childhood and Older Adulthood

Given the limited research on category learning in older adults, a better understanding of this topic may be obtained by examining category learning in children. On the surface, it may appear as though these two populations have little in common. In addition, there are also vast differences in semantic knowledge between these two groups, which prompt some caution in making comparisons and inferences between them. Despite these

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differences, these groups do share some key similarities that can inform theorization. For example, research suggests that the prefrontal cortex develops later than other areas (Bunge & Zelazo, 2006; Kolb et al., 2012), and verbal working memory and executive functioning develop substantially during childhood and are related to these physical developments in the prefrontal cortex (Gathercole, 1999). As a result, children are often impaired relative to younger adults when learning categories that rely heavily on working memory and executive functioning abilities (Minda et al., 2008; Rabi & Minda, 2014). Similarly, research has shown that prefrontal brain regions atrophy with normal aging, which is associated with a reduction in executive functioning abilities (Greenwood, 2000; Grieve, Williams, Paul, Clark, & Gordon, 2007). Furthermore, one might expect that older adults should also be impaired when learning category sets that depend on working memory and executive functioning.

Research by Minda and colleagues (2008) showed that children performed worse than younger adults on categories that were optimally learned by a complicated rule. However, children and younger adults performed similarly when learning non-rule-based family-resemblance (FR) categories, which could be learned based on the overall similarity of the stimulus dimensions rather than via a rule. Interestingly, children were able to learn simple, single-dimensional rules about as well as younger adults, suggesting that children are capable of learning rules if they are easy to identify (i.e., do not heavily tax working memory and inhibitory control abilities). Along the same lines, Huang-Pollock et al. (2011) found that adults outperformed children on rule-based (RB) categories because children overly relied on suboptimal single dimensional rules when solving both category sets. Recent research by Rabi and Minda (2014) extended the results of Huang-Pollock et al. by showing that not only are children impaired at RB category learning compared to adults, but that these impairments are also related to their executive functioning abilities. That is, Rabi and Minda demonstrated that working memory and inhibitory control are associated with RB category learning, and as these abilities improved with age, so did RB category learning performance. Furthermore, given that prefrontal functioning changes with age and there are observed reductions in executive functioning abilities (Braver et al., 2001; Raz, 2000) it is reasonable to expect to see larger RB deficits in older adults compared to non-rule-based FR deficits.

2.2 Rule-Use in Older Adults

Aside from developmental research on category learning, examining general rule-learning abilities in older adults can help shed light on how and why category learning abilities change with age. The Wisconsin Card Sorting Test (WCST) has frequently been used to assess rule learning. In this task, participants learn to categorize multidimensional stimuli based on a single-dimensional rule (e.g., shape), using feedback to determine when to switch rules. Various studies have revealed that WCST performance tends to decline with age (Axelrod & Henry, 1992; Hayslip & Sterns, 1979; but see Gorlick, Giguère, Glass, Nix, Mather, & Maddox, 2013 for an exception). More specifically, Ridderinkhof et al. (2002) found that decrements in WCST performance could be attributed to the fact that older adults perseverated on previously correct sorting rules, even when provided with explicit cues (e.g., "shift to colour") to aid learning. These findings suggest that older adults may struggle to use rules appropriately because of difficulties with hypothesis testing and set-shifting abilities. Along the same lines, Chasseigne, Mullet, and Stewart (1997) examined the effects of aging on multiple cue probability learning (i.e., learning the probabilistic relationship between cues and events) in older adults (65-75 and 76-90 years old) and younger adults. When there was a direct relationship between cues and events, all participants performed similarly. However, when the cue and event were inversely related to each other, younger adults outperformed older adults. Interestingly, in a second task where participants were explicitly told about the inverse relationship, 65-75 year-olds showed improved performance, but 76-90 year-olds continued to show impairments. Furthermore, these findings suggest that older adults may find it difficult to use explicit rules in specific situations, possibly due to declining working memory abilities. That is, arriving at the inverse relationship would involve creating a verbal rule, which could be quite taxing on working memory.

2.3 Category Learning in Older Adults

While studies have clearly shown an age-related reduction in the propensity to use rules, research has also demonstrated more specific category learning deficits in older adulthood. For example, research conducted by Filoteo and Maddox (2004) examined the ability of younger adults and older adults to learn information-integration categories, which are a subset of non-rule-based categories. One category set was defined by a linear boundary, thus making it comparable to a family resemblance category set, and the other was defined by a non-linear boundary. In both cases, younger adults performed better than the older adults. One reason was that younger adults were more adept at switching to an information integration strategy whereas older adults were more likely to use a rule-based approach (which resulted in suboptimal performance).

Other research examined rule-based category learning. Racine, Barch, Braver, and Noelle (2006) asked older adults (ages 66 to 82) and younger adults to learn a set of categorization tasks that varied in rule complexity. Results revealed that older adults performed similarly to younger adults when applying a simple, single-dimensional rule, but showed performance deficits when applying a more complicated rule. Racine's findings converge nicely with Minda et al.'s (2008) developmental results. Similar to Racine and colleagues, Minda et al. (2008) also found that children struggled with learning complex rules, but performed similarly to younger adults when learning simpler, single-dimensional categorization rules. Maddox, Pacheco, Reeves, Zhu, and Schnyer (2010), also examined RB category learning in older adults (ages 60 to 81), paying special attention to strategy use differences in younger and older adults. Findings revealed that as a group, older adults showed RB deficits compared to younger adults. Computational modeling provided further insight into the types of strategies being used by older adults, revealing that older adults were marginally less likely to use the task appropriate strategy in the RB condition compared to younger adults. Among the older adults who did not use an explicit, hypothesis-testing strategy, these participants tended to rely on either a non-rule-based implicit strategy or guessing. Maddox et al. (2010) also showed that older adults who adopted the task appropriate strategy (i.e., a hypothesis-testing strategy) in the RB condition performed similarly to younger adults using the task appropriate strategy. Additionally, Maddox et al. demonstrated that older adults who used the task appropriate strategy were also those who showed better inhibitory control (on the WCST and Stroop task) and working memory (on the digit span task) abilities. These findings are clearly in line with research showing the executive functioning abilities are closely tied to RB category learning (Miles and Minda, 2011; Minda et al., 2008) and tend to decline with age (Greenwood, 2000; Raz, 2000).

Another type of category learning that has been examined in older adults is rule and exception learning. Davis, Love, and Maddox (2012) asked older and younger adults to learn to categorize pictures of beetles on the basis of trial and error. Most of the beetles were rule-following items that could be categorized using a single dimensional rule. However, each category also contained an exception item. Davis and colleagues found that while both older and younger adults performed quite well on the rule-following items by the end of training, older adults were impaired at categorizing the exception items. In line with the findings of Racine and colleagues (2006), Davis et al. demonstrated that older adults could learn RB category sets, granted that the verbal rule was straightforward (e.g., beetles with pointy antenna go in Category A). However, older adults struggled more than younger adults, when they had to exert additional resources (e.g., hypothesis testing, working memory) to determine the exception to the rule.

2.4 Changes in Executive Functioning with Age

Given the limited number of studies investigating category learning in older adults, a useful next step would be to outline some of the factors that may impact category learning in older adults. One of the factors that are known to influence category learning is executive functioning. According to widely held views, the prefrontal cortex plays a key role in executive functioning. However, this brain region has also been shown to deteriorate with age (Uylings & de Brabander, 2002; van der Molen & Ridderinkhof, 1998). Future research should closely examine the link between category learning deficits in older adults and executive functioning abilities, since many types of category learning tasks depend on executive functioning abilities like inhibitory control and working memory (Miyake, Friedman, Emerson, Witzki, Howerter, & Wager, 2000).

2.4.1 Inhibitory Control

Older adults have been shown to display deficits in a wide range of inhibition tasks. For example, prior research has shown that older adults find it more difficult to look away from an onset stimulus when the correct response is to look in the opposite direction (Butler et al., 1999; Olincy et al., 1997). Additionally, when older adults are required to stop their response when a target stimulus is presented (i.e., stop-signal task), they have more difficulty withholding their response than younger adults (May & Hasher, 1998; Williams et al., 1999). With regards to the Stroop task, research has shown that older adults find it more difficult to suppress the word reading response to a colour word when asked to indicate the font colour of the word (Davidson, Zacks, & Williams, 2003; West, 1999). Furthermore, these findings demonstrate that inhibitory processes are impaired in older adults, which may have an impact on how well older adults can learn categories. That is, reduced inhibitory control abilities may lead to more difficulty restricting access of irrelevant/salient information to working memory, as well as difficulty removing information from working memory that has been deemed irrelevant.

2.4.2 Working Memory

Age related decrements in working memory performance have also been documented. Research has revealed decreases in working memory in old age in both verbal and spatial working memory tasks (Bopp & Verhaeghen, 2005; Park et al., 2002). With regards to category learning, Lewandowsky (2011) found that working memory capacity mediated performance on RB tasks. As well, Maddox et al. (2010) found that digit span performance was associated with RB category learning in older adults. Based on prior research, we know that older adults are capable of learning simple, single-dimensional RB categories, but struggle to learn more complex RB categories (Racine et al., 2006). One might speculate that older adults struggled to learn the more complicated RB category set, because it placed more strain on their working memory capacity to test different rules, update the information, and maintain the complex rule in memory.

2.5 Motivation for the Current Research

The current study examined category learning in younger and older adults using an adapted version of the Shepard, Hovland, and Jenkins' (1961) classification tasks (hereafter referred to as the SHJ tasks). This category set has been used in many studies across different population types (e.g., younger adults, children, depressed individuals, monkeys), but to our knowledge, it has yet to be examined in older adults. Because it has been used so extensively, performance on the SHJ tasks serves as an important benchmark for understanding category learning. It follows that performance on these category sets should be examined in relation to normal aging. Among the six SHJ category sets, three (Type I, Type II, and Type IV) were of particular interest in the present study. Type I is considered an easy RB category set, where only one feature is used to indicate category membership, and participants can achieve perfect performance by using a single-dimensional rule. The rule that would result in perfect performance in Figure 2.1 is “Black shapes belong in Category A, white shapes belong in Category B” because the feature used to indicate category membership is colour. Previous research has demonstrated that the Type I category set is the easiest set to learn among younger adults and results in the highest performance (Nosofsky et al., 1994; Shepard et al., 1961). Type II is considered a hard RB category set, where two features are used to indicate category membership, and participants can achieve perfect performance using a disjunctive rule. The verbal rule that would result in perfect performance in Figure 2.1 would be “Black triangles and white squares belong in Category A, white triangles and black squares belong in Category B”. Therefore, neither colour nor shape is individually useful in assigning category membership, but the combination of colour and shape is. Type II is considered the second easiest set to learn out of the six category sets, despite the increased logical complexity of the rule. Type IV is considered a family resemblance category set, where all three features are used to indicate category membership. This means that the members of Category A have features in common with one another, for example in Figure 2.1, they are mostly large, mostly black, and mostly triangles, whereas Category B members are mostly small, mostly white, and mostly squares. This task can be learned by looking at the overall similarity of stimuli, and thus does not require the abstraction and use of a rule. However, the Type IV category set can also be construed as a rule-plus-exception category learning task because another possible method of achieving perfect performance is to memorize the exceptional outlying stimuli (in Figure 2.1, this is the big white triangle and the small black square). The verbal rule would be “big shapes (except the white square), plus the small black triangle belong in Category A, and small shapes (except the black triangle), plus the large white square belong in Category B”. The Type IV category set is considered the third hardest to learn out of the six category sets.

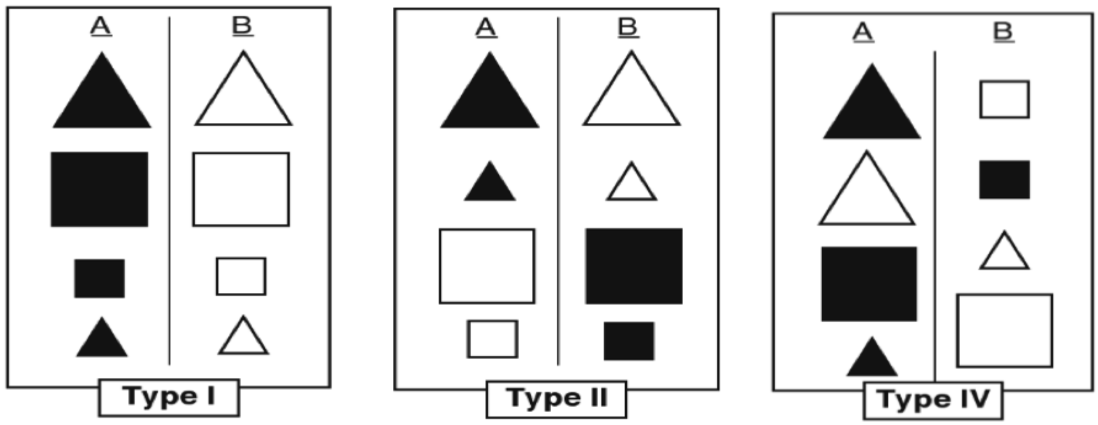

Figure 2.1: Category learning tasks from Shepard, Hovland, and Jenkins (1961): Type I (easy rule-based), Type II (hard rule-based), and Type IV (non-rule-based).

As mentioned earlier, performance on the SHJ tasks has been examined in many different populations, including children (Minda et al., 2008), monkeys (Smith et al., 2004), and in individuals with depression (Nadler, 2013). Additionally, SHJ tasks have been studied in relation to unsupervised category learning (Love, 2002), working memory capacity (Lewandowsky, 2011), and stimulus composition (Love & Markman, 2003; Mathy & Bradmetz, 2011). An important next step is to examine SHJ performance in older adults. Interestingly, in contrast to the Type II advantage typically found in SHJ studies, prior research has shown that children and monkeys actually find Type II harder to learn than Type IV (Minda et al., 2008; Smith et al., 2004). Minda and colleagues (2008) speculated that children struggled with Type II learning because the brain areas thought to mediate the explicit rule-based system and working memory are not fully developed in children. Similarly, Smith et al. (2004) suggested that monkeys struggled with Type II learning because of their smaller prefrontal cortex and lack of verbal abilities.

Based on the research reviewed above, we expected that older adults will perform similarly to younger adults on Type I categories. However, we expect that older adults will struggle to learn Type II categories compared to younger adults, because executive function declines with age. Furthermore, since the disjunctive RB Type II category set heavily relies on executive functioning abilities to test rules, inhibit incorrect rules, and maintain rules in working memory, older adults are expected to be at a disadvantage at learning this category set, relative to younger adults. Lastly, the Type IV category set can be learned via family resemblance or a complicated rule (i.e., rule-plus-exception). Given past research demonstrating that older adults struggle with learning rule-plus-exception categories (Davis et al., 2012) and the fact that stimulus dimensions in the Type IV category set are inter-correlated encouraging family-resemblance-based learning, it is expected that older adults will perform better on the Type IV category set relative to Type II because older adults are expected to have access to the cognitive processes that allow for family resemblance leaning strategies.

In terms of the relationship between category learning and executive functioning abilities, it is expected that better executive function (i.e., a larger working memory capacity and stronger inhibitory control abilities) will be associated with higher performance on the two rule-based category sets, Types I and II. Since the disjunctive RB category set is thought to rely most heavily on executive functioning, the strongest relationship with executive functioning abilities should occur for this category set.

2.6 Method

2.6.1 Participants

Participants included 35 younger adults (*M* = 18.34 years; 8 males & 27 females) from the University of Western Ontario who participated for course credit and 34 older adults between the ages of 65 and 85 (*M* = 71.44 years; 6 males & 28 females) recruited from the Kiwanis Seniors' Community Centre and the Boys & Girls Club recreational facility. Older adults received $20 for participating in the study. Participants were pre-screened to ensure that they were fluent in English, they were in good health, and they did not have vision or hearing impairments. Participants were excluded from the study if they indicated that they had a history of neurological disorders, psychiatric illness, substance abuse, a cerebral vascular event, head trauma, and/or any other neurological conditions.

2.6.2 Materials

2.6.2.1 Category Learning Task

Three category learning tasks were chosen from the original set of six created by Shepard, Hovland, and Jenkins (1961). In each category set there are three features (shape, size, and colour) that can have one of two dimensions (square or triangle, large or small, black or white), as shown in Figure 2.1. In each category set there are eight stimuli, and four belong in each of two separate categories. There were 80 trials (10 blocks) total per category set. The Type I set was a single-dimensional category with one of the three features acting as the single-dimensional rule. The Type II set was a disjunctive rule category set with two of the three features relevant for the disjunctive rule. The Type IV set was a family resemblance category set in which each category member shared the majority of its features with the other category members and all the features were relevant. All category sets were counterbalanced across participants such that some participants were presented with a Type I set for which colour was the relevant dimensions, others were presented with a set for which size was the relevant dimension, and so on.

2.6.2.2 Memory Tasks

2.6.2.2.1 Digit Span

Participants heard a recording of a two-digit number sequence at a rate of approximately one digit per second, and the participants were asked to repeat the sequence back to the experimenter in the same order. Participants heard three sequences at each sequence length and as long as they repeated at least one of them correctly they continued on to the next sequence length, for a maximum length of ten digits. The task was over once the participant was unable to repeat any of the sequences at a given length. The procedure for the backward digit span was the same as that for the forward digit span except that the participant was required to recall the digits in reverse order so that the last number was said first and the first number was said last, for a maximum of eight digits. The task was scored as the total number of correct responses.

2.6.2.3 Inhibitory Control Tasks

2.6.2.3.1 Flanker Task

A version of the Flanker task adapted from Botvinick, Nystrom, Fissel, Carter, and Cohen (1999) was used. A set of five arrows was presented in a row on the computer screen and participants were asked to indicate the direction of the central arrow (target). The target was flanked by two identical arrows on either side (distractors) that were either pointing in the same direction (congruent trial) or the opposite direction (incongruent trial) of the target arrow. The task consisted of 60 trials (30 congruent and 30 incongruent) presented in randomized order. Prior to the experiment participants received five practice trials that were not analyzed. The difference in mean reaction time between correct responses on congruent and incongruent trials (i.e., a difference score) was used as a measure of inhibitory control. Larger difference scores were indicative of less efficient interference control.

2.6.2.3.2 Simon Task

In the Simon task, participants were first presented with a fixation cross in the center of the screen (Simon & Rudell, 1967). Immediately after the cross had disappeared, participants were instructed to press the left key in response to the red circle or the right key in response to a blue circle as fast as possible, regardless of stimulus location. The timing began with the onset of the stimulus, and the response terminated the stimulus. On congruent trials, the stimulus location was on the same side as the required response and on incongruent trials the stimulus location was on the opposite side of the required response. The whole task consisted of 64 trials (32 congruent trials and 32 incongruent trials) presented in randomized order to each participant. Prior to the experiment, participants received five practice trials that were not analyzed. Difference scores were calculated by computing the difference in mean reaction time between correct responses on congruent and incongruent trials.

2.6.2.3.3 Stroop Task

In the Stroop task (Stroop, 1935), participants were instructed to indicate, as quickly and accurately as possible, whether each word presented on the computer screen was written in red, blue, green, or yellow ink using the properly labeled response buttons. Participants were instructed to ignore the meaning of the words and to focus on the ink colour only. The timing began with the onset of the word, and the response terminated the stimulus. Participants first completed 12 practice trials, with accuracy feedback after each trial. The actual task consisted of 72 trials without feedback: 24 congruent trials (i.e., "RED" in red ink), 24 incongruent trials (i.e., "RED" in blue ink) and 24 neutral trials (i.e., non-colour word names like "TREE"). Difference scores were calculated by computing the difference in mean reaction time between correct responses on congruent and incongruent trials.

2.6.2.4 Wechsler Abbreviated Scale of Intelligence (WASI) Test

Standardized scores on the WASI vocabulary and matrix reasoning sub-tests (Wechsler, 1999) were used to calculate the Full Scale Intellectual Quotient. WASI subtests were used to provide estimates of verbal and nonverbal intelligence.

2.6.3 Procedure

Participants were tested individually across two testing sessions, approximately one week apart. Younger adults were tested in the Categorization Lab at the University of Western Ontario. Older adults were tested in a quiet room in the senior centre. Participants completed all three (Types I, II, and IV) SHJ category sets in one of three orders: I/II/IV, II/IV/I or IV/I/II. A pilot study with 52 university students confirmed that the order of the SHJ category sets did not have an effect on the categorization performance. Participants were told that they would be presented with abstract shapes and asked to classify them as belonging to category A or category B. Participants saw each stimulus one-at-a-time on the computer screen and were instructed to press the button labeled "A" or "B" to indicate whether each shape belonged in category A or B respectively. After responding, participants were given corrective feedback (the words "correct" or "incorrect" appeared above the stimulus object). Another trial began following this feedback. Stimuli were presented in random order within each block of eight and blocks were presented in an unbroken fashion. Following completion of the first category set, participants completed the second and third category set. Before completing the next two category sets, participants were told that even though the objects would look the same as before, the category set is different and they should adopt a new strategy. Participants were told that they could take a break between category sets if they wished.

During the second testing session, participants first completed three inhibitory control tasks: the Flanker task, Simon task, and Stroop task. Following the Stroop task, participants received a short break, after which they were administered the forward and backward digit span. Lastly, participants completed the WASI. Each testing session lasted approximately one hour.

2.7 Results

2.7.1 Category Learning

The average categorization performance of younger and older adults across the three SHJ category sets is displayed in Figure 2.2. The learning curve of the younger adults is similar to one originally reported by Shepard et al. (1961), with the Type I category set having the highest performance, followed by Type II, and the Type IV category set. Similar to younger adults, older adults found Type I the easiest. However, unlike younger adults, older adults performed worse on Type II relative to Type IV. Learning curves for each age group and category set across learning blocks is displayed in Figure 2.3. A 3 (category type: Type I, II, IV) x 2 (age: younger, older) x 10 (blocks) mixed ANOVA was conducted to further examine how younger and older adults learned the three category sets. If the sphericity assumption was violated, (p < .05, Mauchly's test of sphericity), a Greenhouse-Geisser correction was performed.

Results revealed a significant main effect of category type, $F(2, 134) = 151.42$, $p < .001$, $\eta^2 = .69$, *power* = 1.00, as well as a main effect of age, $F(1, 67) = 111.45$, $p < .001$, $\eta^2 = .63$, *power* = 1.00. There was also a main effect of block, $F(7, 439) = 72.15$, $p < .001$, $\eta^2 = .52$, *power* = 1.00. Additionally, there was a significant interaction between category type and age group, $F(2, 130) = 21.88$, $p = < .001$, $\eta^2 = .25$, *power* = 1.00, The Category

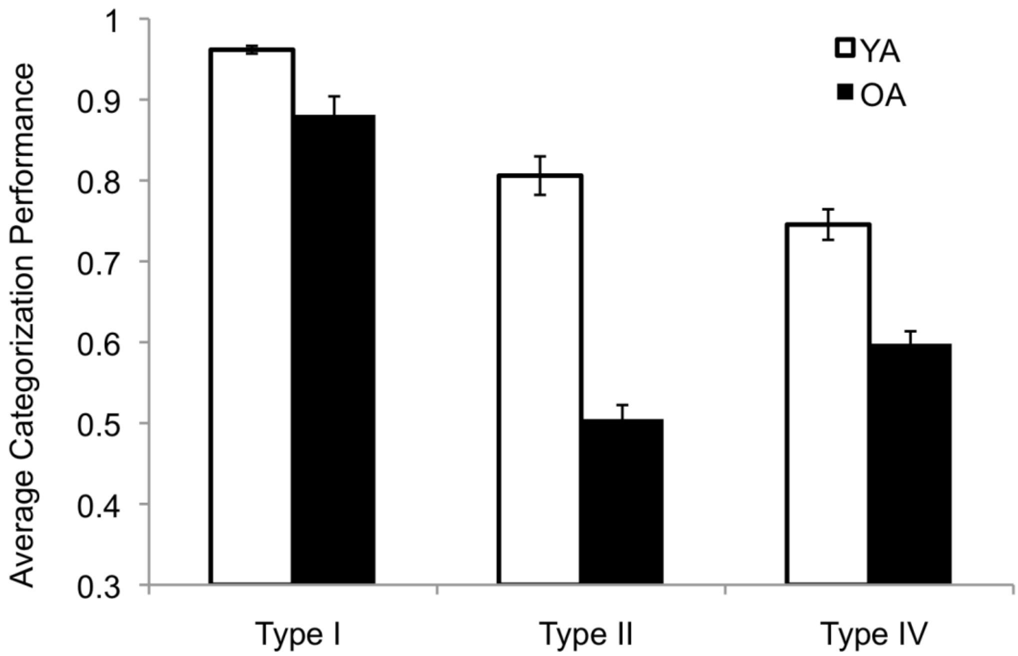

Figure 2.2: Average categorization performance of younger adults (YA) and older adults (OA) across the learning blocks. Error bars denote standard error of the mean.

Type x Age Group interaction is of particular interest, because it demonstrates a crossover effect, where younger adults perform better on Type II compared to Type IV and older adults show the reverse effect, performing better on Type IV compared to Type II (see Figure 2.2). Lastly, there was a three-way interaction between age, category, and block, $F(12, 763) = 3.93$, $p = < .001$, $\eta^2 = .06$, *power* = 1.00. In order to further explore the three-way type interaction, three separate analyses of variance were conducted (one for each of the three category sets).

2.7.1.1 Type I Categorization Performance

For the Type I (single-dimensional rule) category set, there was a main effect of age. The Type I categorization performance of older adults was significantly lower than younger adults, $F(1, 67) = 12.20$, $p = .001$, $\eta^2 = .99$, *power* = .93. There was a significant main

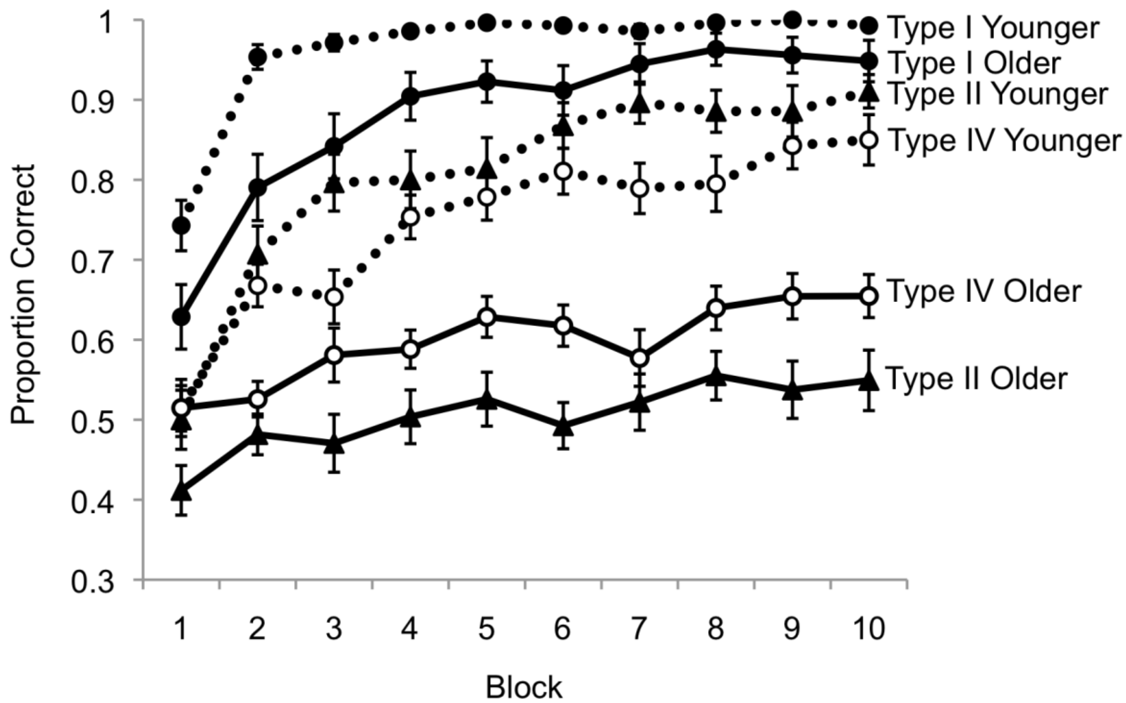

Figure 2.3: Categorization performance of younger and older adults across learning blocks in each of the three category sets. Error bars denote the standard error of the mean.

effect of block, $F(4.4, 296) = 50.14$, $p < .001$, $\eta^2 = .43$, *power* = 1.00 [Greenhouse-Geisser corrected], suggesting that learning occurred across the blocks. There was also a significant interaction between age and block, $F(4.4, 296) = 2.93$, $p = .02$, $\eta^2 = .04$, *power* = .81, demonstrating that younger adults learned the Type I category set faster than older adults.

2.7.1.2 Type II Categorization Performance

For the Type II (disjunctive rule) category set, there was a main effect of age, $F(1, 67) = 103.34$, $p < .001$, $\eta^2 = .61$, *power* = 1.00, suggesting that younger adults outperformed older adults. There was also a main effect of block, $F(7.3, 494) = 19.64$, $p < .001$, $\eta^2 = .23$, *power* = 1.00 [Greenhouse-Geisser corrected]. A significant age x block interaction was also found, $F(7.3, 494) = 5.61$, $p < .001$, $\eta^2 = .08$, *power* = 1.00 [Greenhouse-Geisser corrected], showing that younger adults learned the Type II category set faster than older adults.

2.7.1.3 Type IV Categorization Performance

For the Type IV (family resemblance) category set, there was a main effect of age, $F(1, 67) = 36.19$, $p < .001$, $\eta^2 = .35$, *power* = 1.00, with younger adults outperforming older adults. There was a main effect of block $F(6.8, 454) = 17.73$, $p < .001$, $\eta^2 = .21$, *power* = 1.00 [Greenhouse-Geisser corrected]. Lastly, there was a significant age x block interaction, $F(6.8, 454) = 3.33$, $p = .002$, $\eta^2 = .05$, *power* = .96 [Greenhouse-Geisser corrected], suggesting that younger adults learned the Type IV category set faster than older adults.

2.7.1.4 Order Effects

To ensure that order effects were not present, three separate ANOVAs were conducted for each of the category sets, examining each of the three randomized orders (i.e., I/II/IV, II/IV/I or IV/I/II). This analysis was done to eliminate the possibility that some participants performed better on certain category sets than other participants, because they completed certain category sets first. There were no order effects for the Type I category set, $F(2, 63) = .63$, $p = .54$, the Type II category set, $F(2, 63) = .36$, $p = .70$, or the Type IV category set, $F(2, 63) = .06$, $p = .94$. This means that performance on the three category sets were not impacted by whether participants received Type I, Type II or Type IV, first, in the middle, or last.

2.7.2 Strategy Analysis

In addition to category learning performance, we were also interested in whether participants used a single-dimensional rule strategy in learning any of the three category sets. This is important to know because in many cases, what might appear to be moderate performance on the Type IV family resemblance category set might actually be a result of participants learning a suboptimal single-dimensional rule (e.g., attention to a single dimension in the Type IV category set would result in 75% correct). The same type of strategy analysis was performed by Minda et al. (2008) when examining SHJ learning in children.

For each participant, we identified the response made (either Category A or B) for each stimulus. Next, we calculated for each block the correlation between the value of each dimension (e.g., square or triangle) and the response. If a participant responded to a single dimension, then the correlation between stimulus and response would be 1.0 regardless of which category that participant was learning. This analysis would indicate if a participant had adopted a single-dimensional rule, even if the rule was suboptimal. Following the correlational analysis, we counted how many participants displayed at least two blocks (including nonconsecutive blocks) of perfect rule-response correlations. As Table 2.1 shows, we typically observed single-dimensional responding only in Type I categories, with the exception of 4 older adults who never consistently applied a single-dimensional rule-based strategy when completing the Type I category set. Zero younger adults and only 2 of the 34 older adults showed a single-dimensional performance-dimension correlation for the Type II categories. The fact that older adults were performing at chance on Type II category set, yet the majority was not fit by a single-dimensional rule, suggests that older adults frequently switched their strategies throughout the task. Given the fact that one could only achieve 50% by applying a single-dimensional rule in the Type II category set, it makes sense that older adults did not consistently apply a single-dimensional rule, but rather switched rules to avoid negative feedback. Lastly, 8 of the 35 younger adults and 9 of the 34 older adults showed a single-dimensional performance-dimension correlation for the Type IV category set, suggesting that roughly a quarter of participants (both younger and older adults) relied on single-dimensional rules to learn the Type IV category set[2]. It should also be noted, that these participants were fit by a single-dimensional rule across at least two learning blocks, in the Type IV condition. The majority of these participants were fit by a single-dimensional

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[2] Roughly 75% of both younger and older adults were not employing a single-dimensional rule in the Type IV category set. This analysis does not exclude the possibility that participants may have learned the Type IV categories via a multidimensional rule. However, given the low dimensionality of the FR categories, a multidimensional rule might be difficult to distinguish from family resemblance responding. We favor the conclusion that most older adults relied on a family resemblance strategy to solve the Type IV category set, because given their difficulty learning the Type II disjunctive rule-based category set, it is unlikely that older adults would successfully be able to apply a complex, multi-dimensional rule-based strategy when learning the Type IV category set.

Table 2.1: Percentage of Participants Using Single-Dimensional Rules

Age Group	Type I	Type II	Type IV
Younger Adults	100%	0%	23%
Older Adults	88%	6%	26%

Note. A total of 35 younger adults and 34 older adults completed the study.

rule quite early in the task, and did not persist in using a single-dimensional strategy for more then two learning blocks, implying that they most likely used a family-resemblance based strategy for the remainder of the task[3].

2.7.3 Executive Functioning and IQ

Mean scores of younger and older adults on the inhibitory control and working memory measures were compared. There was a significant difference between younger (M = 57.41, SD = 55.26) and older adults (M = 1183.36, SD = 196.50) on the Stroop task, $t(38) = -3.6$, $p = .001$. Younger adults (M = 19.45, SD = 2.90) outperformed older adults (M = 17.73, SD = 2.77) on the forward digit span task, $t(67) = 2.52$, $p = .014$. Younger adults (M = 12.2, SD = 3.88) also outperformed older adults (M = 9.71, SD = 3.28) on the backward digit span task, $t(66) = 2.88$, $p = .005$. There was no significant difference between younger (M = 45.94, SD = 22.04) and older adults (M = 46.42, SD = 31.13) on the Flanker task, $t(57) = -.07$, $p = .94$. There was also no significant difference between younger (M = 38.72, SD = 30.24) and older adults (M = 56.80, SD = 48.17) on the Simon task, $t(55) = -1.85$, $p = .07$.

To examine the relationship between category learning performance and executive functioning abilities in younger and older adults, correlational analyses were conducted.

[3] When a stricter criterion based on three learning blocks rather than two was used to identify single-dimensional rule users, there was no evidence of single-dimensional rule use, suggesting that if subjects were using a single-dimensional rule in Type IV, they did not appear to use it consistently.

Average categorization performance across the last five learning blocks was correlated with the different measures of inhibitory control and working memory. For both younger and older adults, the only signification correlation found was between Type II categorization performance and backward digit span (see Tables 2.2 and 2.3). This suggests that having a larger working memory capacity is advantageous for learning Type II (complicated) RB category sets. Furthermore, the lack of correlations between executive functioning measures (Stroop, Flanker, and Simon) and Type I and Type II performance is not surprising, given the lack of variability in categorization performance scores. The majority of younger and older adults learned the Type I category set, with the exception of a few older adults. In contrast, most younger adults learned the Type II category set but few older adults did. No correlations were expected between Type IV categorization performance and executive functioning measures, since Type IV category learning is thought to rely less heavily on executive functioning compared to Types I and II. When controlling for age, partial correlations revealed that backward digit span correlated with both Type II (r = .318, p = .009) performance and Type IV performance (r = .260, p = .035). No other correlations were significant. The partial correlational analyses revealed that when age is controlled for, participants with greater working memory capacities perform better on the Type II and Type IV category sets.

In order to examine more closely the relationship between category learning and digit span, we conducted a partial correlation to examine the relationship between Type II performance and backward digit span, controlling for forward digit span. For younger adults, the relationship was significant (r = .44, p = .009). For older adults, the relationship between Type II performance and backward digit span was no longer significant (r = .28, p = .10; two-tailed). This suggests that the lower performance on Type II categories by older adults may not be purely a result of a decline in working memory performance.

A t-test was conducted to determine whether younger and older adults differed on IQ scores. Results showed that older adults (M = 117, SD = 14.4) had a significantly higher IQ score compared to younger adults (M = 109, SD = 7.5), t(49) = - 2.8, p = .007. However, this effect was driven by the fact that older adults performed much better on

Table 2.2: Intercorrelations among the study variables for younger adults

Variable	Type I	Type II	Type IV
1. Age (months)	.061	.165	-.036
2. Forward Digit Span	.203	-.053	.253
3. Backward Digit Span	.132	.325†	.303
4. Flanker Difference Score	.031	-.138	-.104
5. Simon Difference Score	.012	-.163	-.176
6. Stroop Difference Score	-.186	.024	.301

Note. Age, inhibitory control and working memory measures were correlated with average Type I, Type II, and Type IV categorization performance over the last 5 learning blocks. †$p < .06$

Table 2.3: Intercorrelations among the study variables for older adults

Variable	Type I	Type II	Type IV
1. Age (months)	-.142	-.164	.105
2. Forward Digit Span	.014	-.227	.163
3. Backward Digit Span	.040	.353*	.252
4. Flanker Difference Score	.187	.140	-.281
5. Simon Difference Score	.289	-.071	-.236
6. Stroop Difference Score	.076	-.171	-.042

Note. Age, inhibitory control and working memory measures were correlated with average Type I, Type II, and Type IV categorization performance over the last 5 learning blocks. *$p < .05$

the Vocabulary sub-test of the WASI compared to younger adults, most likely due to increased life experience. This is not a concern, given that younger adults still outperformed older adults on all three SHJ category sets, ruling out the possibility that the IQ difference influenced category learning performance between the groups.

Among older adults, IQ was not correlated with average categorization performance over the last five blocks on the Type I (r = -.09, p = .62), Type II (r = .17, p = .34), or Type IV (r = .33, p = .06) category set. Among younger adults, IQ was not correlated with the average categorization performance over the last five blocks on the Type I (r = -.21, p = .24) and Type II (r = .28, p = .10) category set. Type IV did correlate with IQ in younger adults (r = .51, p = .002), though we made no specific prediction about this relationship and did not analyze it further.

2.8 Discussion

The current study examined the relationship between executive functioning and performance on three different types of category learning tasks: an easy RB task (Type I), a complex disjunctive RB task (Type II), and a FR task (Type IV). Category learning differences between younger and older adults revealed that while both age groups learned the Type I category set quite well, older adults struggled significantly more than younger adults when learning Type II. With the majority of younger adults learning the Type II category set, and almost all older adults performing at chance, it was clear that older adults had difficulty discovering the more complex rule. Younger adults also outperformed older adults on the Type IV category set, which required adopting an implicit, overall similarity type strategy.

Findings from the current study share many similarities with findings from Minda et al.'s (2008) study examining SHJ learning in children. Contrary to prior research with younger adults usually showing a Type II advantage over Type IV (Nosofsky et al., 1994; Shepard et al., 1961; Smith et al., 2004), present findings along with those from Minda and colleagues (2008) have demonstrated a reversal in learning, with Type IV being learned significantly better than Type II by older adults and children. This reversal of the traditional SHJ ordering is quite interesting, and may shed some light on the role of the prefrontal cortex and working memory on different types of category learning. Similar to our older adults, children in the Minda et al. (2008) study performed comparably well when learning the Type I category set because the rule was based on a simple, single-dimensional rule. Even though the areas that mediate the explicit rule-based system are not fully developed in children (Bunge & Zelazo, 2006), the single-dimensional rule is easy to find and verbalize with a single proposition and places minimal demands on hypothesis testing and working memory abilities. We draw similar conclusions in regards to our findings with older adults. Functioning of the prefrontal cortex is known to decline with age, however, given the relative simplicity of the Type I rule, older adults are still able to learn this category set quite well. Even though younger adults (96% correct) performed significantly better than older adults (88% correct) on the Type I category set, older adults still demonstrated high performance on this category set. Older adults' lower Type I performance relative to younger adults is most likely the result of a lapse in memory. Prior literature suggests that it is common for older adults to learn a task/rule fairly well, but at times experience dips in performance due to memory lapses (West, 2001; West et al., 2002). Often referred to as transient goal neglect, older adults experience periods of active rule maintenance failure, rather than a difficulty actively maintaining the appropriate rule. Since there were eight trials per learning block, older adults periodically made one error during the learning block (i.e., which equates to 88% correct).

Minda et al.'s (2008) findings offer an intriguing parallel to the present research. Similar to children in the Minda et al. study, older adults in our study demonstrated difficulty learning the Type II disjunctive rule-based category set. Minda et al. attributed children's difficulty in learning the Type II category set to an under-developed explicit rule system. That is, Type II category learning requires more complex verbal rules, relative to the single propositional rule required in the Type I category set. As a result, children do not fully possess the executive functioning abilities required for learning this more complex category set. Working memory and executive functioning abilities are known to decline with age (Peters, 2006; West, 1996), which may have led to older adult's difficulty learning the Type II category set in the current study. Along the same lines, Smith et al. (2004) found that Type II was the second easiest for young adults but were the second most difficult category set for monkeys. They attributed this difficulty to the fact that monkeys have a much smaller prefrontal cortex and no verbal abilities, which are key for Type II learning.

Lastly, the present results also differed from the findings of Minda and colleagues (2008) showing that younger adults and children performed similarly on the Type IV category set. The current study demonstrated that older adults significantly underperformed younger adults on Type IV, suggesting that the correspondence between younger children and older adults does not extend to every task. Minda et al. suggest that children and younger adults perform comparably on Type IV because family resemblance learning is mediated by areas that are equally developed in both children and adults. Our findings are in line with research by Filoteo and Maddox (2004) and Maddox et al. (2010) showing that older adults struggled with learning several varieties of non-rule defined category sets. Filoteo and Maddox suggested that older adults were more likely to adopt a rule strategy that was not optimal for learning information-integration categories. Maddox et al. (2010) suggested that this deficit in FR category learning may be because older adults find it more difficult to transition from the default, explicit RB system to the implicit FR system. Furthermore, younger adults may have performed better than older adults on the Type IV category set in the current study because executive functioning abilities are required to inhibit the explicit RB system, and switch over to the implicit overall-similarity based system. However, the Maddox et al. (2010) FR category set (four category sets with lines varying across length and orientation) was quite different from our category set (two category sets with shapes varying along three dimensions), so direct comparisons may not be possible, since it is also possible to learn our Type IV category set with a complicated rule rather than strictly through FR learning. Additionally, given that research has shown that implicit learning takes longer than explicit, RB learning (Ashby et al., 1998), it may be the case that older adults needed more time to discover the correct implicit-based strategy. If given more trials to complete, older adults may have begun to perform more similarly to younger adults.

Our key finding is that older adults found the Type II categories (a complex, disjunctive rule) more difficult to learn than the Type IV categories (a family resemblance set). This is contrary to findings examining category learning in younger adults, which has shown that Type IV is more difficult than Type II. The finding that older adults struggled more with the Type II category set highlights the fact that executive functioning may be responsible for the performance differences in category learning between younger and older adults. Results showed that among both younger and older adults, a larger working memory capacity (as measured by the backwards digit span) was associated with better Type II category learning performance. Additionally, when controlling for age, we found that that working memory capacity was associated with Type II and Type IV categorization performance. This suggests that working memory may be important for learning disjunctive rules, and possibly also for speeding up hypothesis testing so individuals can switch between systems. The fact that a relationship was not found between inhibitory control abilities and category learning can mean either of two things: inhibitory control is not necessary for learning certain types of categories or alternatively, that the lack of variability in categorization performance scores between each age group, masked important effects. Given a different category set with more variability in performance, where a subset of older adults were performing well and others were not, we might see a relationship between inhibitory control and category learning emerge. The current findings do suggest that Type II category learning may place a higher demand on working memory and not so much executive functioning abilities like inhibitory control. Overall, these results support previous research showing that older adults struggle with both RB and non-rule-based FR category learning (Davis, 2012; Filoteo and Maddox, 2004; Maddox et al., 2010; Racine et al., 2006).

It is possible that if additional learning trials were added to the Type II category set, older adults might have improved to a level that is comparable to younger adults. This would not have changed our interpretation of our results for two reasons. First, even with extended training, we would have still observed the reversal in rank order difficulty between Type II and Type IV. Second, our primary conclusion was that it is the reduced working memory capacity associated with cognitive aging that brings about the learning differences. This would still hold even if the additional trials allowed for eventual mastery of the category set.

In addition to the explicit (Types I and II) /implicit (Type IV) distinction often used to describe the SHJ category sets, Boolean complexity is another way of conceptualizing the different types of categories. That is, SHJ types can be considered from the perspective of mathematical logic, where Boolean complexity refers to the length of the shortest logically equivalent propositional formula. Furthermore, Feldman (2000) demonstrated that the subjective difficulty of the category set is directly proportional to its Boolean complexity, with Type I being the easiest, followed by Type II, and Type IV being the hardest. That is, the Type I structure requires attention to only one dimension and is easiest to learn. Type II requires attention to two dimensions and is the next easiest to learn. Lastly, Type IV requires attention to all three dimensions and is considered by many to be the hardest to learn. Using this logic, Goodman et al. (2008) proposed a rational rules model that combines logical rule induction with Boolean complexity. This model predicts that Type II could be more difficult to acquire under certain conditions – when the participant or experimental setting favours unidimensional rules. This makes sense, as applying a unidimensional rule when learning the Type II category set would result in chance performance. That being said, with respect to Boolean complexity, it is quite impressive that older adults learned the harder Type IV category set better than the easier Type II category set. Even though our strategy analysis findings did not indicate that older adults were heavily relying on single-dimensional rules to learn the Type II category set, we suspect that older adults relied on single-dimensional rules more so than younger adults. The reason being that applying a single-dimensional rule during Type II learning would result in a large number of errors. It is unlikely that older adults would internalize this negative feedback and continue to apply a single-dimensional rule that resulted in numerous errors. The most logical alternative is that older adults applied single-dimensional rules during Type II learning, but frequently switched rules during the course of the task to avoid negative feedback.

Weighing all possible conclusions, it seems more likely that the reason why older adults did not demonstrate a Type II advantage is because Type II learning places the heaviest demands on cognitive resources (i.e., working memory load) and it is not as intuitive as the other category sets. That is, Type I is relatively simple to learn because it involves identification of a straightforward single dimensional rule, placing minimal demands on hypothesis testing and working memory abilities, and is encountered quite frequently in everyday life. Secondly, Type IV is considered the next easiest category set for older adults to learn because of its family resemblance structure, which is reminiscent of natural categories (Rosch & Mervis, 1975). Again, minimal working memory abilities are required to identify the overall similarity structure of the Type IV category set, realizing which features most of the category members have in common with each other. In contrast, Type II learning requires a high degree of verbal working memory to acquire and combine rules together to arrive at the correct rule. Due to declines in verbal working memory with normal aging, it is possible that the Type II category representation was not actively acquired and maintained in working memory in a manner which would allow older adults to apply the disjunctive rule accurately. This conclusion is consistent with theories of age-related impairment in working memory (Craik et al., 1990), stating that older adults struggle to test various rules and maintain this information in working memory. These findings suggest that small declines in working memory capacity relative to younger adults may have a big impact on the complex rule-based category learning abilities of older adults. It is clear that future research is required to identify the importance of working memory in older adults' ability to learn disjunctive rule-based category sets. Given the fact that individuals of all ages rely on Type II, disjunctive rule-based learning in day-to-day life, it is important to understand the cognitive mechanisms involved.

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Chapter 3

3 Improving Complex Rule-Based Category Learning Performance in Older Adults Through the Use of Pre-Training

On a daily basis, we continually make categorization judgments to help us organize the world around us. Being able to categorize promotes cognitive economy by reducing the amount of information that an individual needs to remember and learn about. The improved cognitive economy provided by categorization is particularly important for older adults to offset the decline in cognitive functioning that typically accompanies normal aging.

A prominent theory that has been developed to explain how new categories are acquired and represented in the mind is the COVIS (COmpetition between Verbal and Implicit Systems) theory (Ashby et al., 1998; Maddox and Ashby, 2004; Minda and Miles, 2010). COVIS assumes that two cognitive systems are involved in learning categories. The verbal system uses executive functioning (i.e., working memory, inhibitory control) to learn rule-based (RB) categories that can be described using a verbal rule. For example, members of family X all have brown eyes. The nonverbal system learns non-rule-based (NRB) categories that cannot be described via a verbal rule, but rather is learned implicitly by identifying which objects share an overall similarity with each other. For example, most, but not all family members are tall, have blue eyes, and blonde hair. In this case, no one feature can act as a rule. Prior research has shown that enhancing executive functioning improves performance on RB categories (Nadler, Rabi, & Minda, 2010; Rabi & Minda, 2014), while reducing/taxing executive functioning abilities impairs performance on RB categories (Minda & Rabi, 2015), leaving NRB categorization performance unaffected. Such findings illustrate that executive functioning is necessary for optimal RB learning and it is not as crucial for NRB category learning. Given that executive functions supported by the prefrontal cortex are necessary for RB category learning and show decrements with age, it is important to understand how category learning abilities change in older adulthood.

3.1 Aging and Categorization

Although significant progress has been made with respect to our understanding of category learning in young adults, much less is known about how older adults learn categories. Among the limited research that has been conducted, findings have shown that older adults struggle with both RB and NRB category learning (Davis et al., 2012; Filoteo & Maddox, 2004; Maddox et al., 2010; Racine et al., 2006), with impairments in RB category learning increasing as rule complexity increases (e.g., learning rule-plus-exception category structures; Davis, 2012). To better understand category learning deficits among older adults, a set of standardized and robust category learning experimental paradigms need to be used, since they are well understood. The category set created by Shepard, Hovland, and Jenkins (1961) is a widely used, standardized category set, consisting of both RB and NRB category structures that vary in complexity. While this category set has been used in studies involving a range of populations (e.g., young adults, children, individuals with depression, monkeys), in Chapter 2, Rabi and Minda (2016) were the first to examine the categorization abilities of older adults on the Shepard, Hovland, and Jenkins category set. Results revealed that older adults performed comparably to younger adults when learning a single-dimensional RB category set (termed *Type I*), however unlike younger adults, older adults found the complex RB (termed *Type II*) category set harder to learn than the family resemblance (termed *Type IV*) category set. The majority of younger adults learned the Type II category set quite well, but older adults performed at chance, suggesting that older adults struggled to discover the more complex rule. Rabi and Minda (2016) speculated that older adults struggled with learning the Type II complex RB category set because that particular category set placed the heaviest demands on working memory, which is a cognitive process known to decline with age (Bopp & Verhaeghen, 2005; Park et al., 2002).

3.2 Understanding Rule-Based Category Learning Deficits in Older Adulthood

Two key questions emerge from the findings of Rabi and Minda (2016): Are declining executive functioning abilities to blame for the difficulties older adults experience when learning complex RB categories? Secondly, what can be done to improve the complex

RB category learning performance of older adults? To address the first question, neuropsychological research has shown that the same brain regions (i.e., the prefrontal cortex) that mediate executive function and in later age decline, are also recruited during RB category learning (Bharani, Paller, Reber, Weintraub, Yanar, & Morrison, 2015; Nomura & Reber, 2012). Additionally, behavioural research examining the effects of aging on working memory also provides support for the idea that increasing rule complexity places a heavier burden on the working memory abilities of older adults relative to younger adults. For example, a number of studies have shown that as working memory task complexity increases, the performance of older adults decreases relative to younger adults (Bopp & Verhaeghen, 2005; Oosterman, Boeschoten, Eling, Kessels, & Maes, 2014; Verhaeghen, Cerella, & Basak, 2006). As well, research has demonstrated that aging is associated with a decrease in the efficiency with which individuals can update the contents of working memory, with older adults requiring more effort to perform updating tasks relative to younger adults (De Beni & Palladino, 2004; Fiore, Borella, Mammarella, & De Beni, 2012). In relation to prior category learning findings, older adults may have struggled with complex rule learning because they found it difficult to test various rules and update their working memory with current rule information. During Type II category learning, it is critical that the participant does not give up on hypothesis testing after two dimensions have been scanned. Otherwise, the participant is unlikely to realize that there are two maximally diagnostic dimensions. That is, in order to formulate the complex Type II rule (e.g., black triangles and white squares belong in Category A), a participant must rule out all three single-dimensional rules, before moving on to testing two-dimensional rules. Older adults may have struggled with the ease with which they were able to test the various rules and remember which rules were unsuccessful.

The inhibitory deficit hypothesis of cognitive aging purports that as individuals get older, it becomes more difficult to selectively maintain attention in situations with multiple competing stimuli (Hasher & Zacks, 1988; Hasher, Lustig, & Zacks, 2007; Healey, Campbell, & Hasher, 2008; Pettigrew & Martin, 2014). Recently activated but task irrelevant information has been shown to have a greater influence on older adults compared to younger adults. For example, older adults require significantly longer to reject a lure from an irrelevant memory set relative to younger adults (Oberauer, 2001). Based on the inhibition deficit hypothesis, older adults may have struggled with complex rule learning because they had greater difficulty ignoring incorrect hypotheses compared to younger adults. In contrast to the inhibition deficit hypothesis that asserts that age-related memory deficits may result from attending to too much information (a lot of which is irrelevant), the binding deficit hypothesis of aging proposes that age-related memory deficits may result form storing too little information. According to the binding deficit hypothesis, older adults struggle to bind together the different elements of a representation within working memory, so that the information can be stored successfully into a memory representation that can later be retrieved (Chalfonte & Johnson, 1996; Mitchell, Johnson, Raye, Mather, & D'Esposito, 2000). Support for this hypothesis comes from research showing that older adults are impaired at binding multiple items together at encoding, but not at encoding the individual items themselves. Chalfonte and Johnson (1996) compared feature memory and feature binding in younger and older adults, finding age-related deficits in feature binding (e.g., remembering object + colour combinations) but not in memory for individual features. The connection between age-related binding deficits and category learning has not been made directly, but a plausible interpretation is that older adults may struggle to combine information from two dimensions in order to formulate the complex Type II rule.

3.3 Minimizing Age-Related Changes in Rule-Based Category Learning

Aside from understanding why older adults struggle with complex RB learning, it is also important to understand what can be done to improve complex RB learning among older adults. Individuals rely on RB learning (of varying complexity) in everyday life, and it would be beneficial to develop a training protocol that would improve this type of learning in older adults. Despite age-related declines in working memory, numerous training studies have suggested that older adults are able to improve their working memory performance (Borella, Carretti, Riboldi, & De Beni, 2010; Brehmer, Westerberg, & Bäckman, 2012; Karbach & Verhaeghen, 2014; Richmond, Morrison, Chein, & Olson, 2011). Research has yet to be conducted examining methods of improving categorization performance in older adults. In fact, a recent study on category learning performance in older adults pointed out the need for future research to address ways older adults can be trained to improve performance on categorization tasks (Bharani et al., 2015). While this type of research remains to be done with older adults, it has been conducted with children. Minda, Desroches, and Church (2008) found that similar to older adults, children too struggled with complex rule learning. Since executive functioning abilities develop throughout childhood (Gathercole, 1999; Swanson, 1999), it is not surprising that children struggled to learn complex categorization rules. In an effort to improve the RB performance of children, Minda et al. (2008) reduced task demands with a pre-training task that familiarized children with the category exemplars prior to the category learning task. Results revealed that decreasing the categorization task demands for children resulted in more adult-like performance on the complex RB category set.

3.4 The Current Study

In attempt to improve the complex RB category learning abilities of older adults, the current study examined whether reducing task demands (via pre-training with categorization stimuli) would enable older adults to identify and apply complex rules in a similar manner to younger adults. While the Rabi and Minda (2016) study revealed that older adults showed greater impairments on Type II learning compared to Type IV learning, I was also interested in seeing whether pre-training would have any effect on Type IV learning since it depends less heavily on executive functioning. Both younger adults and older adults were randomly assigned to a category set (Type II or Type IV) and a condition (control or pre-train). The Type II and IV category sets were adapted from the Shepard, Hovland, and Jenkins' (1961) classification tasks. Type II is considered a hard/complex RB category set, where two features are used to indicate category membership, and participants can achieve perfect performance using a disjunctive rule. The verbal rule that would result in perfect performance in Figure 1 would be “Black triangles and white squares belong in Category A, white triangles and black squares belong in Category B”. Therefore, neither colour nor shape are individually useful in assigning category membership, but the combination of colour and shape is. Type IV is considered a family resemblance category set, where all three features are used to indicate category membership. This means that the members of Category A have features in common with one another, for example in Figure 1, they are mostly large, mostly black, and mostly triangles, whereas Category B members are mostly small, mostly white, and mostly squares. This task can be learned by looking at the overall similarity of stimuli, and thus does not require the abstraction and use of a rule. However, the Type IV category set can also be construed as a rule-plus-exception category learning task because another possible method of achieving perfect performance is to memorize the exceptional outlying stimuli (in Figure 3.1, this is the big white triangle and the small black square). The verbal rule would be “big shapes (except the white square), plus the small black triangle belong in Category A, and small shapes (except the black triangle), plus the large white square belong in Category B”. The Type IV category set is considered harder to learn than the Type II category set.

The Type II category learning task utilizes executive function resources to selectively attend to relevant dimensions, update and apply new hypotheses/rules, and inhibit incorrect rules. In addition, sufficient working memory resources are needed to verbalize and apply the rule. I attempted to reduce some of these task demands by familiarizing participants with the category exemplars. Prior to the category learning task, participants were asked to describe each of the category exemplars. This was done in an effort to familiarize participants with the fact the categories varied along three dimensions (size, shape, and colour), to speed up the hypothesis testing process, and to make it easier to encode and maintain information in working memory. Additionally, when completing this description activity, participants were told that each group of items belonged to one “category” of objects (i.e., Category A and B). While there was no explicit mention of the rule or the relationship between exemplars, this manipulation made participants aware that they would have to group the items into categories. By familiarizing participants with the exemplars, I hoped to reduce the overall processing load of the category learning task, so that older adults in particular, could better formulate the complex Type II rule. The current pre-train task was used for a number of reasons. First, prior research has used a similar pre-training paradigm with children (Minda et al., 2008). Secondly, the Rabi and Minda (2016) study did not find any order effects. That is, participants sequentially completed three different category sets (i.e., Type I, II, and IV) in various orders and the

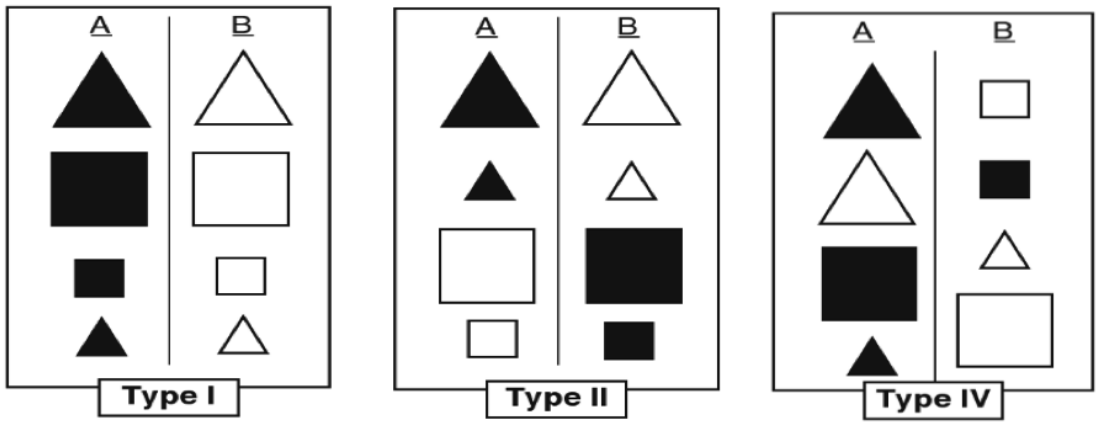

Figure 3.1: Category learning tasks from Shepard, Hovland, and Jenkins (1961): Type I (easy rule-based), Type II (hard rule-based), and Type IV (non-rule-based).

categorization performance of older adults who completed the Type II task first did not differ from those who completed it last. Older adults who completed the Type II task, last, in the Rabi and Minda study were exposed to two category sets (160 trials) before beginning the Type II task. This should have given older adults sufficient time to become familiar with the three different category dimensions. The fact that older adults did not benefit from completing the Type II category set last, suggests that passively viewing a large set of the categorization stimuli was not sufficient to improve Type II performance. Furthermore, in the current study, I included a more interactive pre-training task, where participants had to actively describe the stimuli, as to improve the efficiency of hypothesis testing and reduce working memory demands. Lastly, the aim of the pre-training procedure was not to give participants the rule because I was interested in examining whether reducing task demands would enable older adults to better formulate the rule. That being said, the form of pre-training I used encouraged participants to describe the category exemplars, so that they could come to realize on their own that two out of the three features, in conjunction, were maximally diagnostic. The pre-training instructions and task itself did not encourage memorization, as participants were not instructed to study or memorize the items, and participants only briefly viewed the categorization stimuli as they described them.

In the present study, there are three main questions of interest. The first question is: can pre-training improve the Type II performance of older adults relative to baseline performance (i.e., Type II control performance)? It is expected that pre-training should improve the Type II performance of both younger adults and older adults. However, given that executive functions declines in older adulthood, I am particularly interested in examining within group effects, to determine the impact of pre-training versus no pre-training in older adults. Since older adults performed at chance on the Type II category set in the Rabi and Minda (2016) study, I expected that pre-training should significantly boost the Type II performance of older adults. More specifically, pre-training should facilitate the hypothesis testing process, allowing older adults to complete the Type II category set more efficiently. Working memory training has proven successful to working memory performance in a number of studies and the present study will validate whether a similar form of pre-training will present benefits to complex RB category learning.

The second question the present study set out to address was: can pre-training lead to a Type II advantage in older adults? In contrast to the Type II advantage (performance on Type II is better than Type IV) typically found in studies involving young adults, the Rabi and Minda (2016) showed a reversal in learning, with Type IV being learned better than Type II by older adults. I expected that in the current study, pre-training would be more beneficial to Type II learning compared to Type IV learning, since reducing executive functioning demands should help participants learn rules via the explicit/verbal system and be less beneficial to more implicit, Type IV category learning. Furthermore, I predicted that, similar to younger adults, pre-training would lead to a Type II advantage (relative to Type IV) among older adults.

The third question of interest in the current study was: are executive functions important for Type II and Type IV category learning? Category learning is a core cognitive process that intersects with other cognitive process likes working memory, inhibitory control, and set shifting. Executive functioning is a critical component of the COVIS verbal system and RB category sets, like Type II, are learned best by the verbal system because they draw upon working memory, inhibitory control, rule selection and switching. Type IV is most often learned by the nonverbal system, and relies less heavily on executive functions. For this reason, I expected that performance on executive functioning tasks would be associated with Type II performance and less so with Type IV performance.

3.5 Method

3.5.1 Participants

Participants included 89 younger adults (*M* = 19.0 years, *SD* = 2.0; 42 males & 47 females) from the University of Western Ontario who participated for course credit and 84 older adults between the ages of 63 and 88 (*M* = 73.4 years, *SD* = 6.6; 38 males & 46 females). Among the older adults there 33 were in their 60s, 32 in their 70s, and 19 in their 80s. Older adults were recruited from senior community centres, senior exercise groups and from the University of Western Ontario alumni lecture series. Older adults received $20 for participating in the study. Participants were pre-screened to ensure that they were fluent in English, they were in good health, and had normal or corrected-to-normal vision and hearing. Participants were excluded from the study if they indicated that they had a history of neurological disorders, psychiatric illness, substance abuse, a cerebral vascular event, head trauma, and/or any other neurological conditions. All participants included in the study had at least 20/30 corrected vision (0.18 logMAR equivalent, in line with prior cognitive aging research from Bharani et al., 2015) as determined by the Freiburg Visual Acuity and Contrast Test (FrACT; Bach, 2007). The education level of younger adults (*M* = 12.3 years, *SD* = 0.6) was significantly lower ($t(162) = 7.76$, $p < .001$)[4] than that of older adults (*M* = 14.6, *SD* = 2.6) because our younger adult sample were still in university. Furthermore, their years of education is not likely to reflect their final education level.

[4] Data regarding education level was not collected from 4 younger adults and 5 older adults.

3.5.2 Materials

3.5.2.1 Category Learning Task

Two category learning tasks were chosen from the original set of six created by Shepard, Hovland, and Jenkins (1961). In each category set there are three features (shape, size, and colour) that can have one of two dimensions (square or triangle, large or small, black or white), as shown in Figure 3.1. In each category set there are eight stimuli, and four belong in each of two separate categories. There were 80 trials (10 blocks) total per category set. The Type II set was a disjunctive rule category set with two of the three features relevant for the disjunctive rule. The Type IV set was a family resemblance category set in which each category member shared the majority of its features with the other category members and all the features were relevant. Both category sets were counterbalanced across participants such that some participants were presented with a Type II set for which shape and size were the relevant dimensions, others were presented with a Type II set for which size and colour were the relevant dimensions, and so on.

3.5.2.2 Memory Tasks

3.5.2.2.1 Digit Span

Participants heard a recording of a two-digit number sequence at a rate of approximately one digit per second, and the participants were asked to repeat the sequence back to the experimenter in the same order. Participants heard three sequences at each sequence length and as long as they repeated at least one of them correctly they continued on to the next sequence length, for a maximum length of ten digits. The task was over once the participant was unable to repeat any of the sequences at a given length. The procedure for the backward digit span was the same as that for the forward digit span except that the participant was required to recall the digits in reverse order so that the last number was said first and the first number was said last, for a maximum of eight digits. The task was scored as the total number of correct responses.

3.5.2.2.2 Alpha Span

In this verbal working memory task created by Craik (1986), participants listened to recorded lists of common one-syllable words ranging in length from two to eight words presented at the rate of one word per second, and repeated the words back in correct alphabetical order. Two lists were provided at each list length, for a total of 14 lists. Participants were asked to recall all 14 lists in alphabetical order, regardless of whether they made errors when repeating the lists. In the scoring system, points were awarded for each word recalled, but only if the word was either the first or last correct word in the recalled series, or was a member of a correct adjacent pair during recall. For example, if a list of five items is recalled correctly, the score is 5 points; if the correct recall sequence for a list of five items is “bed, hall, milk, queen, rose, stick” and the participant responds “bed, hall, rose, queen, stick”, he or she would receive 3 points. “Bed” is in the correct first place, “hall” is in the correct adjacent pair and “stick” is in the correct last place but neither “rose” nor “queen” is in a correct adjacent pair in the correct order. The alpha span score is the total number of points awarded across all presented lists. To encourage participants to keep trying even if they made mistakes, they were told at the start of the task that they may not be able to recall all the words in a list correctly, but to try their best and recall as many words as possible.

3.5.2.3 Inhibitory Control Tasks

3.5.2.3.1 Flanker Task

A version of the Flanker task adapted from Botvinick, Nystrom, Fissel, Carter, and Cohen (1999) was used. The experiment was built using REALbasic 5.1. A set of five arrows was presented in a row on the computer screen and participants were asked to indicate the direction of the central arrow (target). The target was flanked by two identical arrows on either side (distractors) that were either pointing in the same direction (congruent trial) or the opposite direction (incongruent trial) of the target arrow. The task consisted of 60 trials (30 congruent and 30 incongruent) presented in randomized order. Prior to the experiment participants received five practice trials that were not analyzed.

The difference in mean reaction time between correct responses on congruent and incongruent trials (i.e., a difference score) was used as a measure of inhibitory control. Larger difference scores were indicative of less efficient interference control.

3.5.2.3.2 Simon Task

An adapted version of the Psychology Experiment Building Language (PEBL) computerized Simon task (Mueller, 2012; Simon & Rudell, 1967) was used. Participants were first presented with a fixation cross in the center of the screen. Immediately after the cross had disappeared, participants were instructed to press the left key in response to the red circle or the right key in response to a blue circle as fast as possible, regardless of stimulus location. The timing began with the onset of the stimulus, and the response terminated the stimulus. On congruent trials, the stimulus location was on the same side as the required response and on incongruent trials the stimulus location was on the opposite side of the required response. The whole task consisted of 64 trials (32 congruent trials and 32 incongruent trials) presented in randomized order to each participant. Prior to the experiment, participants received five practice trials that were not analyzed. Difference scores were calculated by computing the difference in mean reaction time between correct responses on congruent and incongruent trials.

3.5.2.3.3 Stroop Task

An adapted version of the PEBL computerized Stroop task (Mueller, 2012; Stroop, 1935) was used. Participants were instructed to indicate, as quickly and accurately as possible, whether each word presented on the computer screen was written in red, blue, green, or yellow ink using the properly labeled response buttons. Participants were instructed to ignore the meaning of the words and to focus on the ink colour only. The timing began with the onset of the word, and the response terminated the stimulus. Participants first completed 12 practice trials, with accuracy feedback after each trial. The actual task consisted of 72 trials without feedback: 24 congruent trials (i.e., “RED” in red ink), 24 incongruent trials (i.e., “RED” in blue ink) and 24 neutral trials (i.e., non-colour word names like “TREE”). Difference scores were calculated by computing the difference in mean reaction time between correct responses on congruent and incongruent trials.

3.5.2.4 Berg Card Sorting Test (BCST)

Set shifting ability was assessed using the computerized PEBL abbreviated 64-card version of the Wisconsin Card Sorting Test (Mueller, 2012; Berg, 1948). The PEBL BCST-64 is highly correlated with the longer original version (perseverative errors r = .77, categories completed r = .86, Fox, Mueller, Gray, Raber & Piper, 2013). Participants were instructed to match each response card that appeared to one of the four reference cards at the top of the screen without being told how to match them. The objects on the cards differed in colour, shape, and number. Following each card placement, participants received feedback as to whether their response was correct or incorrect. After ten sequentially correct responses, the rule was changed without notice and the participants had to use the feedback to identify the new sorting rule. Participants completed 64 trials of this task. The dependent measures were the number of categories completed (the number of blocks of 10 consecutive correct matches) and the number of perseverative errors (an incorrect response to a changed/new category that would have been correct for the immediately preceding category).

3.5.2.5 Wechsler Abbreviated Scale of Intelligence (WASI) Test

Standardized scores on the WASI vocabulary and matrix reasoning sub-tests (Wechsler, 1999) were used to calculate the Full Scale Intellectual Quotient. WASI subtests were used to provide estimates of verbal and nonverbal intelligence.

3.5.3 Procedure

3.5.3.1 Session 1

Participants were tested individually across two testing sessions, approximately one week apart. Younger adults were tested in the Categorization Lab at the University of Western Ontario. Older adults were tested in the Categorization Lab at the University of Western Ontario or in a quiet room in the senior centre. Participants first completed the FrACT vision test so that an objective measure of visual acuity could be obtained in addition to the participant's subjective report of their vision. Next participants completed a rule-based or information integration category learning task (this data were collected for the study in Chapter 4 which was not part of the current study). Following the category learning task, participants received a short break, after which they completed the BCST and the alpha span task.

3.5.3.2 Session 2

Participants were randomly assigned to one of four conditions: Type II control, Type II pre-training, Type IV control, and Type IV pre-training. Participants in the Type II and Type IV *control* conditions were given the category learning task instructions where they were told that they would be presented with abstract shapes and asked to classify them as belonging to category A or category B. Participants in the Type II and Type IV *pre-training* conditions were familiarized with each of the 8 category exemplars prior to the category learning task. Participants were first shown the 4 category A exemplars and asked to describe each of the exemplars. Participants were then shown the 4 category B exemplars and asked to name each of the exemplars. For the category A exemplars the experimenter pointed to the first exemplar and said (for example), "This is a big black square, can you name the other members of category A?". The participant was then required to name the other category A members and the category B members in the same manner and was corrected if he or she failed to name all of the features of any given exemplar (e.g., calling the next exemplar a white triangle instead of a small white triangle). The participant was then briefly shown the category A and category B exemplars simultaneously, with each category group labeled, and told "here are the members of category A and category B, now you can begin the categorization task". As soon as the experiment finished saying the last statement, the final display was removed and the participant began the category learning task. It should be noted that while participants in the pre-training condition were familiarized with the category exemplars in the Type II or Type IV category set, the correct categorization strategy was not given to them. Instead the participant would need to take the next step and identify the correct strategy on their own using the information they obtained from the pre-training task. For example, after viewing the Type II category exemplars, a participant in the pre-training condition would still need to formulate the disjunctive rule on their own by realizing which two of the three category features were part of the correct verbal rule. All participants (regardless of category type or condition) saw each stimulus one-at-a-time on the computer screen and were instructed to press the button labeled “A” or “B” to indicate whether each shape belonged in category A or B respectively. After responding, participants were given corrective feedback (the words “correct” or “incorrect” appeared above the stimulus object). Another trial began following this feedback. Stimuli were presented in random order within each block of eight and blocks were presented in an unbroken fashion. There were a total of 80 trials (10 blocks total).

Following completion of Type II or Type IV category set, participants completed the Flanker task, Simon task, and Stroop task. Following the Stroop task, participants received a short break, after which they were administered the forward and backward digit span. Lastly, participants completed the WASI. Each testing session lasted approximately one hour.

3.6 Results

A 2 age group (younger v. older) x category type (Type II vs. Type IV) x 10 block ANOVA was conducted to determine whether categorization performance in the control conditions were similar to that found by the Rabi and Minda (2016) study in Chapter 2. Older adults in the control conditions of our study had an average categorization performance of 54% in Type II and 60% in Type IV, similar to the 50% in Type II and 60% in Type IV reported in the Rabi & Minda (2016) study. In line with the findings from Rabi and Minda (2016), we also found an age x category type interaction [$F(1, 80) = 5.69$, $p = .019$, partial $\eta^2 = .07$], demonstrating that younger adults showed a Type II advantage and older adults showed a Type IV advantage in the control conditions. As shown in Figure 3.2, younger adults outperformed older adults across all of the different

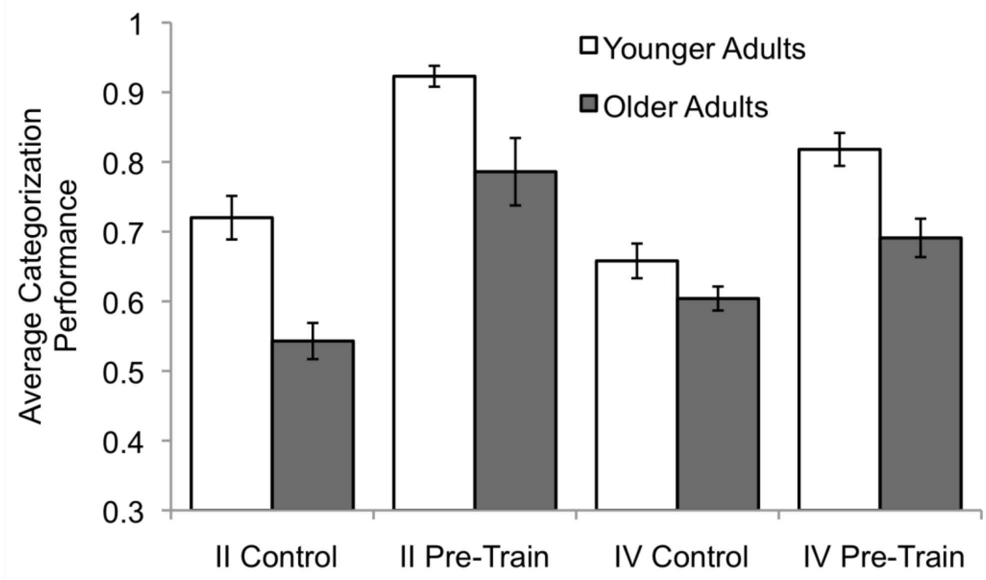

Figure 3.2: Average categorization performance of younger adults and older adults across 10 learning blocks. Error bars denote the standard error of the mean.

category sets and conditions[5]. The main goal of this study was to examine whether older adults given pre-training would show improved categorization performance relative to older adults in the control condition (i.e., baseline performance). For this reason, we were more interested in within age-group analyses, rather than between age-group analyses. That being said, we examined category learning performance by conducting two separate 3-way ANOVAs: one for older adults and one for younger adults.

3.6.1 Categorization Performance in Older Adults

A 2 category type (Type II vs. Type IV) x 2 condition (Control vs. Pre-Train) x 10 block ANOVA was conducted. There were 21 older adults in Type II Control, 21 in Type II Pre-Train, 20 in Type IV Control, and 22 in Type IV Pre-Train. The main effects of

[5] Older adults (M = 115, SD = 14.3) had a significantly higher IQ score compared to younger adults (M = 110, SD = 10.4), $t(145) = 2.52$, p = .01, confirming that younger adults were not outperforming older adults because of differences in IQ. The WASI was not administered to 12 older adults and 14 younger adults due to time limitations.

condition [$F(1, 80) = 26.31$, $p < .001$, partial $\eta^2 = .25$] and block [$F(9, 720) = 9.48$, $p < .001$, partial $\eta^2 = .11$] were significant and suggested better overall performance in the pre-train condition ($M = .74$) than in the control condition ($M = .57$), not accounting for category type, and that categorization accuracy improved over time. There was no main effect of category type [$F(1, 80) = .27$, $p = .60$, partial $\eta^2 = .003$] because the data were collapsed across condition, which washed out the strong effect of pre-training on categorization performance. The category type x condition interaction was significant [$F(1, 80) = 5.84$, $p = .02$, partial $\eta^2 = .07$] but the block x category type [$F(9, 720) = .29$, $p = .98$, partial $\eta^2 = .004$], block x condition [$F(9, 720) = 1.28$, $p = .25$, partial $\eta^2 = .016$], and block x category type x condition [$F(9, 720) = 1.66$, $p = .09$, partial $\eta^2 = .02$] interactions were not significant[6].

To further examine the significant category type x condition interaction, Bonferroni corrected pairwise post hoc comparisons were conducted. As shown in Figure 3.3A, older adults in the Type II pre-training ($M = .79$) condition performed significantly better than those in the Type II control ($M = .54$) condition ($p < .001$), suggesting that pre-training helped older adults with Type II category learning. In contrast, older adults performed only marginally better in the Type IV pre-training ($M = .69$) condition compared to the Type IV control ($M = .60$) condition ($p = .06$). These results indicate that while pre-training was somewhat helpful for Type IV category learning, the benefits from pre-training were more pronounced in Type II category learning. Additionally, older adults performed significantly better in the Type II pre-train ($M = .79$) condition compared to the Type IV pre-train ($M = .69$) condition ($p = .039$), indicating that pre-training was more effective for explicit, rule-based category learning compared to more implicit, family-resemblance-based category learning.

Among older adults, IQ was not correlated with average categorization performance across the last five blocks in the Type II control [$r = .35$, $p = .17$], Type II pre-training [r

[6] Among older adults, age was not correlated with II control ($r = -.30$, $p = .18$), II pre-train ($r = -.17$, $p = .45$), IV control ($r = -.21$, $p = .36$), and IV pre-train ($r = -.09$, $p = .67$) performance.

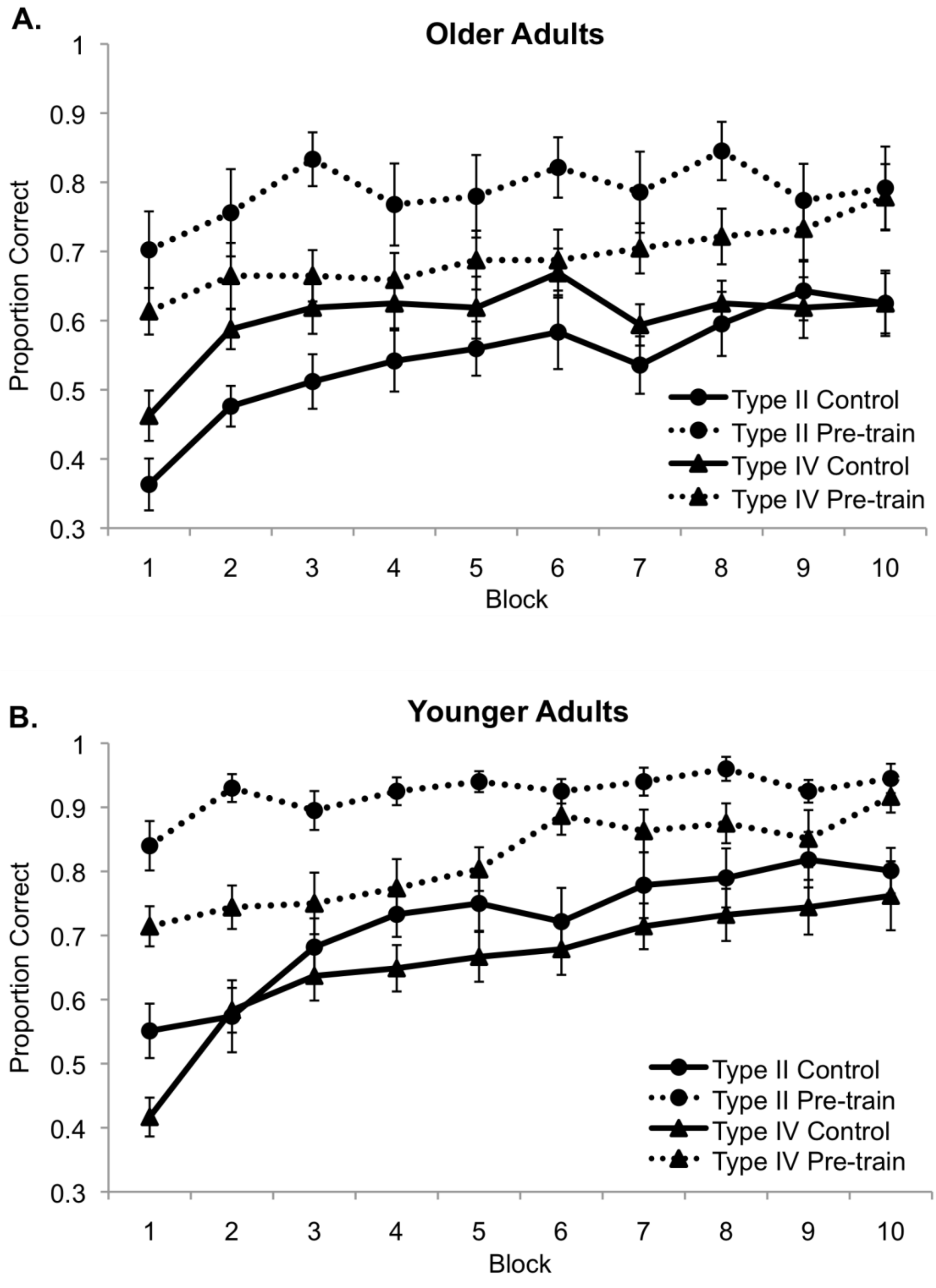

Figure 3.3: Categorization performance of (A.) younger and (B.) older adults across learning blocks in each of the four conditions. Error bars denote standard error of the mean.

= .39, p = .12], Type IV control [r = .34, p = .18], and Type IV pre-training conditions [r = -.13, p = .57].

3.6.2 Categorization Performance in Younger Adults

A 2 category type (Type II vs. Type IV) x 2 condition (Control vs. Pre-Train) x 10 block ANOVA was conducted. There were 22 older adults in Type II Control, 25 in Type II Pre-Train, 21 in Type IV Control, and 21 in Type IV Pre-Train. The main effects of category type [$F(1, 85) = 12.02$, $p = .001$, partial $\eta^2 = .12$], condition [$F(1, 85) = 57.1$, $p < .001$, $\eta^2 = .40$] and block [$F(7, 594) = 23.2$, $p < .001$, $\eta^2 = .21$; Greenhouse-Geisser corrected] were significant, suggesting that Type II average categorization performance (M = .82) was better than Type IV (M = .74) performance (collapsed across condition type), pre-training overall performance (M = .87) was better than control performance (M = .69) (collapsed across category type), and that categorization accuracy improved over time. The block x condition interaction was significant [$F(7, 594) = 3.70$, $p = .001$, partial $\eta^2 = .04$; Greenhouse-Geisser corrected], suggesting that performance remained relatively stable starting from the 6th block onwards in the pre-training conditions, whereas learning continued in the control conditions. The category type x condition [$F(1, 85) = 0.81$, $p = .37$, partial $\eta^2 = .009$], block x category type [$F(7, 594) = 1.17$, $p = .32$, partial $\eta^2 = .014$; Greenhouse-Geisser corrected], and block x category type x condition [$F(7, 594) = 1.25$, $p = .27$, partial $\eta^2 = .015$; Greenhouse-Geisser corrected] interactions were not significant. It is not surprising that the category type x condition interaction was not significant for younger adults even though it was significant for older adults, because younger adults greatly benefitted from pre-training in both the Type II (i.e., a 20% increase in Type II performance with pre-training) and Type IV (i.e., a 16% increase in Type IV performance with pre-training) conditions (see Figure 3.3B). Similar to older adults, it is clear from Figures 3.2 and 3.3B that younger adults performed better in the Type II pre-training condition compared to the Type IV pre-training condition. To confirm this apparent trend in the data, Bonferroni corrected pairwise comparisons confirmed that the Type II pre-training (M = .92) categorization performance of younger adults was significantly better than their Type IV pre-training (*M* = .82) performance (*p* = .002)[7].

Among younger adults, IQ was not correlated with average categorization performance across the last five blocks in the Type II control [*r* = .04, *p* = .86], Type II pre-training [*r* = .14, *p* = .56] and Type IV pre-training conditions [*r* = .02, *p* = .94]. Performance in the Type IV control condition did correlate with IQ [*r* = .49, *p* = .03]. Rabi & Minda (2016) also found a correlation between Type IV performance and IQ in younger adults. We made no specific prediction about this relationship and did not analyze it further. However, given that this finding was replicated, it may be useful for future studies to further explore this relationship.

3.6.3 Comparison of Pre-trained Older Adults and Younger Adult Controls

While younger adults outperformed older adults across all category types and conditions, we were particularly interested in how older adults in the pre-train condition performed relative to younger adults in the control condition. Results revealed that for the Type II category set, the categorization performance of older adults in the pre-training condition (*M* = .79) did not significantly differ from that of younger adults in the control condition (*M* = .72), *t*(34) = 1.14, *p* = .26 (see Figure 3.4A). For the Type IV category set, the categorization performance of older adults in the pre-training condition (*M* = .69) also did not significantly differ from that of younger adults in the control condition (*M* = .66), *t*(41) = .93, *p* = .36 (see Figure 3.4B). Furthermore, pre-training made older adults perform at a level similar to that of younger adults in the control conditions.

3.6.4 Strategy Analysis

In order to better understand the categorization performance of younger adults and older adults, we conducted a strategy analysis to determine whether participants used a single-dimensional rule strategy when learning the two category sets. This is important to know

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[7] Bonferroni post-hoc tests also confirmed that younger adults performed significantly better in the Type II pre-train (*M* = .92) condition compared to Type II control (*M* = .72) condition (*p* < .001) and in the Type IV pre-train (*M* = .82) condition compared to Type IV control (*M* = .66) condition (*p* < .001).

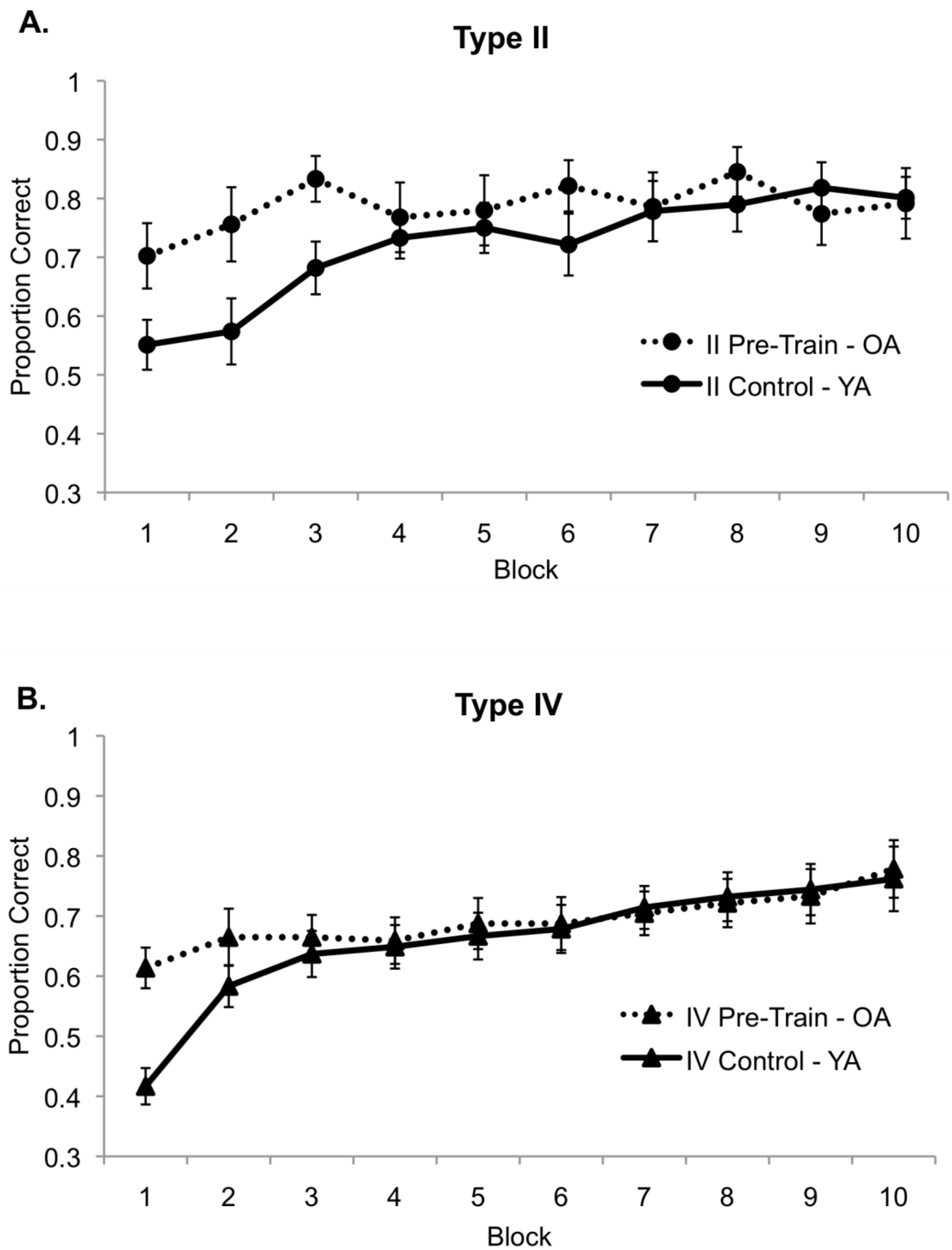

Figure 3.4: Category learning performance of (A.) older adults in Type II pre-training and younger adults in Type II control and of (B.) older adults in Type IV pre-training and younger adults in Type IV control. Error bars denote the standard error of the mean.

because in many cases, what might appear to be moderate performance on the Type IV family resemblance category set might actually be a result of participants learning a suboptimal single-dimensional rule (e.g., attention to a single dimension in the Type IV category set would result in 75% correct). If a participant relied on a RB strategy when learning the NRB Type IV category set, this may indicate that they had difficulty transitioning from the verbal system to the nonverbal system. The same type of strategy analysis was performed by Minda et al. (2008) when examining SHJ learning in children. For each participant, we identified the response made (either Category A or B) for each stimulus. Next, we calculated for each block the correlation between the value of each dimension (e.g., square or triangle) and the response. If a participant responded to a single dimension, then the correlation between stimulus and response would be 1.0 regardless of which category that participant was learning. This analysis would indicate if a participant had adopted a single-dimensional rule, even if the rule was suboptimal. Following the correlational analysis, we counted how many participants displayed at least two blocks (including nonconsecutive blocks) of perfect rule-response correlations. As Table 3.1 shows, for the Type II category set (control and pre-train conditions), no younger adults showed a single-dimensional performance-dimension correlation. In comparison, 2/21 older adults in the Type II control condition and no older adults in the Type II pre-training condition applied a single-dimensional rule. The fact that older adults were performing around chance in the Type II control condition, yet the majority was not fit by a single-dimensional rule, suggests that older adults frequently switched their strategies throughout the task. Given the fact that one could only achieve 50% by applying a single-dimensional rule in the Type II category set, it makes sense that older adults did not consistently apply a single-dimensional rule, but rather switched rules to avoid negative feedback. Pre-training appeared to eliminate the consistent use of single-dimensional rules among older adults when learning the Type II category set. Lastly, 9/21 younger adults and 5/20 older adults in the Type IV control condition applied a single-dimensional rule across at least 3 blocks of trials. While a substantial portion of participants (bother younger and older adults) relied on single-dimensional rules to learn the Type IV category set, it should be noted that these participants were fit by a single-

Table 3.1: Percentage of participants using single-dimensional rules.

Age Group	II Control	II Pre-Train	IV Control	IV Pre-Train
Younger Adults	0%	0%	43%	9.5%
Older Adults	9.5%	0%	25%	14%

dimensional rule in at least two learning blocks, not for the full duration of the task. The majority of these participants were fit by a single-dimensional rule early in the task, and did not persist in using a single-dimensional strategy for more then two learning blocks[8]. Furthermore, implying that they most likely used a family-resemblance based strategy for the remainder of the task. It should also be noted that the percentage of participants using a single-dimensional strategy in the Type IV condition dropped (more substantially for younger adults) when pre-training was introduced. Only 2/21 younger adults and 3/22 older adults relied on single-dimensional rules in the Type IV pre-training condition[9].

3.6.5 Executive Functioning

Younger adults generally performed better on the executive functioning tasks compared to older adults, with the exception being the digit span task and Flanker task where both age groups performed similarly (see Table 3.2). Scores on the executive functioning

Table 3.2: Executive functioning performance of younger and older adults.

[8] When a stricter criterion based on three learning blocks rather than two was used, the percentage of older adult single-dimensional rule users dropped to 5% in Type II control, 5% in Type IV control, and 9% in Type IV pre-train. The percentage of younger adult single-dimensional rule users dropped from 43% to 14% in the Type IV control condition when this stricter criterion was introduced.

[9] This analysis does not exclude the possibility that participants may have learned the Type IV categories via a multidimensional rule. However, given the low dimensionality of the FR categories, a multidimensional rule might be difficult to distinguish from family resemblance responding. We favor the conclusion that most older adults relied on a family resemblance strategy to solve the Type IV category set, because given their difficulty learning the Type II disjunctive rule-based category set, it is unlikely that older adults would successfully be able to apply a complex, multi-dimensional rule-based strategy when learning the Type IV category set.

	Younger Adults		Older Adults	
	M	*SD*	*M*	*SD*
Forward Digit Span	19.3	3.3	18.7	3.4
Backward Digit Span	11.4	3.4	10.4	3.5
Alpha Span	45.3	6.7	37.4	8.8
Flanker Difference Score	47.1	23.0	46.8	43.8
Simon Difference Score	30.8	35.7	58.8	46.8
Stroop Difference Score	62.5	76.6	164.3	147.7
BCST Categories Completed	4.1	0.8	3.1	1.3
BCST Perseveration Errors	7.1	2.3	9.5	4.6

measures were correlated with average categorization performance across the last five learning blocks for older adults and younger adults separately[10]. In line with prior aging research, for the three inhibition tasks, response times that were more than 3,000 ms (for the Simon and Stroop task) and 2,000 ms (for the Flanker task) were removed as outliers, which eliminated less than 1% of trials for each age group across tasks (Langley, Vivas, Fuentes, & Bagne, 2005; Bugg, Jacoby, & Toth, 2008; Drueke, Boecker, Mainz, Gauggel, & Mungard, 2012). Additionally, outlying trials were removed from analyses of the inhibitory control data, defined as ≥3 SDs from each individual's mean within each trial category (congruent, incongruent, and neutral).

[10] The scores of some participants were not included in the analyses because the task was not completed due to time limitations, computer error, or because the participant made too many errors on the task indicating a lack of understanding (this was in reference to the inhibition tasks where participants made errors on more than 50% of the incongruent trials and on the BCST where participants learned 0 categories). Flanker data was missing from 7 older adults and 2 younger adults. Stroop data was missing from 7 older adults. Simon data was missing from 1 older adult. Alpha span data was missing from 3 older adults and 1 younger adult. BCST data was missing from 11 older adults and 1 younger adult.

3.6.5.1 Older Adults

Among older adults, performance in the Type II control condition was correlated with alpha span and Simon task performance and marginally correlated with backward digit span (see Table 3.3). Performance in the Type II pre-training condition was correlated with forward digit span, backward digit span, and alpha span and was marginally correlated with Simon task performance[11]. Type II performance was most strongly correlated with the working memory measures, indicating that working memory plays an important role in learning complex rule-based categories. Type II performance was moderately correlated with inhibitory control measures suggesting that inhibition may play a role in complex rule-based category learning, but to a lesser degree compared to working memory abilities. The fact that Type II pre-training performance still correlated with working memory measures implies that individuals with better working memory abilities benefitted more from the pre-training task. Type IV control performance was correlated with forward digit span and marginally correlated with backward digit span and Stroop performance. This relationship is less clear, however these findings may suggest that better executive functioning abilities can assist with transitioning from the explicit rule-based system to the implicit system, which is useful for learning Type IV categories lacking a clear verbal rule. Type IV pre-training performance was marginally correlated with the number of categories completed on the BCST[12]. To control for age-related changes in executive functioning within the older adult age group (e.g., differences between 65 & 85 year-olds), we conducted partial correlations on the significant correlations, controlling for age. Type II control performance was still

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[11] There was an unexpected marginal positive correlation between Flanker difference score and Type II pre-training performance in older adults, implying that older adults who performed better in the Type II pre-training condition also took longer to respond to incongruent Flanker trials relative to congruent trials. However, this was most likely due to the speed-accuracy tradeoff, because the Flanker accuracy data revealed that higher Type II pre-training performance among older adults was associated with fewer errors on incongruent Flanker trials [r = -.52, p = .03]. After controlling for age, this relationship was still significant [r = -.53, p = .03].

[12] The accuracy data from the inhibition tasks was also examined in older adults. In addition to the correlation between Type II pre-training performance and incongruent errors on the Flanker task (mentioned earlier), there was a correlation between Type IV pre-train performance and incongruent errors on the Stroop task [r = -.62, p = .003]. After controlling for age, this relationship remained significant [r = -.54, p = .014].

Table 3.3: Intercorrelations among the study variables for older adults.

	II-Con	II-PT	IV-Con	IV-PT
Forward Digit Span	.082	.537*	.525*	.320
Backward Digit Span	.400†	.613**	.405†	.367
Alpha Span	.633**	.650**	.315	.286
Flanker Difference Score	-.009	.478†	-.161	-.366
Simon Difference Score	-.473*	-.436†	-.070	-.096
Stroop Difference Score	-.017	.230	-.445†	-.345
BCST Categories Completed	.416	.354	.391	.415†
BCST Perseveration Errors	-.248	-.351	-.102	-.070

Note. Executive functioning measures were correlated with categorization performance over the last 5 learning blocks. Two-tailed t-tests: ** $p < .01$, * $p < .05$, † $p < .07$.

Table 3.4: Intercorrelations among the study variables for younger adults.

	II-Con	II-PT	IV-Con	IV-PT
Forward Digit Span	.224	.181	.074	.199
Backward Digit Span	.272	.133	.345	.598**
Alpha Span	-.070	.040	.364	.527*
Flanker Difference Score	-.152	.104	.096	-.132
Simon Difference Score	-.225	.185	.030	.312
Stroop Difference Score	.143	.398	-.138	.040
BCST Categories Completed	-.198	.183	.004	-.420
BCST Perseveration Errors	.213	-.042	-.307	.100

Note. Executive functioning measures were correlated with categorization performance over the last 5 learning blocks. Two-tailed t-tests: ** $p < .01$, * $p < .05$.

correlated with alpha span [$r = .60$, $p = .005$] and Simon scores [$r = -.46$, $p = .039$]. Type II pre-train performance was still correlated with backward digit span [$r = .56$, $p = .025$] and alpha span [$r = .59$, $p = .016$], but no longer correlated with forward digit span [$r = .37$, $p = .16$]. Type IV control performance was still correlated with forward digit span [$r = .51$, $p = .032$]. These findings suggest (aside from forward digit span) that differences in age did not influence the relationship between category learning and executive functioning among older adults.

3.6.5.2 Younger Adults

There were no correlations between Type II performance (control or pre-training) and executive functioning measures. Type IV pre-train performance was correlated with backward digit span and alpha span (see Table 3.4). This suggests that among younger adults who received pre-training, those with stronger working memory abilities were better able to remember the individual exemplars allowing them to more easily identify the overall similarity structure of the Type IV category set[13].

3.7 Discussion

The current study examined older and younger adults' complex RB (Type II) and family-resemblance (Type IV) category learning ability. In line with findings from the Rabi and Minda (2016) study, in the control conditions, older adults were more successful at learning Type IV categories compared to Type II and younger adults were more successful at learning Type II categories compared to Type IV. Furthermore, the present study confirmed the existence of a Type IV advantage in older adults and a Type II advantage in younger adults. The fact that older adults struggled more with the Type II category set suggests that executive functioning may be responsible for the performance differences in category learning between younger and older adults. I reduced the executive function demands associated with the category learning tasks in the current study by familiarizing participants with the category exemplars. While I minimized

[13] The inhibitory control accuracy data of younger adults revealed that Type IV pre-training performance was also correlated with incongruent errors on the Simon task [$r = -.49$, $p = .026$].

categorization task demands in my study, given that executive functioning abilities decline in older adulthood, I still expected younger adults to outperform older adults in the pre-train conditions. Nonetheless, my primary aim of this study was to determine whether pre-training would improve Type II performance relative to baseline (control performance) and for that reason, I compared categorization performance within each age group. In support of my predictions, I found that older adults in the Type II pre-training condition performed significantly better than those in the Type II control condition, demonstrating that pre-training helped older adults with Type II category learning. Furthermore, the implementation of a short pre-training session allowed older adults to the learn the Type II category set quite well, performing at almost 80% correct, compared to the near chance performance seen in the Type II control condition.

On the contrary, older adults performed only marginally better in the Type IV pre-training condition compared to Type IV control condition, signifying that while pre-training was helpful in Type IV learning, the benefits to Type II learning were greater. These findings are comparable to research by Minda et al. (2008), showing that familiarizing children with category exemplars improved their RB categorization performance. These results suggest that familiarizing older adults with the category exemplars aided their ability to test more complex rules, by reducing the working memory demands of the task, allowing the explicit RB system to operate optimally. Minda et al. (2008) also found that pre-training did not significantly improve family-resemblance performance in children but it did improve family-resemblance performance in young adults. Like young adults in the Minda et al. (2008) study, older adults in the Type IV condition may have benefitted to a small extent from pre-training because it helped to reinforce the association between the features and category labels, helping older adults to pick up on the overall similarity between category exemplars in each group. Younger adults in the current study significantly benefitted from pre-training during both Type II and Type IV category learning. Similar to older adults, it appears that reducing task demands enabled younger adults to better learn both category sets. That is, pre-training may have sped up the hypothesis testing process helping younger adults to identify the complex rule more quickly during Type II learning. Additionally, in line with predictions from COVIS, pre-training may have improved Type IV learning by helping participants to transition from the verbal RB system to the nonverbal implicit system used to learn Type IV categories. That is, the verbal system is considered the default category learning system, in that individuals tend to use it during initial learning, but may switch to the nonverbal system when the verbal system is unsuccessful. Therefore, in the present study, pre-training may have facilitated the switch from the verbal to nonverbal system.

In line with my predictions, I also found that pre-training led to a Type II advantage in older adults, which was absent when pre-training was not administered (control condition). In younger adults, the Type II advantage, which was evident in the control condition, remained when pre-training was introduced. More specifically, for both older and younger adults, pre-training led participants to perform better on the Type II category set compared to the Type IV category set. This finding suggests that pre-training may have been more effective for RB Type II category learning which relies on executive functioning compared to more implicit family-resemblance-based Type IV category learning. Based on the finding that both older adults and younger adults performed significantly better on the Type II category set following pre-training compared to no-pre-training, one might speculate that pre-training encouraged participants to memorize the category exemplars. However, due to a number or reasons, this possibility is unlikely. First, following pre-training, both older adults and younger adults performed better on the Type II category set compared to the Type IV category set. Participants in the pre-train conditions were given identical instructions (were asked to describe either the Type II category exemplars or the Type IV category exemplars), so if individuals were memorizing category exemplars, there should not have been significant performance differences on the Type II and IV category sets. The fact that a Type II advantage emerged among older and younger adults, suggests that pre-training assisted participants with testing rules and ultimately formulating the complex rule. Secondly, participants were not instructed to “study” or “memorize” the category exemplars, rather they were told to describe them. Lastly, participants only viewed the category exemplars for a very brief period of time. Essentially, they viewed the category exemplars as they described them, after which they began the category learning task. Participants were not given extra time to look at the category exemplars after they finished describing them. All that being said, it seems unlikely that participants relied on memorization strategies to learn the category exemplars. Especially given that the working memory abilities of older adults decline with age, it seems improbable that they could memorize all the category exemplars after just viewing them for a brief period of time. In addition to ruling out memorization strategies as an extraneous reason for why performance differences may have occurred, IQ and age of older adults was also ruled out as variables that may have influenced performance.

Single-dimensional rule strategy use was also considered as a factor that may have impacted performance on the Type II and Type IV category set. That is, I wanted to determine whether changes in categorization performance among older and younger adults could be explained by the inappropriate use of single-dimensional rules in the Type II and Type IV category set. The present findings showed that almost 10% of older adults in the Type II control condition relied on a single-dimensional rule across at least two learning blocks compared to 0% of older adults in the Type II pre-train condition. No younger adults relied on a single-dimensional strategy when learning the Type II category set, regardless of condition. These findings suggest that among older adults, pre-training eliminated single-dimensional strategy use during Type II learning. Based on the low Type II performance of older adults in the control condition, it is evident that more than 10% of older adults struggled with identifying the correct rule. Given the fact that one could only achieve 50% by applying a single-dimensional rule in the Type II category set, it seems likely that rather than consistently apply a single-dimensional rule, older adults in the Type II control condition switched between different single-dimensional rules throughout the task to avoid negative feedback. This resulted in low Type II performance because older adults failed to identify the complex rule. In the Type IV category set, a subset of both younger and older adults relied on single-dimensional rules during the Type IV categorization task. However, the proportion of participants relying on single-dimensional rules during Type IV learning, decreased in both age groups following pre-training, possibly suggesting that pre-training helped participants to transition from the verbal to nonverbal system.

While my main point of interest was in comparing pre-train to control performance in each age group separately, I also examined how the pre-train performance of older adults compared to the categorization performance of younger adults. Younger adults outperformed older adults across all of the study conditions, and for this reason I examined how the pre-train performance of older adults compared to the control performance of younger adults. Results revealed that for both the Type II and Type IV category set, the pre-train performance of older adults did not significantly differ from the control performance of younger adults. This suggests that pre-training may have reduced the executive function demands of the categorization task enough so that older adults could perform at a similar level to younger adults. This finding converges nicely with prior research showing that completing a secondary task that taxes executive functions either concurrently or prior to RB category learning interferes with the categorization performance of younger adults (Maddox & Ashby, 2004; Miles, Matsuki, & Minda, 2014; Minda & Rabi, 2015; Zeithamova & Maddox, 2007). Therefore, it appears that learning RB categories via the verbal system depends on having access to working memory and other executive functions, and so by increasing task demands (as shown by prior research), RB performance in turn will suffer. In comparison, the present findings demonstrate that by reducing task demands (via pre-training), RB performance can be improved. Additionally, fMRI research has shown that areas of the prefrontal cortex are more active during RB category learning compared to NRB category learning (Nomura & Reber, 2008). Together, this research illustrates that executive functions are used by the verbal system during RB category learning and greater recruitment of executive functions are needed for successful RB category learning.

Executive functioning performance was also measured in the present study to further examine the relationship between category learning accuracy and executive functioning. While some executive function measures were marginally correlated with category learning performance, I was most interested in the strongest correlates of performance. Most notably, when controlling for the age of older adults, Type II control performance was significantly correlated with alpha span and Simon task performance and Type II pre-train performance was significantly correlated with backward digit span, alpha span, and Flanker task accuracy in older adults. These findings suggest that, independent of the age of older adults; complex RB category learning is associated with working memory and inhibitory control abilities. The fact that reducing task demands via pre-training did not eliminate the relationship between executive functioning and Type II learning, suggests that having strong executive functioning abilities may have allowed older adults to benefit more from pre-training. These findings are supported by prior research showing that, in comparison to young adults, individuals with weaker working memory abilities (e.g., children, monkeys) struggle with Type II category learning (Minda et al., 2008; Smith et al., 2004). That is, older adults with stronger working memory and inhibitory control abilities may have been able to better extract the complex rule following the pre-training task, inhibit competing rules, and store the correct rule in working memory. Among older adults, better Type IV control performance was associated with forward digit span and better Type IV pre-train performance was associated with accuracy on the Stroop task. While not as many executive function measures correlated with Type IV performance compared to Type II performance, the fact that some did, suggests that executive functioning may also be somewhat important for NRB category learning. The nonverbal system is thought to operate independently of executive functions, however recent research suggests that executive functions may be useful in transitioning from the verbal (dominant/default system) to nonverbal system (Nomura & Reber, 2012; Miles et al., 2014; Schnyer et al., 2009). Additionally, the prefrontal cortex has been shown to play an important role not only in executive functioning but also in mediating the transition between the categorization systems. Furthermore, it may be that older adults with stronger executive function abilities were able to reject the verbal system more quickly and switch to the optimal, nonverbal system when learning the Type IV category set. In comparison, among younger adults, only Type IV pre-train performance was correlated with executive function measures (backward digit span, alpha span, and Simon task accuracy). Given that Type II performance did not correlate with executive functioning in younger adults is not particularly surprising, since younger adults learned this category set quite well and executive function skills operate optimally during young adulthood and start to decline in older adulthood. Since Type IV category learning is generally considered to be a more difficult category set to learn relative to Type II, the correlation between Type IV pre-train performance and executive functions in younger adults may signify that stronger executive functions helped facilitate the switch to the nonverbal system.

The findings from the present study provide support for both the inhibition deficit account and the binding deficit account of cognitive aging. In support of the inhibition deficit view, pre-training may have reduced the amount of task irrelevant information older adults encountered, allowing them to perform better on the Type II task. The binding hypothesis also provides an explanation for the current findings, in that pre-training familiarized older adults with the category exemplars enough so that they could bind together the different elements and formulates the categorization rule within working memory. Future research may benefit from further exploring which account of cognitive aging better explains the differences in category learning performance seen among younger and older adults. It may be the case that older adults not only encode and store too much irrelevant information, but they also struggle with binding task relevant information together.

In summary, the difficulty older adults in the present study experienced when learning the Type II category set in the control condition supports prior literature showing that the rule complexity metric predicts categorization performance (Minda et al., 2008; Rabi & Minda, 2016; Racine, 2006). One of the most important contributions of the current work was that I established that pre-training in older adults could be used to attenuate well-established age-related RB category learning deficits. Additionally, I showed that executive function abilities are associated with the ability of older adults to learn Type II and Type IV categories, suggesting that working memory and inhibitory control may be important for learning RB categories and for switching systems in order to learn NRB categories. Categorization not only helps individuals' structure and organize the world around them, but it is the foundation for processing, remembering, and incorporating new information. For this reason, it is important to understand the cognitive processes involved in categorization and how they change with age. In the current study, pre-training was able to considerably improve complex RB category learning, providing support for the effectiveness of working memory training with older adults. Quite possibly, current technology can be used to assist with RB category learning, reducing executive function demands among older adults. For example, many older adults require regular medication but struggle to kept track of medication-related information using RB categories. With new technology (e.g., phone apps), older adults can store their medication information in their phone (e.g., size, shape, and colour of the pill, time of day pill should be consumed, and proper dosage) in organized categories, familiarizing the individual with their medical information and increasing medical adherence. My results highlight the difficulty older adults encounter when learning complex RB categories and provide a potential solution to improve learning. This is an important first step and future research on this topic can shed light on alternative methods for enhancing category learning performance among older adults.

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Chapter 4

4 Towards a Better Understanding of Category Learning in Older Adulthood: Insights from Strategy Analysis

Categorization is a fundamental cognitive process, which we rely on to make decisions on a daily basis. For example, when we discover new produce at the grocery store and attempt to determine whether it is a fruit or vegetable or when we try to distinguish weeds from desirable plants in our garden we are making categorization judgments. Given the importance of this decision-making process, it is essential that we understand the cognitive processes underlying categorization. Despite the plethora of research examining category learning in young adults and children, relatively little research has been conducted on category learning in older adults. This is important, because if significant differences in performance are found between younger and older adults, this would suggest that aging influences the ability of individuals to learn categories.

Both behavioural and neuroimaging research has provided support for the COVIS theory of category learning, which assumes that new categories are acquired by two cognitive systems (Ashby et al., 1998; Maddox and Ashby, 2004; Minda and Miles, 2010; Nomura et al., 2008; Nomura & Reber, 2012). The explicit, verbal category learning system is mediated by the prefrontal cortex and relies on working memory and executive functions to learn categories that can be defined by an easily verbalizable rule (i.e., rule-based (RB) categories). This system is assumed to be the dominant or default approach for learning new categories in adults (Ashby et al., 1998). The implicit, non-verbal or non-rule-based (NRB) system relies on associative learning mechanisms to learn categories that lack an easily verbalizable rule. The nonverbal system is mediated by subcortical structures in the tail of the caudate nucleus and category learning using this system is thought to take place gradually and does not rely heavily on executive functioning. The two category learning systems have been proposed to be in competition with one another and executive functions may assist with transitioning from the default verbal system to the nonverbal system. Furthermore, executive functions are important for RB category learning because it assists with rule testing, identification, and application. Additionally, while the NRB system does not rely on executive functioning to learn NRB categories, executive functioning may help to mediate the transition from the verbal to nonverbal system.

4.1 RB and NRB Category Learning in Older Adulthood

A key finding reported in the cognitive aging literature is that deficits in RB category learning become more pronounced as rule complexity increases. Racine and colleagues (2006) found a large performance deficit among older adults when the rule was complex, which they suggested was due to a need for enhanced cognitive control. In order to test the hypotheses that rule-forgetting may contribute to older adults' difficulty learning RB categories, Racine et al. provided external rule reminders in a prompt condition. Results revealed that older adults did not display any benefit of prompts. Furthermore, older adults in the Racine et al. study could report the rule at the end of the task, but displayed difficulties applying the rule under conditions that had high cognitive control requirements. This suggests that age-related deficits in RB learning are not specifically due to rule forgetting, but may possibly be due to difficulties with rule application.

Maddox et al. (2010) also examined complex RB category learning in older adults using a conjunctive RB task, where participants were required to assign stimuli (lines varying in length and angle) to one of four categories. Findings showed that relative to younger adults, older adults struggled with RB category learning. Similarly, Davis, Love and Maddox (2012) found that older adults struggled with category learning when the optimal strategy involved rule-plus-exception learning. That is, older adults found it difficult to learn exception items relative to rule-following items in the RB category set. In support of prior research, a recent study by Rabi and Minda (2016) also showed that older adults struggled with learning complex RB categories requiring the integration of two stimulus dimensions but performed quite well when learning relatively simple single-dimensional RB categories.

It is evident from reviewing the category learning literature that older adults find it difficult to learn complex categorization rules (Davis et al., 2012; Maddox et al., 2010;

Rabi & Minda, 2016; Racine et al., 2006). Additionally, Rabi and Minda (2016) have shown that older adults perform quite well when learning simple, single-dimensional categorization rules. The question which remains is: how do older adults perform when learning complex single-dimensional RB categories? More specifically, the complex RB tasks used in past studies involved combining two stimulus dimensions together to arrive at a complex rule. Is it the case that older adults struggle with combining information together into a complex rule? Or is it that older adults struggle with any RB task (single-dimensional or multi-dimensional) that places strain on their executive functioning resources? A newly published study by Bharani, Paller, Reber, Weintraub, Yanar, and Morrison (2016) examined RB category learning in older adults using a more complicated single-dimensional RB category set. Event-related potentials (ERPs) were monitored as participants categorized Gabor patches varying in spatial frequency and spatial orientation. Bharani and colleagues found that older adults struggled with RB learning relative to younger adults, supporting the idea that taxing executive function resources is responsible for the category learning deficits seen in older adults. Additionally, ERP findings revealed that older adults who successfully learned the rule displayed larger frontal ERPs compared to younger adults. In comparison, low-performing older adults' frontal activity did not significantly differ from that of younger adults. This increase in frontal activity in high-performing older adults' suggests that recruitment of prefrontal resources may have improved performance. Moreover, Bharani et al. concluded that the increase in frontal activity seen in high-performing older adults occurred because they recruited the additional circuitry needed to learn the category set despite age-related neural deterioration.

In addition to RB category learning, NRB category learning has also been examined in older adults, most notably with the information-integration (II) category set. These categories are learned by the nonverbal/implicit system by integrating information from two or more dimensions at some pre-decisional stage (Ashby & Waldron, 1999). Filoteo and Maddox (2004) examined II category learning in older and younger adults. Results revealed that older adults learned the II category set less well than younger adults, suggesting that aging can negatively influence not only RB category learning, but II category learning too. Maddox et al. (2010) also found that older adults were impaired at

II category learning relative to younger adults. While older adults were no less likely than younger adults to use the task appropriate II strategy, older adults still showed II deficits. Maddox et al. suggested that this II deficit in older adults was due to their less consistent application of the task appropriate II strategy. From a neuroscience perspective, the II deficit seen among older adults makes sense since structural and functional declines in the striatum have been documented (Gabrieli, 1996; Li, Lindenberger, & Sikstrom, 2001). These declines are likely associated with age-related deficits in implicit, procedural-based learning (Park et al., 2002; Salthouse, Atkinson, & Berish, 2003).

4.2 Executive Functioning in Normal Aging

To better understand the relationship between category learning and aging, it is important to examine how executive functions change with age. Executive functions are important during RB learning to assist with hypothesis testing, rule identification, maintenance and application. As well, executive functions may be important to NRB learning to assist with transitioning from the dominant verbal system to the nonverbal system. The prefrontal cortex plays a key role in executive functioning, however, this brain region has been shown to deteriorate with age. For example, the prefrontal cortices show large volumetric declines in white and gray matter, associated with aging (Gunning-Dixon & Raz, 2003; Raz et al., 2000, 2005).

Executive function is composed of three related, but separable components: working memory, inhibitory control, and set-shifting (Miyake, Friedman, Emerson, Witzki, Howerter, and Wager, 2000). Aging research has demonstrated that working memory performance declines with advancing age (Bopp & Verhaeghen, 2005; Craik & Bialystok, 2006; Park et al., 2002; Verhaeghen & Salthouse, 1997), suggesting that older adults are less able to effectively process and temporarily store information. Age-related declines in working memory abilities have specific implications for RB category learning. To adequately identify the correct categorization rule, working memory is needed to maintain and update rules that have been tested in memory. A decrease in working memory capacity may result in older adults maintaining less information about the category set and thus relying on suboptimal strategies to learn the RB category set. Several different hypotheses have been proposed to account for age-related declines in working memory. Processing/attentional resources hypotheses propose that aging depletes the cognitive resources available for processing information (Belleville, Rouleau, & Caza, 1998; Craik et al., 1990; Dobbs & Rule, 1989; Just & Carpenter, 1992). Speed of processing hypotheses propose that age-related working memory deficits can be explained in terms of a general slowing of information processing (Salthouse, 1994, 1996; Verhaeghen & Salthouse, 1997). Inhibitory deficit hypotheses propose that a lack on inhibitory control may explain age-related deficits, because individuals fail to suppress irrelevant information in working memory (Hasher & Zacks, 1988; Healey, Campbell, & Hasher, 2008; Lustig, May, & Hasher, 2001; Oberauer, 2001; Pettigrew & Martin, 2014).

The inhibitory deficit hypothesis highlights that inhibitory control is another cognitive process which declines with age with prior research showing that older adults have a reduced ability to suppress irrelevant information (De Beni et al., 2007; Dempster, 1992; Persad et al., 2002). With regards to category learning, inhibitory control may be important for inhibiting incorrect (and possibly salient) rules during RB learning and for inhibiting the verbal system in favour of the nonverbal system during NRB learning. The fact that older adults have difficulty stopping irrelevant information from entering working memory may mean that older adults rely on suboptimal rules when learning RB categories and have difficulty transitioning to the nonverbal system when learning NRB categories.

The third executive function component, set-shifting, has also been shown to decline in healthy aging. Compared to younger adults, older adult display more difficulty shifting attention between two tasks. Ridderinkhof and colleagues (2002) have demonstrated that older adults struggle with the Wisconsin Card Sort Test (WCST), even when given explicit shift cues to change rules. Older adults may perseverate on previously correct sorting rules more frequently than younger adults because they struggle with hypothesis testing and rule shifting (Arbuckle & Gold, 1993; Hartman, Bolton, & Fehnel, 2001; Raz, 2000; Ridderinkhof et al., 2002). A set-shifting deficit could have a number of consequences for category learning. If one is unable to switch between different rules the individual may struggle with identifying the correct rule in a RB category set, because they keep testing previously used rules or rules that are more salient to them. With relation to NRB category learning, a set-shifting deficit may impact one's ability to switch from the verbal to nonverbal system. Moreover, the individual may be perseverating on a rule, even though the rule does not work very well in the context of the NRB category learning task.

4.3 The Current Research

Two studies were conducted to examine the effects of cognitive aging and executive functioning on category learning. The limited research that has been done on category learning has focused on examining complex, multi-dimensional (e.g., conjunctive or disjunctive RB category sets) RB category learning in older adults. More research is needed to better understand single-dimensional RB category learning, as well as NRB category learning in older adults. We used an extremely well studied category learning paradigms for examining RB and NRB category learning. In the task, participants divided Gabor patches (see Figure 4.1) varying in spatial frequency (number of lines in the patch) and spatial orientation (the angle of lines in the patch) into two category groups, based on trial-by-trial feedback. This category learning paradigm was used for a number of reasons. The stimulus dimensions of Gabor patches are separable and have clear verbal labels. Gabor patches are novel stimuli which participants do not have prior experience with, eliminating any bias participants may enter the study with. The Gabor stimuli are numerous and variable enough that it is unlikely that participants could rely on memorization strategies to categorize the stimuli. Prior category learning studies involving older adults have used novel categorization tasks or less well researched categorization tasks, making it somewhat more difficult to draw certain conclusions. Countless studies have been done using this category learning paradigm, allowing us to compare the present study findings with a number of different studies (e.g., Bharani et al., 2016; Filoteo, Maddox, Ing, & Song, 2007; Huang-Pollock et al., 2011; Maddox, Ashby, & Bohil, 2003; Maddox, Ashby, Ing, & Pickering, 2004; Miles, Matsuki, & Minda, 2014; Minda & Rabi, 2015; Nadler, Rabi, & Minda, 2010; Rabi & Minda, 2014; Zeithamova & Maddox, 2006). Lastly, the current category learning paradigm lends itself well to computational modeling of strategy use, giving us

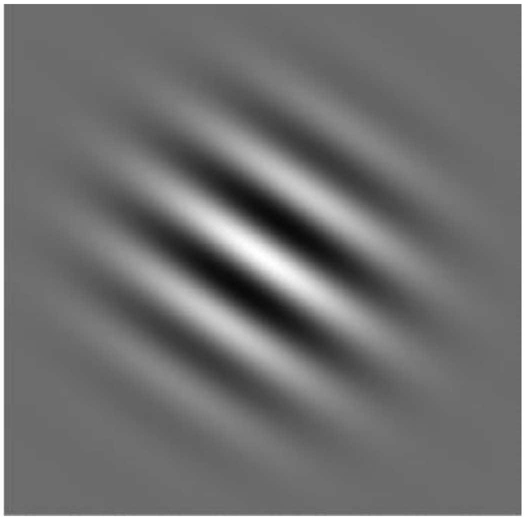

Figure 4.1: An example of a Gabor patch

insight into the specific strategies individuals use to learn novel categories.

In Study 1, single-dimensional RB category learning and NRB category learning in older adults and younger adults was investigated. Bharani and colleagues (2016) examined RB category learning in older adults using the Gabor patch stimuli and I wanted to confirm and extend their findings by also examining NRB category learning in older adults. While RB and NRB category learning have been examined separately in different studies involving older adults, more research is needed comparing RB and NRB performance in older adults. Study 1 will shed light on how both the verbal and nonverbal system functions in older adults when learning a standardized category set. Additionally, executive function measures will be administered to better understand the relationship between category learning and executive functioning in normal aging.

In Study 2, the ability of older adults and younger adults to learn the same RB category set presented in Study 1 was investigated, but this time participants received pre-training prior to beginning the RB category learning task. During pre-training, participants verbally described a sample of Gaussian blur stimuli and upon starting the category learning task, viewed stimuli where the dimensions were more apparent, before transitioning to more difficult stimuli. Category learning deficits have been demonstrated in the aging literature, but aside from the pre-training study carried out in Chapter 3, what is lacking is an examination of methods of improving the category learning abilities of older adults. This shortcoming is addressed in Study 2, by examining the impact of reducing task demands via pre-training on single-dimensional RB category learning in older adults. Similar to Study 1, executive functioning performance was also measured to provide additional insights into the role of executive functioning in RB category learning.

4.4 Study 1

The goal of the first study was to examine single-dimensional RB category learning in older adults. Past studies that have identified RB category learning deficits in older adults have used category sets which require a complex, multi-dimensional rules to solve (i.e., the correct rule requires combining information along at least two stimulus dimensions). Comparably little research has examined single-dimensional RB category learning in older adults. Aside from simple single-dimensional rules, which older adults are quite good at learning (Rabi & Minda, 2016), we were interested in examining how older adults would learn a more complex single-dimensional RB category set. If older adults struggle with complex single-dimensional RB category learning, this would suggest that taxing executive functions in general is responsible for RB category learning deficits. However, if older adults perform well on the complex, single-dimensional RB category set, this would suggest that the age-related category learning deficit is limited to learning multi-dimensional rules requiring the integration of two dimensions because the integration aspect of rule learning is particularly taxing for older adults. We used a RB category set where the frequency of lines in the Gaussian blur was the correct rule, but the orientation of the lines in the Gaussian blur was the more salient dimension. Participants would need to inhibit the more salient dimension in favor of the correct, but less-salient stimulus dimension in order to learn this complex, single-dimensional RB task. In line with the findings of Bharani and colleagues (2016), it was expected that younger adults would outperform older adults on the RB category set, since this type of category learning places demands on executive functions, which are known to decline with healthy aging (Gunning-Dixon & Raz, 2003; Raz et al., 2000, 2005).

NRB category learning was also examined in older and younger adults, which provided an important point of comparison between RB and NRB category learning using the same type of categorization stimuli (i.e., Gaussian blurs). Based on prior findings showing that older adults struggle with NRB category learning (Filoteo & Maddox, 2004; Maddox et al., 2010) it was expected that older adults in the present study would struggle with NRB category learning. We reasoned that older adults would have more difficulty compared to younger adults, because executive functioning is needed to transition from the verbal to nonverbal system. Given the popularity of the Gaussian blur category paradigm it is surprising that, to my knowledge, no other studies have examined NRB category learning in older adults using this paradigm. By investigating NRB category learning in the current study I will be able to better understand how older adults learn implicit-based category sets for which no easily verbalizable rule exists.

In addition to measuring accuracy-based performance on the RB and NRB category learning tasks, computational modeling was also used to examine strategy use among older adults and younger adults. Since it is possible for different strategies to result in similar categorization performance scores, it is important to examine whether the types of strategies older adults use differ from that of younger adults. It is expected that relative to younger adults, older adults will rely on suboptimal rules (i.e., rule based on the more salient but incorrect stimulus dimension - orientation) in the RB condition. With regards to NRB category learning, relative to younger adults, it is expected that older adults would rely on RB strategies more so than NRB strategies because they may have difficulty switching from the dominant verbal system to the nonverbal system.

To better understand differences in categorization performance between older and younger adults, we also examined the executive functioning performance of participants using a number of tasks that tap into working memory, inhibitory control, and set-shifting abilities. If RB and NRB category learning involves executive processes, then categorization performance should be associated with executive function measures.

4.4.1 Method

4.4.1.1 Participants

Participants included 64 younger adults (*M* = 18.4 years, *SD* = 0.61; 27 males & 37 females) from the University of Western Ontario who participated for course credit and 55 older adults between the ages of 63 and 88 (*M* = 73.4 years, *SD* = 6.1; 27 males & 28 females)[14]. Among the older adults there were 20 in their 60s, 24 in their 70s, and 11 in their 80s. Older adults were recruited from senior community centres, senior exercise groups and from the University of Western Ontario alumni lecture series. Older adults received $20 for participating in the study. Participants were pre-screened to ensure that they were fluent in English, they were in good health, and had normal or corrected-to-normal vision and hearing. Participants were excluded from the study if they indicated that they had a history of neurological disorders, psychiatric illness, substance abuse, a cerebral vascular event, head trauma, and/or any other neurological conditions. All participants included in the study had at least 20/30 corrected vision (0.18 logMAR equivalent) (in line with prior cognitive aging research from Bharani et al., 2015) as determined by the Freiburg Visual Acuity and Contrast Test (FrACT; Bach, 2007). The education level of younger adults (*M* = 12.2 years, *SD* = 0.5) was significantly lower ($t(113) = 7.05$, $p < .001$)[15] than that of older adults (*M* = 14.5 years, *SD* = 2.6) because my younger adult sample were still in university so their years of education is not likely to reflect their final education level.

4.4.1.2 Materials

Category Learning Task

For the category learning task, participants classified sine-wave gratings that varied in spatial frequency and orientation. 80 stimuli were generated for each category set (Ashby

[14] Of the 64 younger adults, 49 subjects also participated in the Chapter 3 study and 15 subjects were newly recruited. Of the 55 older adults, 51 subjects also participated in the Chapter 3 study and 4 subjects were newly recruited to keep the sample size of the conditions relatively equal.

[15] Data regarding education level was not collected from 4 older adults.

and Gott, 1988; Zeithamova and Maddox, 2006), with 40 stimuli in each category. We randomly sampled 40 values from a multivariate normal distribution described by each category's parameters (shown in Table 4.1). The resulting category structures for RB and II category sets are illustrated in Figure 4.2. We then used the PsychoPy package (Peirce, 2007) to generate sine wave gratings corresponding to each coordinate sampled from the distributions above. For both category sets sine wave grating frequency was calculated as $f = 0.25 + (x_f/50)$ cycles per stimulus and orientation was calculated as $o = x_o \times (\pi/20)$ degrees.

Digit Span

Participants heard a recording of a two-digit number sequence at a rate of approximately one digit per second, and the participants were asked to repeat the sequence back to the experimenter in the same order. Participants heard three sequences at each sequence length and as long as they repeated at least one of them correctly they continued on to the next sequence length, for a maximum length of ten digits. The task was over once the participant was unable to repeat any of the sequences at a given length. The procedure for the backward digit span was the same as that for the forward digit span except that the participant was required to recall the digits in reverse order so that the last number was said first and the first number was said last, for a maximum of eight digits. The task was scored as the total number of correct responses.

Alpha Span

In this verbal working memory task created by Craik (1986), participants listened to recorded lists of common one-syllable words ranging in length from two to eight words presented at the rate of one word per second, and repeated the words back in correct alphabetical order. Two lists were provided at each list length, for a total of 14 lists. Participants were asked to recall all 14 lists in alphabetical order, regardless of whether they made errors when repeating the lists. This was done to provide a finer grain measure of working memory performance. In the scoring system, points were awarded for each word recalled, but only if the word was either the first or last correct word in the recalled

Table 4.1: Distribution parameters for rule-based and information integration category sets.

Category Structure	μ_f	μ_o	σ^2_f	σ^2_o	$cov_{f,o}$
Rule-defined					
Cat. A	280	125	75	9,000	0
Cat. B	320	125	75	9,000	0
Non-rule-defined					
Cat. A	268	157	4,538	4,538	4,351
Cat. B	332	93	4,538	4,538	4,351

Note. Dimensions are in arbitrary units; see the materials section for a description of the scaling factors. The subscripted letters *o* and *f* refer to orientation and frequency, respectively.

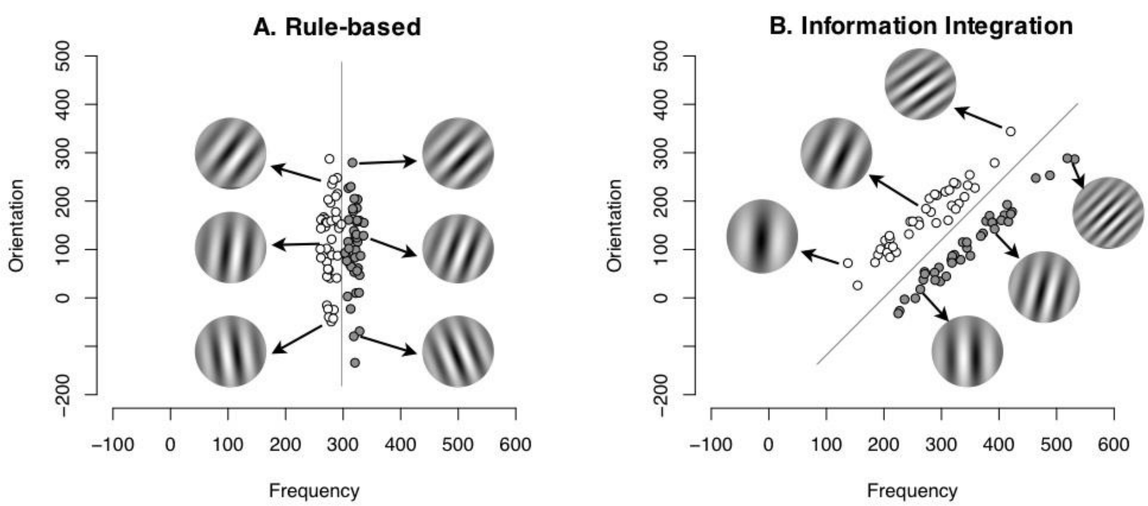

Figure 4.2: (A) Category structure for the rule-based category set. Each light circle represents a stimulus from Category A and each dark circle represents a stimulus from Category B. The line shows the optimal boundary between the stimuli. The six sine-wave gratings demonstrate examples of the actual stimuli seen by participants. **(B)** Category structure for the information-integration category set.

series, or was a member of a correct adjacent pair during recall. For example, if a list of five items is recalled correctly, the score is 5 points; if the correct recall sequence for a list of five items is “bed, hall, milk, queen, rose, stick” and the participant responds “bed, hall, rose, queen, stick”, he or she would receive 3 points. “Bed” is in the correct first place, “hall” is in the correct adjacent pair and “stick” is in the correct last place but neither “rose” nor “queen” is in a correct adjacent pair in the correct order. The alpha span score is the total number of points awarded across all presented lists. To encourage participants to keep trying even if they made mistakes, they were told at the start of the task that they may not be able to recall all the words in a list correctly, but to try their best and recall as many words as possible.

Flanker Task

A version of the Flanker task adapted from Botvinick, Nystrom, Fissel, Carter, and Cohen (1999) was used. The experiment was built using REALbasic 5.1. A set of five arrows was presented in a row on the computer screen and participants were asked to indicate the direction of the central arrow (target). The target was flanked by two identical arrows on either side (distractors) that were either pointing in the same direction (congruent trial) or the opposite direction (incongruent trial) of the target arrow. The task consisted of 60 trials (30 congruent and 30 incongruent) presented in randomized order. Prior to the experiment participants received five practice trials that were not analyzed. The difference in mean reaction time between correct responses on congruent and incongruent trials (i.e., a difference score) was used as a measure of inhibitory control. Larger difference scores were indicative of less efficient interference control.

Simon Task

An adapted version of the Psychology Experiment Building Language (PEBL) computerized Simon task (Mueller, 2012; Simon & Rudell, 1967) was used. Participants were first presented with a fixation cross in the center of the screen. Immediately after the cross had disappeared, participants were instructed to press the left key in response to the red circle or the right key in response to a blue circle as fast as possible, regardless of stimulus location. The timing began with the onset of the stimulus, and the response terminated the stimulus. On congruent trials, the stimulus location was on the same side as the required response and on incongruent trials the stimulus location was on the opposite side of the required response. The whole task consisted of 64 trials (32 congruent trials and 32 incongruent trials) presented in randomized order to each participant. Prior to the experiment, participants received five practice trials that were not analyzed. Difference scores were calculated by computing the difference in mean reaction time between correct responses on congruent and incongruent trials.

Stroop Task

An adapted version of the PEBL computerized Stroop task (Mueller, 2012; Stroop, 1935) was used. Participants were instructed to indicate, as quickly and accurately as possible, whether each word presented on the computer screen was written in red, blue, green, or yellow ink using the properly labeled response buttons. Participants were instructed to ignore the meaning of the words and to focus on the ink colour only. The timing began with the onset of the word, and the response terminated the stimulus. Participants first completed 12 practice trials, with accuracy feedback after each trial. The actual task consisted of 72 trials without feedback: 24 congruent trials (i.e., “RED” in red ink), 24 incongruent trials (i.e., “RED” in blue ink) and 24 neutral trials (i.e., non-colour word names like “TREE”). Difference scores were calculated by computing the difference in mean reaction time between correct responses on congruent and incongruent trials.

Berg Card Sorting Test (BCST)

Set shifting ability was assessed using the computerized PEBL abbreviated 64-card version of the Wisconsin Card Sorting Test (Mueller, 2012; Berg, 1948). The PEBL BCST-64 is highly correlated with the longer original version (perseverative errors r = .77, categories completed r = .86, Fox, Mueller, Gray, Raber & Piper, 2013). Participants were instructed to match each response card that appeared to one of the four reference cards at the top of the screen without being told how to match them. The objects on the cards differed in colour, shape, and number. Following each card placement, participants received feedback as to whether their response was correct or incorrect. After ten sequentially correct responses, the rule was changed without notice and the participants had to use the feedback to identify the new sorting rule. Participants completed 64 trials of this task. The dependent measures were the number of categories completed (the number of blocks of 10 consecutive correct matches) and the number of perseverative errors (an incorrect response to a changed/new category that would have been correct for the immediately preceding category).

Wechsler Abbreviated Scale of Intelligence (WASI) Test

Standardized scores on the WASI vocabulary and matrix reasoning sub-tests (Wechsler, 1999) were used to calculate the Full Scale Intellectual Quotient. WASI subtests were used to provide estimates of verbal and nonverbal intelligence.

4.4.1.3 Procedure

Session 1

Participants were tested individually across two testing sessions, approximately one week apart. Younger adults were tested in the Categorization Lab at the University of Western Ontario. Older adults were tested in the Categorization Lab at the University of Western Ontario or in a quiet room in the senior centre. Participants first completed the FrACT vision test so that an objective measure of visual acuity could be obtained in addition to the participant’s subjective report of their vision.

Next participants completed the RB or II category learning task. They were given initial instruction that they would be seeing a “crystal ball” on the screen and their job was to determine whether that crystal ball belonged to the blue wizard category or the green wizard category (see Figure 4.3). They were instructed to press the key labeled “green” to make a green wizard response and to press the key labeled “blue” to make a blue wizard response. Participants were told they would receive feedback after every response, and that they should use this feedback to help them learn to make as many correct responses as possible. Participants were presented with four blocks of the 80 stimuli, 320 trials in

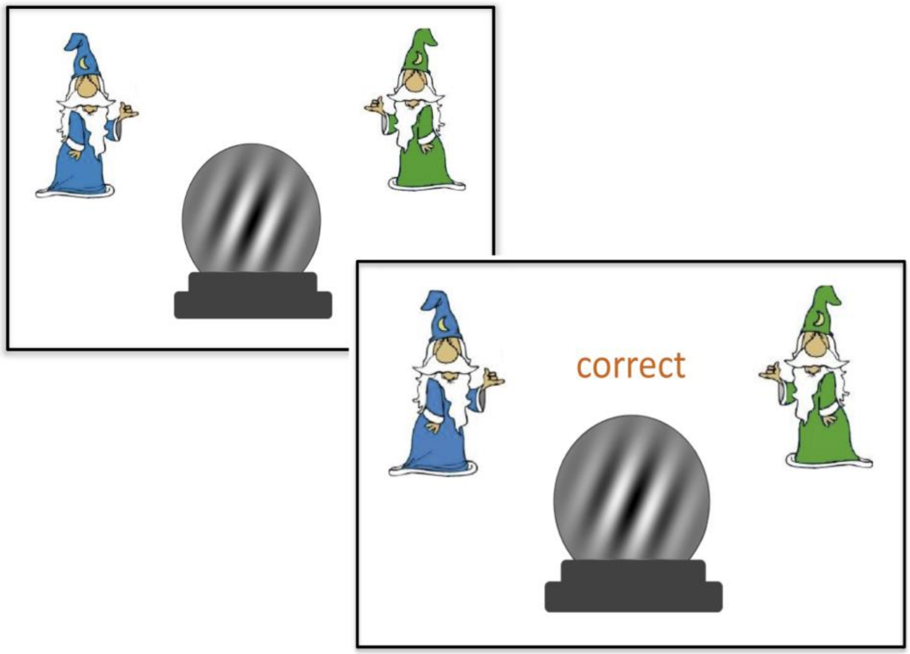

Figure 4.3: An example of a correct trial in the categorization task. Feedback was presented after each response (“correct” or “incorrect”).

total. Within a block, the order of presentation of all 80 stimuli in the category set was randomized. On each trial, participants saw the crystal ball in the center of the screen and a blue wizard and green wizard in the upper left and upper right corner of the screen. Upon making a response, feedback was delivered in the space between the stimulus and the two wizards. The word “correct” or “incorrect” was presented after each response.

Following the category learning task, participants received a short break, after which they completed the BCST and the alpha span task.

Session 2

Participants completed either the Type II or Type IV Shepard, Hovland, and Jenkins category set (this data were collected for the study in Chapter 3 which was not part of the current study). Following completion of Type II or Type IV category set, participants completed the Flanker task, Simon task, and Stroop task. Following the Stroop task, participants received a short break, after which they were administered the forward and backward digit span. Lastly, participants completed the WASI. Each testing session lasted approximately one hour.

4.4.2 Results

4.4.2.1 Category Learning Accuracy

The RB and II categorization performance of younger adults and older adults was calculated for each 80-trial block. The resulting RB and II learning curves are presented in Figure 4.4. A 2 (age group: older vs. younger) x 2 (category type: RB vs. II) x 4 (learning block) ANOVA was conducted. Results revealed a main effect of age group [$F(1, 115) = 52.85$, $p < .001$, partial $\eta^2 = .315$], category type [$F(1, 115) = 18.51$, $p < .001$, partial $\eta^2 = .139$] and block [$F(2.7, 306) = 37.14$, $p < .001$, partial $\eta^2 = .244$; Greenhouse-Geisser corrected]. The age group x block interaction [$F(2.7, 306) = 4.98$, $p = .003$, partial $\eta^2 = .042$; Greenhouse-Geisser corrected] and the category type x block interaction [$F(2.7, 306) = 9.56$, $p < .001$, partial $\eta^2 = .077$; Greenhouse-Geisser corrected] were significant. The age group x condition interaction [$F(1, 115) = 1.32$, $p = .253$] and the three-way interaction [$F(2.7, 306) = .49$, $p = .687$] were not significant. In order to further explore the effects of age within each category type of the category type x block interaction, we conducted two separate ANOVAs (one for the RB category set and one for the II category set).

A 2 (age group) x 4 (block) ANOVA was carried out on RB categorization performance and revealed a main effect of age group [$F(1, 58) = 27.07$, $p < .001$, partial $\eta^2 = .318$], suggesting better overall RB performance for the younger ($M = .78$) than the older ($M = .63$) adults. There was also a main effect of block [$F(2.6, 150) = 34.1$, $p < .001$, partial $\eta^2 = .370$; Greenhouse-Geisser corrected], indicating that participants learned across the study. The age group x block interaction was marginally significant [$F(2.6, 150) = 2.74$, $p = .054$, partial $\eta^2 = .045$; Greenhouse-Geisser corrected], suggesting the two groups differed slightly more later in learning compared with earlier in learning.

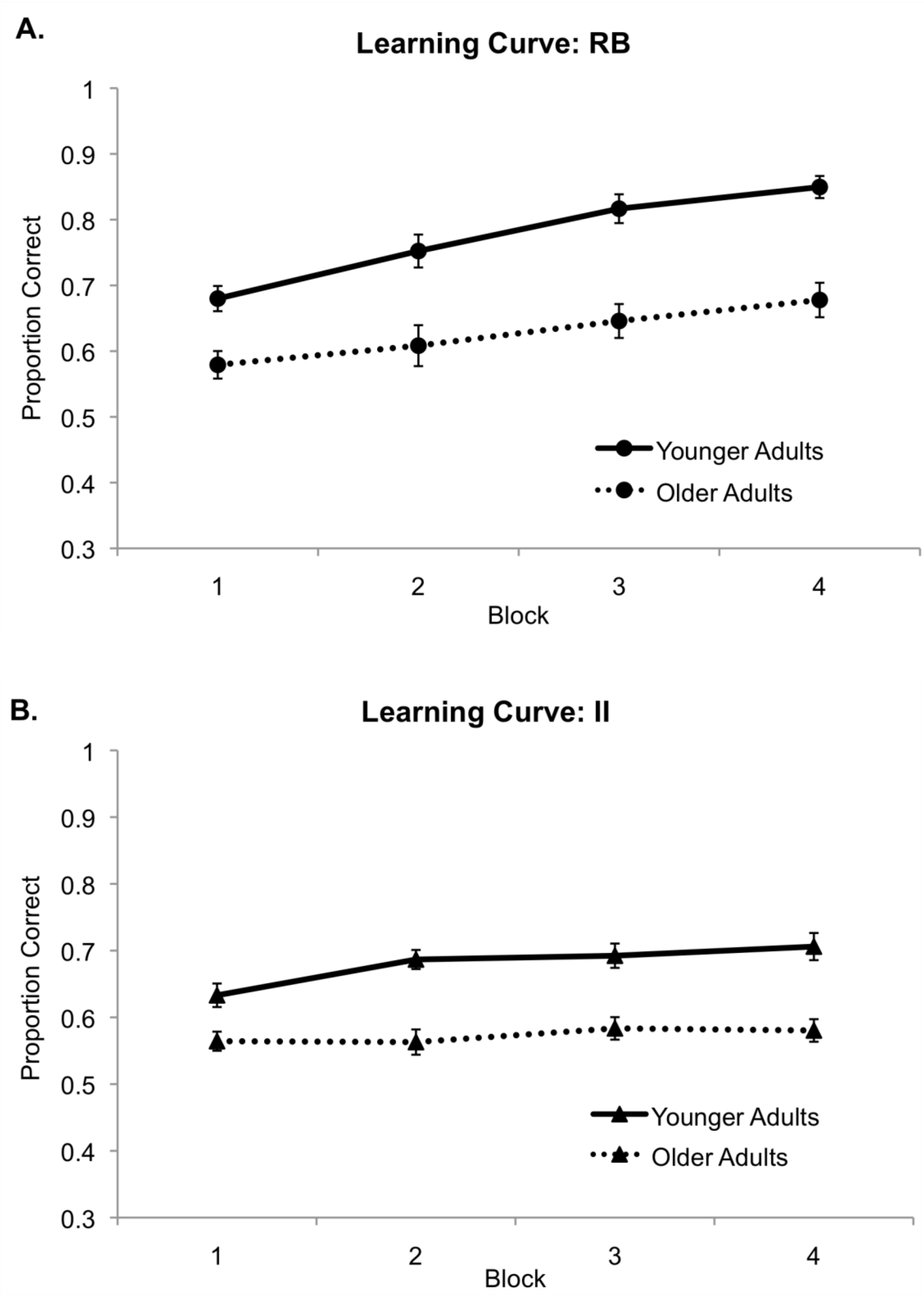

Figure 4.4: Categorization performance of younger adults and older adults across learning blocks in (A) the RB category set and (B) the II category set. Error bars denote the standard error of the mean.

A 2 (age group) x 4 (block) ANOVA was also carried out for II categorization performance and revealed a main effect of age group [$F(1, 57) = 27.45$, $p < .001$, partial $\eta^2 = .325$], suggesting better overall II performance for the younger ($M = .68$) than the older ($M = .57$) adults. There was also a main effect of block [$F(3, 171) = 6.26$, $p < .001$, partial $\eta^2 = .099$], indicating that participants learned across the study. The age group x block interaction was significant [$F(3, 171) = 2.76$, $p = .044$, partial $\eta^2 = .046$], suggesting the two groups differed to a larger extent later in learning compared with earlier in learning.

IQ scores were also examined to determine whether categorization performance was associated with performance on the WASI. Among older adults, IQ was not correlated with average categorization performance on the RB category set [$r = .28$, $p = .18$] and the II category set [$r = .26$, $p = .21$]. Similarly, among younger adults, IQ was not correlated with average categorization performance on the RB category set [$r = -.16$, $p = .38$] and the II category set [$r = .25$, $p = .18$]. In addition, the IQ scores of older adults ($M = 115$, $SD = 14.7$) did not significantly differ from the IQ scores of younger adults ($M = 113$, $SD = 10.4$), $t(111) = .88$, $p = .38$, suggesting that younger adults were not outperforming older adults because they had significantly higher IQ scores. The WASI was not administered to 5 older adults and 1 younger adult due to time limitations.

The age of older adults was also considered, and it was determined that age was not correlated with RB categorization performance [$r = .12$, $p = .54$] in older adults, but was marginally correlated with II categorization performance [$r = -.37$, $p = .052$].

4.4.2.2 Computational Modeling

The accuracy-based analyses of the categorization data suggested that older adults struggled relative to younger adults when learning both RB and II category sets. While accuracy data are a useful measure of overall categorization performance, it provides little information about the types of decisions strategies that participants use to learn the category set. Qualitatively different strategies can result in similar accuracy rates among participants. For example, applying a single-dimensional RB strategy can result in reasonable categorization performance when applied in the information integration category set (i.e., up to 70% correct), which is comparable to what might be seen by participants employing procedural-based II strategies. For these reasons, we fit a set of decision bound models to each block of each participant's data (for details see Ashby and Maddox, 1992; Maddox and Ashby, 1993; Miles et al., 2014; Rabi and Minda, 2014). These models work by comparing the actual response of the participant to the response they would have given had they used a specific type of strategy. The model is considered to fit the participant's data when the model's predicted response corresponds with the participant's categorization response.

Two specific RB models were applied to the data. The first is the single-dimensional frequency model, which assumes each participant's performance was based on a single-dimensional rule along the frequency dimension with a fixed intercept. The second is the single-dimensional orientation model, which assumes a single-dimensional rule along the orientation dimension with the intercept as a free parameter. A second class of models is consistent with the assumption that performance is based on the two-dimensional, information-integration boundary with a fixed intercept and slope. A third class of models is the random responder model ("guessing model"), which assumes that the participant guessed or applied different strategies across trials within a block. I fit two random responder models that assumed no dimensional strategy (one assumed that participants randomly responded *A* or *B* with equal probability for each response and the other assumed unequal probability). These models were fit to each subject's data by maximizing the log likelihood. Model comparisons were carried out with the AIC index, which penalizes a model for the number of free parameters (Ashby and Maddox, 1992). For every participant, at every block, the class with the best fitting strategy (i.e., the one with the lowest AIC value) was identified. For the RB category set, the single-dimensional frequency model was the optimal model and for the II category set, the two-dimensional II model was the optimal model.

The proportion of older adults and younger adults who were best fit by the optimal model for the category set that they learned is shown in Figure 4.5. Panel A shows that for both older adults and younger adults, RB category learning improved over time, evidenced by

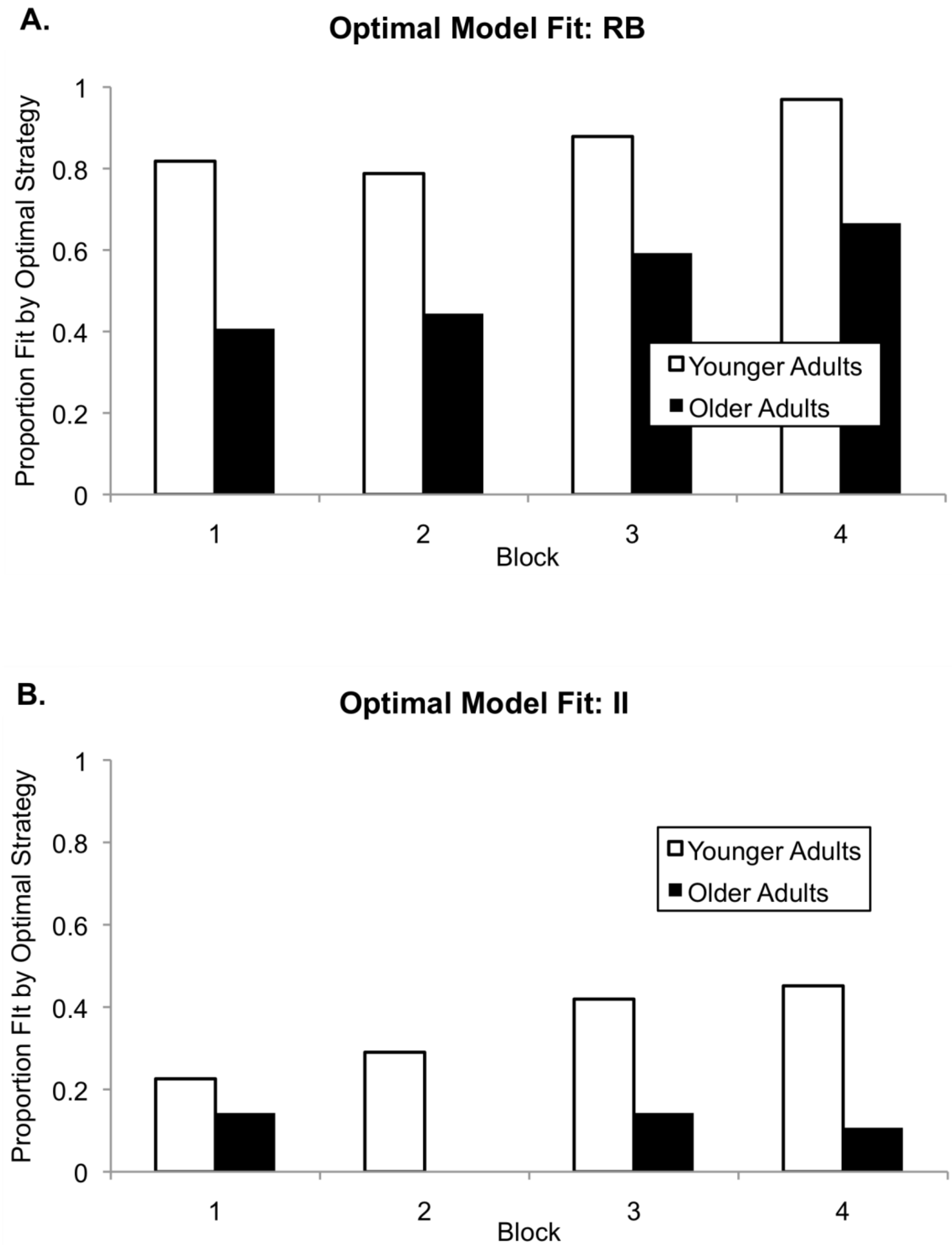

Figure 4.5: The proportion of participants, by block, whose data were fit by the optimal model. (A) shows data from participants who learned the RB category set and (B) shows the data from participants who learned the II category set.

an increase in the number of participants fit by the optimal RB model across learning blocks. However, a larger proportion of younger adults were using the optimal RB strategy compared to older adults. A χ^2 –test comparing the frequency of optimal RB strategy users with other strategy users during the final learning block, confirmed that younger adults were more likely to use the task appropriate strategy in the RB condition compared to older adults [$\chi^2(1) = 9.82$, $p = .002$]. Table 4.2 displays the proportion of participants best fit by each type of model, showing that by the final RB learning block, 33% of older adults were best fit by the guessing model (compared to only 3% of younger adults). Aside from not applying the correct strategy during the RB task, the overall categorization performance of older adults could also have been lower because they took longer to transition to the correct strategy compared to younger adults. For example, Table 4.2 shows that 11% of older adults were using a suboptimal rule based on orientation during block 3 but by block 4 no older adults relied on an orientation based strategy. Results supported this line of thought, showing that older adults ($M = 2.1$) applied the optimal RB strategy across significantly fewer blocks than younger adults ($M = 3.5$), $F(1, 58) = 17.46$, $p < .001$, partial $\eta^2 = .231$. Use of the correct strategy was associated with categorization performance, in that the number of blocks in which a participant used the optimal RB strategy significantly predicted final block categorization performance in both older adults [$R^2 = .535$, $F(1, 25) = 28.74$, $p < .001$] and younger adults [$R^2 = .388$, $F(1, 31) = 19.63$, $p < .001$].

For the II category set, Panel B shows that among younger adults, the proportion fit by the optimal II model increased over learning blocks, however very few older adults applied a procedural-based II strategy across blocks. A χ^2 –test comparing the frequency of optimal II strategy users with other strategy users during the final learning block, confirmed that younger adults were more likely to use the task appropriate strategy in the II condition compared to older adults [$\chi^2(1) = 8.51$, $p = .004$]. As shown in Table 4.2, aside from using the optimal II strategy (45%), a subset of younger adults also used a RB frequency strategy (39%), as well as guessing (16%) during the final learning block. In comparison, only 11% of older adults applied an II strategy when learning the II category set. The large majority of older adults adopted a rule based on frequency during II

Table 4.2: Number of participants fit by each class of decision bound models.

	Model							
Category	**Frequency**		**Orientation**		**II**		**Random**	
	OA	**YA**	**OA**	**YA**	**OA**	**YA**	**OA**	**YA**
RB								
Block 1	**0.41**	**0.82**	0.00	0.00	0.00	0.00	0.59	0.18
Block 2	**0.44**	**0.79**	0.04	0.00	0.00	0.03	0.52	0.18
Block 3	**0.59**	**0.88**	0.11	0.00	0.00	0.03	0.30	0.09
Block 4	**0.67**	**0.97**	0.00	0.00	0.00	0.00	0.33	0.03
II								
Block 1	0.43	0.58	0.04	0.03	**0.14**	**0.23**	0.39	0.16
Block 2	0.64	0.55	0.04	0.06	**0.00**	**0.29**	0.32	0.10
Block 3	0.54	0.45	0.04	0.03	**0.14**	**0.42**	0.28	0.10
Block 4	0.61	0.39	0.03	0.00	**0.11**	**0.45**	0.25	0.16

Note. Random refers to a model based on guessing. The optimal model is shown in bold.

learning (61% by block 4), with the remaining older adults applying a suboptimal rule based on orientation (3%) or guessing (25%) during the final learning block. Not surprisingly based on the findings reported in Table 4.2, older adults (M = .40) applied the optimal II strategy across significantly fewer blocks than younger adults (M = 1.4), $F(1, 57) = 10.62$, $p = .002$, partial $\eta^2 = .157$. Given that procedural-based II category learning generally takes longer to master compared to RB learning (i.e., transitioning from the default explicit RB system to the implicit system), it seems reasonable that fewer participants were fit by the optimal model during II category learning compared to RB learning. Interestingly, use of the correct strategy was associated with the categorization performance of younger adults but not older adults. That is, the number of blocks in which a participant used the optimal II strategy significantly predicted final block categorization performance in younger adults [R^2 = .450, F(1, 29) = 23.70, p < .001] but not older adults [R^2 = .00, F(1, 26) = .003, p = .96]. However, frequent use of a RB strategy across blocks was predictive of final block performance on the II task in older adults [R^2 = .451, F(1, 26) = 21.32, p < .001].

4.4.2.3 Categorization accuracy among task appropriate strategy users

To examine whether older adults' general accuracy deficit in average categorization performance resulted form using a non-task appropriate strategy, I examined average categorization performance only for older adults and younger adults who adopted the task appropriate strategy in the final block. In the RB task, for those individuals using the task appropriate strategy, the average categorization performance of older adults (M = .68) still significantly differed from that of younger adults (M = .78) [t(48) = 3.61, p = .001], suggesting that older adults were applying the RB strategy less consistently than younger adults. To confirm this prediction, the AIC model fit values of older adults and younger adults who used the task appropriate strategy in the RB category set were compared. The smaller the fit, the better the rule describes the data. A t-test comparing the RB model fit value of older adult and younger adult learners was significant [t(48) = 5.13, p > .001], confirming that older adults were less consistent in the application of their RB strategy.

In the II category learning task, for those individuals using the task appropriate strategy, the average categorization performance of older adults (M = .60) significantly differed from that of younger adults (M = .74) [t(15) = 4.40, p = .001][16]. However, given that only 3 older adults applied an II strategy when learning the II category set (the majority

[16] For both the RB task and the II task, results were equally significant when final block categorization performance was examined rather than average categorization performance.

applied a RB strategy), this small sample of older adults using the appropriate strategy precluded us from drawing strong conclusions.

4.4.2.4 Executive Functioning

To examine the relationship between RB and II category learning and executive functioning, average categorization performance was correlated with the various executive functioning measures in older and younger adults (see Tables 4.3 and 4.4)[17]. Among older adults, RB performance was correlated with the number of categories completed in the BCST and marginally correlated with backward digit span. When controlling for the age of older adults, RB performance remained significantly correlated with BCST [r = .48, p = .02] but was no longer correlated with BDS [r = .28, p = .20]. The RB performance of younger adults was not correlated with any of the executive functioning measures. Among older adults, II performance was marginally correlated with backward digit span[18]. After controlling for age, since as mentioned earlier II performance was marginally correlated with the age of older adults, II performance was significantly correlated with backward digit span [r = .41, p = .038]. The II performance of younger adults was correlated with the number of categories completed in the BCST. These findings suggest that working memory and task switching may be important for both RB and II category learning.

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[17] The scores of some participants were not included in the analyses because the task was not completed due to time limitations, computer error, or because the participant made too many errors on the task indicating a lack of understanding (this was in reference to the inhibition tasks where participants made errors on more than 50% of the incongruent trials and on the BCST where participants learned 0 categories). Flanker data was missing from 3 older adults and 3 younger adults. Stroop data was missing from 6 older adults. Simon data was missing from 1 older adult. Alpha span data was missing from 2 older adults and 15 younger adults. BCST data was missing from 7 older adults.

[18] Accuracy data was also considered for the inhibition measures (i.e., number of errors on incongruent trials). The II performance of older adults was found to correlate with accuracy on the Simon task [r = -.39, p = .047]. That is, better II performance was associated with fewer errors on incongruent trials in the Simon task. However, after controlling for the age of older adults, this relationship was no longer significant [r = -.28, p = .16] No other accuracy data correlated with the categorization performance of older and younger adults.

Table 4.3: Intercorrelations among the study variables for older adults.

	RB	II
Forward Digit Span	.337	-.051
Backward Digit Span	.347†	.354†
Alpha Span	.231	.237
Flanker Difference Score	-.041	.054
Simon Difference Score	.159	-.038
Stroop Difference Score	-.044	.100
BCST Categories Completed	.462*	.150
BCST Perseveration Errors	-.233	-.282

Note. Executive functioning measures were correlated with average categorization performance. Two-tailed t-tests: * $p < .05$, †$p < .075$.

Table 4.4: Intercorrelations among the study variables for younger adults.

	RB	II
Forward Digit Span	.184	-.144
Backward Digit Span	.022	.237
Alpha Span	.059	.022
Flanker Difference Score	.129	-.036
Simon Difference Score	-.082	-.188
Stroop Difference Score	-.018	-.120
BCST Categories Completed	-.070	.366*
BCST Perseveration Errors	.003	-.058

Note. Executive functioning measures were correlated with average categorization performance. Two-tailed t-tests: * $p < .05$.

In addition to accuracy data, I was also interested in the relationship between strategy use and executive functioning. I compared the executive functioning performance of participants using task appropriate and inappropriate strategies. It is noteworthy that for both the RB task [$t(25) = .29$, $p = .78$] and the II task [$t(26) = .29$, $p = .77$], age did not differ as a function of strategy among older adult participants. For the RB task, forward digit span [$t(25) = 2.0$, $p = .05$], backward digit span [$t(25) = 2.3$, $p = .03$], and BCST [$t(21) = 3.6$, $p = .002$] performance (number of categories completed) was significantly better among older adults using the task appropriate RB strategy compared to older adults using a task inappropriate strategy (appropriate vs. inappropriate strategy: forward digit span [$M = 18.9$ vs. $M = 16.4$], backward digit span [$M = 10.8$ vs. $M = 8.0$], and BCST categories completed [$M = 3.4$ vs. $M = 1.7$]). No other comparisons were significant (all p values > .20) for older adults in the RB condition. I did not compare executive functioning performance and strategy use among younger adults in the RB condition, because only one younger adult used a task inappropriate strategy during the final RB learning block. As well, I did not compare executive functioning performance and strategy use among older adults in the II condition, because only three older adults used the optimal II strategy. Among younger adults in the II condition, Flanker task accuracy [$t(29) = 1.9$, $p = .066$] and BCST performance (number of perseveration errors) [$t(29) = 1.7$, $p = .09$] was marginally better among younger adults using the task appropriate strategy (appropriate vs. inappropriate strategy: Flanker errors on incongruent trials [$M = 1.0$ vs. $M = 2.3$] and BCST perseveration errors [$M = 5.9$ vs. $M = 6.9$]). No other comparisons were significant (all p values > .19).

4.4.3 Discussion

Study 1 compared the ability of older adults and younger adults to learn RB and NRB categories. In line with my predictions, younger adults performed significantly better than older adults on both the RB and NRB category learning task. IQ was not responsible for RB and NRB performance differences between age groups and within age groups, ruling out the possibility that IQ was influencing category learning abilities. When the age of older adults was considered, age did not correlate with the RB performance of older adults and was marginally correlated with NRB performance, suggesting that among older adults, getting older may be associated with declines in the functioning of the nonverbal system.

In the present study, model-based analyses were used to better understand the RB and NRB category learning deficits seen among older adults. Younger adults were more likely to use the task appropriate strategy in the RB condition compared to older adults. Results revealed that random responding (i.e., guessing) accounted for older adult’s poorer performance. This finding is comparable to that of Bharani et al. (2016) who also found that a subset of older adults performed below 60% accuracy on the RB task. While a subset of older adults in the present study were best fit by guessing models during the final block of the RB task, I suspect that this was because older adults were frequently switching rules during the task, rather than because they were randomly responding. Applying the incorrect, but more salient rule based on the orientation of the lines in the Gaussian blur, would result in frequent negative feedback. In line with this theory, when describing their strategy at the end of the task, a large majority of older adults reported starting with the orientation of the lines, but switched after receiving feedback. As a result, it seems likely that older adults kept switching rules to avoid negative feedback, but never arrived at the correct rule. Bharani and colleagues (2016) also suggested that what might have appeared as random responding among the low-performing older adults, may actually have been a result of frequent strategy shifts. Aside from not applying the task appropriate strategy during the RB task, analyses suggest that older adults struggled with the task because they took longer to transition to the correct strategy compared to younger adults. Older adults applied the task appropriate RB strategy across significantly fewer blocks compared to younger adults. Furthermore, it took older adults longer to complete the hypothesis testing process relative to younger adults.

For the NRB category set, again younger adults were more likely to use the task appropriate strategy compared to older adults. The large majority (64% by the final learning block) of older adults adopted a RB strategy during II learning. Additionally, older adults applied the optimal NRB strategy on fewer blocks than younger adults. Model-based analyses confirmed that for younger adults, frequent use of the NRB strategy predicted better categorization performance. In contrast, for older adults, frequent use of a RB strategy was significantly associated with categorization accuracy. Interestingly, while older adults struggled to identify the task appropriate NRB strategy, they managed to identify and consistently apply a RB strategy, even though it was a less effective strategy. Maddox et al. (2010) also established that younger adults showed a performance advantage relative to older adults on the NRB task. Conversely, Maddox et al. found that both age groups relied on the appropriate NRB strategy, but that older adults may have been less consistent in their strategy use which runs counter to the present findings that older adults relied on RB strategies more frequently in the NRB category set. However, the present research is in line with earlier research by Huang-Pollock and colleagues (2011), who showed that children relied on RB strategies during a NRB categorization task. Given the parallels between children and older adults (both age groups show reduced executive function abilities relative to younger adults; Carver, Livesey, & Charles, 2001; Craik & Bialystok, 2006; Dempster, 1992; Gathercole, Pickering, Ambridge, & Wearing, 2004), this finding may suggest that executive functioning plays an important role in category learning.

The categorization performance of older adults and younger adults who adopted the task appropriate RB strategy in the final learning block was also examined. The categorization performance of older adults still significantly differed from younger adults, suggesting that older adults were applying the RB strategy less consistently than younger adults. Model fit values confirmed that older adults were less consistent in the application of the task appropriate RB strategy compared to younger adults. These findings suggest that older adults struggle with single-dimensional RB learning, and even when they do apply the appropriate RB strategy, they struggle to apply it consistently. In the NRB task, among those using the task appropriate strategy, the categorization performance of older adults also significantly differed from younger adults. However, very few older adults relied on a NRB strategy in the NRB task, limiting the conclusions that can be drawn.

The executive function abilities of older adults and younger adults were considered. When controlling for the age of older adults, the RB performance of older adults was correlated with BCST performance. To further explore the relationship between RB category learning and executive functioning in older adults, I compared the executive functioning performance of older adults using task appropriate and inappropriate strategies. Age did not differ as a function of strategy use among older adults, indicating that appropriate RB strategy use was not driven by the age of the older adult participant. Results revealed that forward digit span, backward digit span and BCST performance was significantly better among older adults using the task appropriate RB strategy compared to older adults using a task inappropriate strategy. These findings imply that executive function abilities (specifically set-shifting and working memory) are important when learning RB categories in older adults, which is in line with the COVIS theory of category learning (Filoteo, Lauritzen, & Maddox, 2010; Nomura & Reber, 2008). The RB performance of younger adults was not correlated with any of the executive functioning measures. Younger adults performed very well on the RB task with nearly everyone adopting the correct RB strategy. Given their high categorization accuracy and well-developed executive function abilities, it is not surprising that categorization performance did not correlate with executive function measures in younger adults.

For the NRB category set, after controlling the age of older adults, NRB performance was significantly correlated with backward digit span, suggesting that stronger working memory abilities are associated with better NRB performance. Given that a large subset of older adults relied on a RB strategy in the NRB category set, this finding may imply that working memory is needed to apply a RB strategy in the NRB category set. To few older adults utilized a NRB strategy to compare task appropriate vs. inappropriate strategy use in the NRB task. The NRB task is considered more difficult to learn and is also thought to require more time to learn. For this reason, there was more variability in the NRB performance of younger adults. The NRB performance of younger adults was correlated with BCST performance, which is consistent with prior literature (e.g., Maddox et al., 2010) and suggests that set-shifting abilities are important from shifting from the verbal to nonverbal system. When strategy use was taken into account, Flanker and BCST performance were marginally better among younger adults using the task appropriate strategy compared to younger adults using the task inappropriate strategy. This again suggests that set-shifting and possibly inhibitory control may be important for inhibiting the dominant verbal system, and switching to the nonverbal system.

4.5 Study 2

Study 1 demonstrated that younger adults outperformed older adults on both the RB and NRB category sets. Since executive functions are known to play a key role in learning RB categories, I was particularly interested in examining whether pre-training would reduce RB category learning deficits in older adults. While executive functioning has also been linked to NRB learning, it has more so been associated with the transition between systems (verbal to nonverbal) and does not seem to be strongly associated with the actual learning of implicit, NRB categories. The average categorization performance of older adults in Study 1 was 63%, compared to 78% in younger adults, with a number of older adults relying on guessing strategies (which may reflect constant rule switching which resembles “guessing-like” performance). For this reason, the focus of Study 2 was on improving the performance of older adults on the complex single-dimensional RB category set through a pre-training procedure aimed at reducing executive function task demands. In Study 2, pre-training involved two phases. Participants viewed sample Gabor patches presented in pairs, taken from the category set. They were asked to verbally describe each of the Gabor patches. The second phase of pre-training involved asking participants to complete a small set of trials from an easier version of the RB categorization task. During these 20 trials the Gabor patches were presented in the same manner as in Study 1 (i.e., you see the Gabor patch, make a response, and receive feedback). The only difference being that Category A and B stimuli sat farther away from the optimal decision boundary (the frequency rule). Furthermore, variation in the frequency dimension was a little easier to detect. Next, participants completed the complex single-dimensional RB category set presented in Study 1. By familiarizing participants with the stimuli prior to categorization, as well as presenting them with easier category exemplars before moving to more difficult category exemplars, it was expected that older adults would perform better on the complex RB categorization task. This is because, providing pre-training should reduce the executive function demands of the task. By verbally describing the stimuli, participants should become familiar with the fact that the Gabor patches vary along two dimensions: frequency and orientation. This would in turn, allow participants to inhibit the incorrect but more salient rule more easily, and update this information in their working memory. Likewise, by having participants categorize the easier category exemplars first, this should allow them to rule out different hypothesis testing strategies more easily.

While prior studies have examined RB category learning in older adults, the pre-train study described in Chapter 3, is the only other study to examine methods for improving RB categorization performance in older adults. The Chapter 3 study looked at the impact of pre-training on both multi-dimensional RB and NRB category learning. The present study will not only confirm the effects of pre-training on the RB categorization performance of older adults, but will also extend my Chapter 3 findings by examining a new category set (i.e., single-dimensional RB category set) and provide information regarding the types of categorization strategies used by both older adults and younger adults following pre-training. Yes the RB categorization performance of older adults may improve following pre-training, but it is often difficult to differentiate whether this change in performance is due to a change in strategy type or due to more consistent use of the appropriate strategy. Computational modeling of strategy use will help tease apart which factor is influencing categorization performance. To provide further insights into individual differences in RB categorization performance among older adults, performance on a series of executive function measures was also examined. With regards to this relationship, two possibilities exist. Among older adults, those with stronger executive functioning abilities would benefit more so from pre-training allowing them to formulate and apply the rule more quickly. Conversely, older adults may benefit from pre-training regardless of executive functioning, suggesting that pre-training reduced categorization task demands enough so that participants could perform well on the task regardless of execution functioning abilities.

4.5.1 Method

4.5.1.1 Participants

Participants included 31 younger adults (*M* = 18.6 years, *SD* = 0.85; 18 males & 13 females) from the University of Western Ontario who participated for course credit and 26 older adults between the ages of 63 and 88 (*M* = 72.6 years, *SD* = 7.03; 9 males & 17 females)[19]. Among the older adults there were 12 in their 60s, 9 in their 70s, and 5 in their 80s. Older adults were recruited from senior community centres, senior exercise groups and from the University of Western Ontario alumni lecture series. Older adults received $20 for participating in the study. Participants were pre-screened to ensure that they were fluent in English, they were in good health, and had normal or corrected-to-normal vision and hearing. Participants were excluded from the study if they indicated that they had a history of neurological disorders, psychiatric illness, substance abuse, a cerebral vascular event, head trauma, and/or any other neurological conditions. All participants included in the study had at least 20/30 corrected vision (0.18 logMAR equivalent) as determined by the Freiburg Visual Acuity and Contrast Test (FrACT; Bach, 2007). The education level of younger adults (M = 12.3 years, SD = 0.74) was significantly lower ($t(26.7) = 4.47$, $p < .001$)[20] than that of older adults (M = 14.9 years, SD = 2.8) because my younger adult sample were still in university so their years of education is not likely to reflect their final education level.

4.5.1.2 Materials

The category learning task and executive functioning measures were identical to what was used in Study 1.

4.5.1.3 Procedure

Session 1

Participants were tested individually across two testing sessions, approximately one week apart. Younger adults were tested in the Categorization Lab at the University of Western Ontario. Older adults were tested in the Categorization Lab at the University of Western Ontario or in a quiet room in the senior centre. Participants first completed the FrACT

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[19] Of the 31 younger adults, 26 subjects also participated in the Chapter 3 study and 5 subjects were newly recruited. Of the 26 older adults, 25 subjects also participated in the Chapter 3 study and 1 subject was newly recruited to keep the sample size of the conditions relatively equal.

[20] Data regarding education level was not collected from 1 older adult.

vision test so that an objective measure of visual acuity could be obtained in addition to the participant's subjective report of their vision.

Next participants completed the RB category learning task. Prior to the categorization task, participants received pre-training in an effort to minimize task demands and familiarize participants with the stimulus dimensions. At the beginning of pre-training, participants were shown eight crystal ball sine-wave gratings with varying frequency and orientation. The eight crystal ball stimuli were presented in pairs of two (side by side), to encourage participants to compare sine-wave gratings with each other (see Figure 4.6). Participants were instructed to describe each of the crystal balls aloud. The eight crystal ball stimuli were chosen to have a range of frequency and orientation values. Following the description stage of pre-training, participants began the RB categorization task. The categorization task was similar to Study 1 except that twenty crystal ball images were presented before the standard 320 trials, which were considered easier to categorize (i.e., members of category A and B were more easy to distinguish from one another) than the remaining 320 trials. Initial training with easier stimuli should facilitate RB learning, by reducing the likelihood that older adults will rely on salient but irrelevant rules (i.e., a rule based on the orientation of the lines). The logic for starting with easier trials was based on prior research showing that best way to learn a difficult cognitive task is to

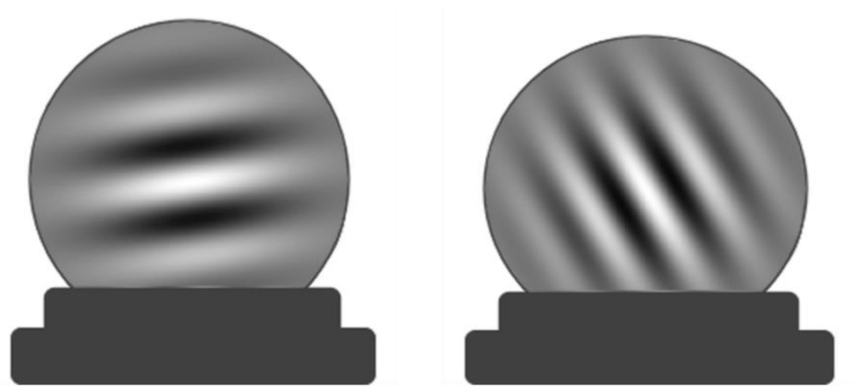

Figure 4.6: Sample crystal ball sine wave gratings seen by participants during the pre-training stage of the category learning task.

begin with easy examples, and then transition to more difficult examples (Squires, Hunkin, & Parkin, 1997; Wilson, Baddeley, Evans, & Shiel, 1994; Ahissar & Hochstein, 1997). The category structure and distribution parameters for the easier rule-based category set are presented in Figure 4.7 and Table 4.5. The frequency parameter was altered so that Category A and B stimuli were slightly more distinct from each other along the frequency dimension (i.e., the varying frequency of the lines were more apparent). As well, variation along the orientation dimension was decreased, so that the orientation dimension was slightly less salient. Eighty stimuli were created using the same protocol as described in Study 1, and 20 stimuli were randomly sampled to be used during the beginning 20 trials of the category learning task.

Following the category learning task, participants received a short break, after which they completed the BCST and the alpha span task.

Session 2

Participants completed either the Type II or Type IV Shepard, Hovland, and Jenkins category set (this data were collected for the study in Chapter 3 which was not part of the current study). Following completion of Type II or Type IV category set, participants completed the Flanker task, Simon task, and Stroop task. Following the Stroop task, participants received a short break, after which they were administered the forward and backward digit span. Lastly, participants completed the WASI. Each testing session lasted approximately one hour.

4.5.2 Results

4.5.2.1 Category Learning Accuracy

Given that declines in executive functioning are associated with normal aging, I expected that following pre-training, younger adults would still outperform older adults on the RB task even though task demands were reduced. For this reason, I was primarily interested in examining how pre-training performance compared to control performance among older adults and younger adults separately. The learning curves are presented in Figure

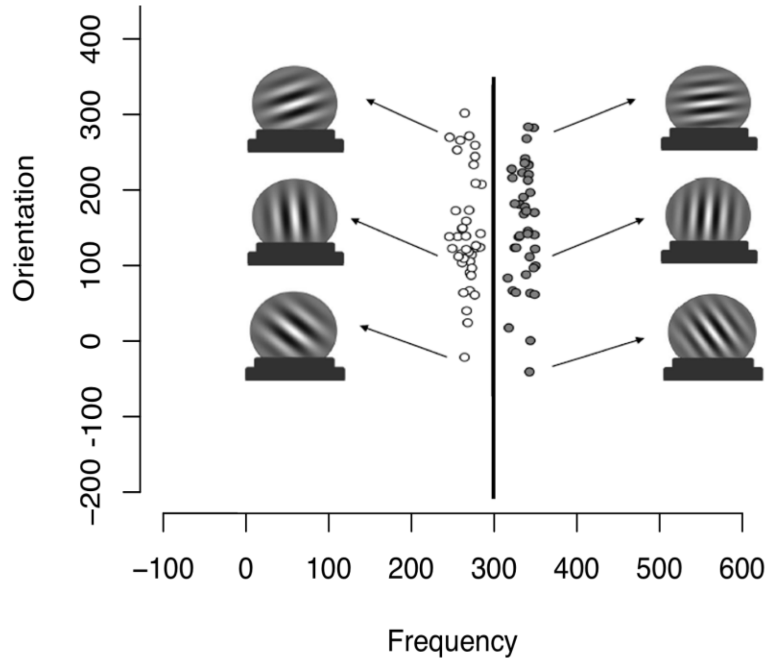

Figure 4.7: The easy rule-based category structure. Twenty stimuli were randomly sampled and presented to participants at the start of the category learning task. The vertical line separating Category A and Category B represents the strategy that maximizes categorization accuracy. Points on the left are members of Category A and points on the right are members of Category B.

Table 4.5: Distribution parameters for categorization stimuli used during the first 20 trials.

Category Structure	μ_f	μ_o	σ^2_f	σ^2_o	$cov_{f,o}$
Cat. A	270	125	75	5,000	0
Cat. B	330	125	75	5,000	0

Note. Dimensions are in arbitrary units; see the materials section for a description of the scaling factors. The subscripted letters *o* and *f* refer to orientation and frequency, respectively.

4.8. RB pre-training data were compared with RB control data (this data were taken from Study 1) by carrying out a 2 (condition: pre-train vs. control) x 4 (block) ANOVA for each age group. Among older adults, there was a main effect of condition; participants in the pre-train condition (M = 0.70) performed significantly better than those in the control condition (M = 0.63) [F(1, 51) = 4.76, p = .03, partial η^2 = .085]. A main effect of block was also found, indicating that categorization accuracy improved over time, [F(2.5, 129) = 14.28, p < .001, partial η^2 = .219; Greenhouse-Geisser corrected]. The group x block interaction was not significant [F(2.5, 129) = 0.24, p = .84, partial η^2 = .005; Greenhouse-Geisser corrected], indicating that older adults in both conditions demonstrated learning across trials. It should be noted that among older adults, age was correlated with average categorization performance on the RB pre-train task [r = -.56, p =.003], indicating that performance declines were associated with being older.

A 2 (condition: pre-train vs. control) x 4 (block) ANOVA was carried out for younger adults. There was a main effect of condition [F(1, 61) = 5.47, p = .02, partial η^2 = .082], indicating that participants in the pre-train condition (M = 0.82) performed significantly better than those in the control condition (M = 0.77). A main effect of block was also found, [F(2.2, 136) = 43.41, p < .001, partial η^2 = .416; Greenhouse-Geisser corrected], indicating that learning occurred across blocks. Lastly, the block x condition interaction was significant [F(2.2, 136) = 4.19, p = .014, partial η^2 = .064; Greenhouse-Geisser corrected]. Bonferroni post-hoc comparisons indicated that younger adults in the pre-training condition performed significantly better than younger adults controls on blocks 1 ($M_{pre\text{-}train}$ = .76, $M_{control}$ = .68; p = .007) and block 2 ($M_{pre\text{-}train}$ = .83, $M_{control}$ = .75, p = .007) but not during blocks 3 ($M_{pre\text{-}train}$ = .84, $M_{control}$ = .81, p = .32) and 4 ($M_{pre\text{-}train}$ = .86, $M_{control}$ = .85, p = .57). These findings suggest that pre-training effects emerged early on, helping younger adults to discover and apply the rule more successfully than those participants in the control condition. IQ was correlated with the average RB pre-train performance of older adults [r = .47, p = .02]. IQ was not correlated with the average RB pre-train performance of younger adults [r = .22, p = .26]. Additionally, older adults (M = 116, SD = 14.3) had a significantly higher IQ score compared to younger adults (M = 107, SD = 11.5), t(50) = 2.51, p = .012, confirming that younger adults were not

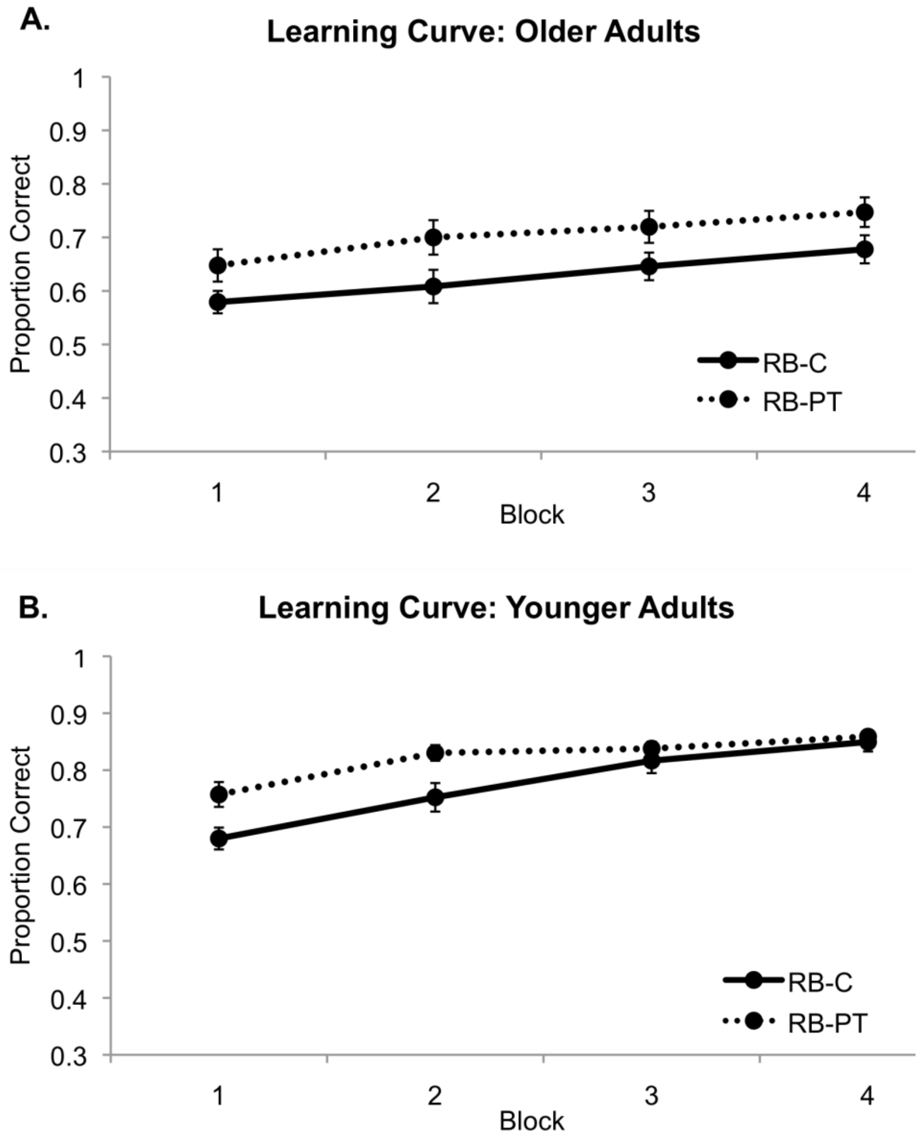

Figure 4.8: Average proportion of correct responses to stimuli in the pre-train and control condition as a function of trial block among (A) older adults and (B) younger adults. Error bars denote standard error of the mean.

outperforming older adults because of differences in IQ. The WASI was not administered to 3 older adults and 2 younger adults due to time limitations.

4.5.2.2 Computational Modeling

For insight into the response strategies used by older and younger adults, I fit decision bound models to each block of each participant's data (for details please see Study 1). The proportion of older adults and younger adults who were best fit by the optimal model for the category set that they learned is shown in Figure 4.9. Panel A and B shows that the proportion of participants fit by the optimal RB model increased over time for both older adults and younger adults. A χ^2 –test comparing the frequency of optimal RB strategy users with other strategy users during the final learning block was conducted. Among older adults, the proportion fit by the task appropriate strategy was not significantly higher among pre-trained participants compared to control participants [$\chi^2(1) = 1.36$, $p = .24$], suggesting that performance differences were a result of strategy consistency rather than appropriate strategy use. AIC model fit values of older adults who used the task appropriate strategy in the control and pre-train conditions were examined. Older adults in the pre-train condition had significantly better model fit values than older adults in the control condition [$t(37) = 2.02$, $p = .05$], suggesting that those in the pre-train condition applied the RB strategy more consistently. Nearly all of the younger adults were fit by the task appropriate strategy by the final learning block (97% of control participants and 100% of pre-trained participants). Tables 4.6 and 4.7 displays the proportion of older adults and younger adults best fit by each type of model. Table 4.6 shows that 4% of older adults in block 2 and 11% of OAs in block 3 relied on the suboptimal orientation RB strategy, whereas no older adults in the pre-training condition relied on the suboptimal orientation strategy. In comparison, the majority of younger adults in both conditions adopted the correct RB strategy, with no younger adults relying on the suboptimal orientation strategy (see Table 4.7).

Use of the correct strategy was associated with categorization performance in the pre-train condition, in that the number of blocks in which a participant used the optimal RB strategy significantly predicted final block categorization performance in older adults [R^2

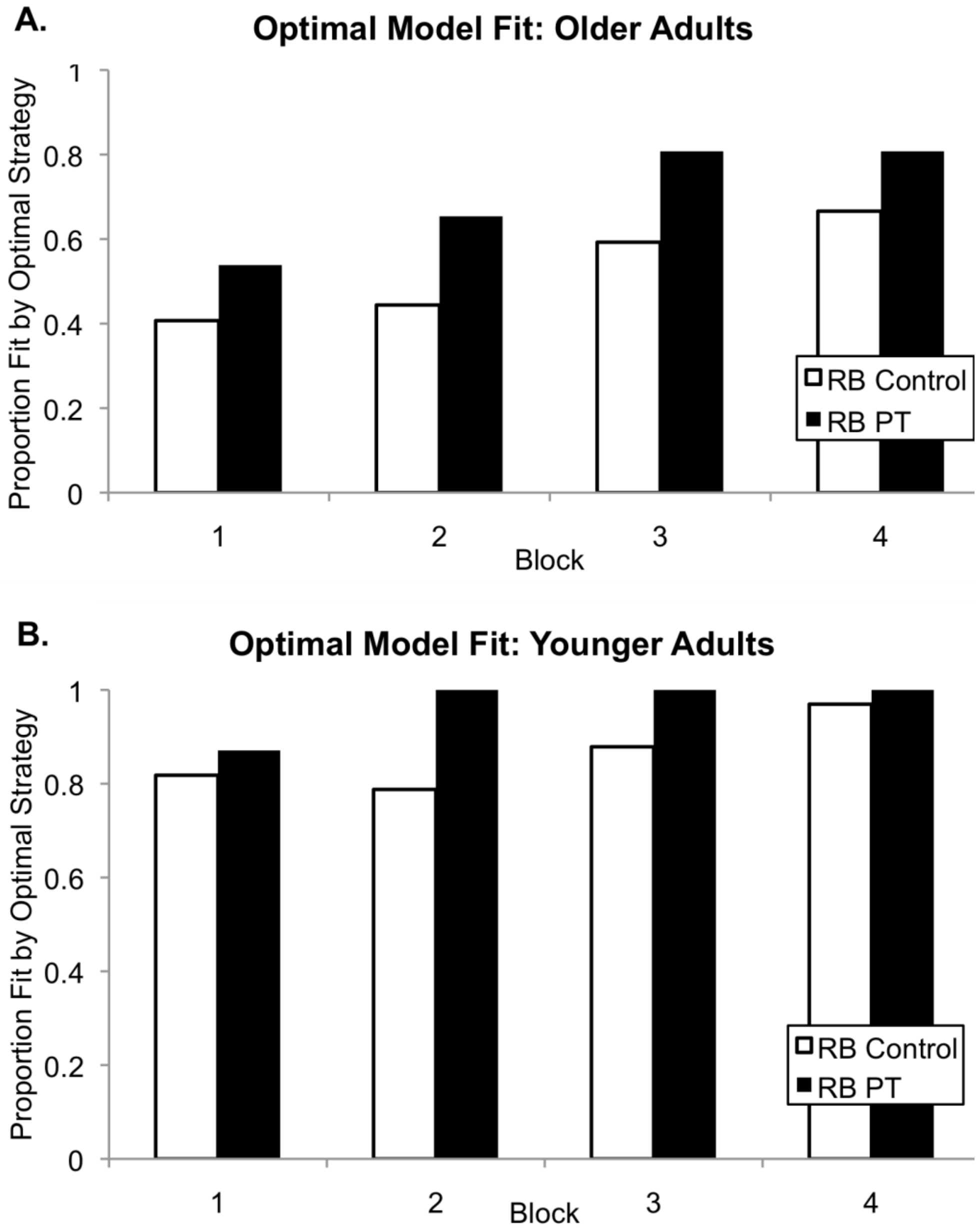

Figure 4.9: The proportion of participants, by block, whose data were fit by the optimal model. (A) shows data from older adults and (B) shows the data from younger adults.

Table 4.6: Number of older adults fit by each class of decision bound models

	Model							
Category	Frequency		Orientation		II		Random	
	C	PT	C	PT	C	PT	C	PT
RB								
Block 1	**0.41**	**0.54**	0.00	0.00	0.00	0.08	0.59	0.38
Block 2	**0.44**	**0.65**	0.04	0.00	0.00	0.04	0.52	0.31
Block 3	**0.59**	**0.81**	0.11	0.00	0.00	0.00	0.30	0.19
Block 4	**0.67**	**0.81**	0.00	0.00	0.00	0.00	0.33	0.19

Note. Random refers to a model based on guessing. The optimal model is shown in bold.

Table 4.7: Number of younger adults fit by each class of decision bound models

	Model							
Category	Frequency		Orientation		II		Random	
	C	PT	C	PT	C	PT	C	PT
RB								
Block 1	**0.82**	**0.87**	0.00	0.00	0.00	0.00	0.18	0.13
Block 2	**0.79**	**1.00**	0.00	0.00	0.03	0.00	0.18	0.00
Block 3	**0.88**	**1.00**	0.00	0.00	0.03	0.00	0.09	0.00
Block 4	**0.97**	**1.00**	0.00	0.00	0.00	0.00	0.03	0.00

Note. Random refers to a model based on guessing. The optimal model is shown in bold.

= .682, $F(1, 24) = 51.55$, $p < .001$]. The number of blocks in which a participant used the optimal RB strategy did not predict final block categorization performance in younger adults [$R^2 = .001$, $F(1, 29) = .015$, $p = .90$]. However this was likely due to the fact that the large majority (87%) of younger adults applied the appropriate strategy across all 4 blocks, with the remaining participants applying the appropriate strategy across all 3 blocks.

To determine whether categorization performance in the two conditions differed among appropriate strategy users only, I examined average categorization performance only for older adults who adopted the task appropriate strategy in the pre-train and control conditions. Results revealed that for older adults using the task appropriate strategy, average categorization performance in the pre-train condition ($M = .74$) was marginally better than the performance of older adults in the control condition ($M = .68$) [$t(37) = 1.85$, $p = .07$], suggesting that pre-training helped older adult learners better apply the categorization rule compared to learners in the control condition. This analysis was not conducted for younger adults, since nearly all younger adults used the task appropriate strategy during the final block.

4.5.2.3 Executive Functioning

In order to better understand RB pre-train performance, average categorization accuracy was correlated with the executive functioning performance of older adults and younger adults[21]. The intercorrelations between RB performance and executive function scores are presented in Table 4.8. Among older adults, RB pre-train performance was marginally correlated with alpha span [$r = .39$, $p = .057$]. However, after controlling for the age and IQ of older adults, the relationship between RB pre-train performance and alpha span was no longer significant [$r = .26$, $p = .26$]. No other executive function

[21] The scores of some participants were not included in the analyses because the task was not completed due to time limitations, computer error, or because the participant made too many errors on the task indicating a lack of understanding (this was in reference to the inhibition tasks where participants made errors on more than 50% of the incongruent trials and on the BCST where participants learned 0 categories). Flanker data was missing from 2 older adults. Stroop data was missing from 1 older adult and 1 younger adult. Digit span data was missing from 2 younger adults. Alpha span data was missing from 1 older adult. BCST data was missing from 3 older adults.

Table 4.8: Intercorrelations between rule-based pre-train performance and executive functioning scores for older adults and younger adults.

	OA	YA
Forward Digit Span	.318	.245
Backward Digit Span	.217	-.009
Alpha Span	.386†	.089
Flanker Difference Score	-.192	-.191
Simon Difference Score	-.245	-.194
Stroop Difference Score	-.182	.102
BCST Categories Completed	.123	.159
BCST Perseveration Errors	.188	-.286

Note. Executive functioning measures were correlated with average categorization performance. Two-tailed t-tests: †$p < .06$.

measures correlated with the RB pre-train performance of older adults, suggesting the possibility that pre-training may reduce task demands enough so that older adults can perform well on the task, regardless of executive function abilities. Among younger adults, executive function measures did not correlate with RB pre-train performance. When accuracy on the inhibition tasks was considered (rather than reaction time differences), no additional measures correlated with categorization performance in older adults, however, accuracy on the Flanker task (the number of errors made on incongruent trials) was correlated with RB pre-train performance in younger adults [$r = -.40$, p = .02]. That is, higher RB pre-train performance was associated with making fewer errors on incongruent Flanker trials among younger adults.

Aside from accuracy data, I was also interested in examining the relationship between strategy use and executive functioning. I compared the executive functioning performance of participants using task appropriate and inappropriate strategies in the RB pre-train task. Age differed significantly across participant's whose data were bit fit by the task appropriate (*M* = 71.3) strategy or task inappropriate (*M* = 78.2) strategy [$t(25)$ =.29, p = .78] suggesting that among older adults, getting older was associated with increased reliance on task inappropriate strategies. IQ also differed significantly across participant's whose data were best fit by the task appropriate (*M* = 118) strategy or task inappropriate (*M* = 100) strategy [$t(21) = 2.18$, $p = .04$]. In terms of the executive function measures, Simon task performance (reaction time difference score) was significantly better (i.e., lower reaction time difference score) among older adults using the task appropriate [*M* = 53.22] RB strategy compared to older adults using a task inappropriate [*M* = 110.58] strategy, $t(24) = 2.24$, $p = .03$. No other comparisons were significant (all p values > .20) for older adults. I did not compare executive functioning performance and strategy use among younger adults in the RB pre-train condition, because all of the younger adults used a task appropriate strategy during the final learning block.

4.5.3 Discussion

Study 2 extended the results of Study 1 by examining a method for improving single-dimensional RB performance among older adults. A pre-training procedure was used where participants were familiarized with the categorization stimuli prior to beginning the categorization task. Older adults in the pre-train condition performed significantly better on the RB category set relative to older adults in the control condition. Unlike Study 1, age and IQ were associated with categorization accuracy and strategy use on the RB pre-train task among older adults, indicating that declines in categorization performance were associated with being older and having a lower IQ. However, this finding is consistent with Maddox and colleagues (2010) who found that among older adults, the older the individual was, the more likely they would be using a task inappropriate strategy. While IQ differences may partly explain within group differences (for older adults) in RB pre-train performance, it does not explain between group differences. That is, older adults had significantly higher IQ scores compared to younger adults, confirming that younger adults were not performing better on the RB task because they had higher IQ scores. Similar to older adults, younger adults in the pre-train condition also performed significantly better than those in the control condition. These findings suggest that pre-training may improve single-dimensional RB category learning in both older and younger adults. These findings are in line with prior research showing that taxing executive functions needed to learn a RB category set interfered with RB learning (Miles, Matsuki, and Minda, 2014). It follows that reducing executive function demands would then improve RB learning, which is what the current findings show. However, further research is needed to better understand the potential relationship between age, IQ, and RB pre-train performance among older adults. Since a major component of the WASI IQ test involves verbal reasoning, this may suggest that older adults with better verbal reasoning skills are more likely to benefit from pre-training, as pre-training involves verbally describing the categorization stimuli. As mentioned, more research is needed in this area.

Like Study 1, computational modeling was used in Study 2 to better understand the types of strategies older and younger adults applied. Among older adults, the proportion fit by the task appropriate strategy was not significantly higher among pre-trained participants compared to control participants, suggesting that performance differences were a result of strategy consistency/application rather than appropriate strategy use. Examination of model fit values confirmed that older adults in the pre-train condition had significantly better model fit values than older adults in the control condition, suggesting that those in the pre-train condition applied the RB strategy more consistently. Additionally, 4% of older adults in block two and 11% of older adults in block three relied on the suboptimal orientation RB strategy, whereas no older adults in the pre-training condition relied on the suboptimal orientation strategy during any of the learning blocks. Further support for the notion that pre-training improved rule application, is that for older adults using the task appropriate strategy, average categorization performance in the pre-train condition was marginally better than the performance of older adults in the control condition. This suggests that pre-training helped older adult learners better apply the categorization rule compared to learners in the control condition. These findings suggests that pre-training may have allowed older adults to better inhibit salient but irrelevant rules, so that they could focus on consistently applying the task appropriate rule. Nearly all of the younger adults were fit by the task appropriate strategy by the final learning block in both the pre-train and control conditions, suggesting that similar to older adults, pre-training improved rule application rather than rule identification (i.e., identification of the task appropriate RB strategy).

When controlling for the age and IQ of older adults, RB pre-train accuracy did not correlate with executive function measures in older adults. When taking into account strategy use rather than accuracy, Simon task performance was significantly better among older adults using the task appropriate strategy compared to older adults using a task inappropriate strategy. This suggests that inhibitory control may be important for older adults to inhibit irrelevant rules. Since RB pre-train accuracy was not correlated with executive function measures, and task-appropriate strategy use was only associated with inhibitory control abilities, this may suggest that pre-training reduced executive function task demands enough, so that older adults could perform relatively well on the RB task, regardless of executive functioning. Among younger adults, RB pre-train accuracy was correlated with Flanker task performance, suggesting that have stronger inhibitory control abilities may better assist with RB learning in younger adults.

4.6 General Discussion

In two studies, I explored category learning in older adults and younger adults. In Study 1, I examined single-dimensional RB category learning and NRB category learning in older adults and younger adults. Younger adults outperformed older adults on both the RB and NRB category set. Strategy analyses revealed that older adults struggled with RB learning relative to younger adults because they relied on guessing more frequently (most likely indicating frequent strategy shifts rather than random responding) and they also took longer to identify and apply the task appropriate RB strategy. Additionally, when taking into consideration task appropriate strategy users only, older adults still performed more poorly than younger adults, indicating that older adults applied the RB strategy less consistently than younger adults. Older adults performed more poorly on the NRB category set relative to younger adults because they relied on RB strategies more frequently than the optimal NRB strategy.

Executive function abilities were also assessed. RB accuracy among older adults was associated with set-shifting abilities. As well, applying the task appropriate RB strategy was associated with better working memory and set-shifting abilities. The RB performance of younger adults was not associated with executive functioning. NRB accuracy was associated with working memory abilities in older adults and set-shifting in younger adults.

In Study 2, my goal was to improve single-dimensional RB category learning in older adults by reducing the executive function demands of the categorization task via pre-training. Older adults struggled with both RB and NRB category learning in Study 1, but since RB learning depends so heavily on executive functions and executive functions are known to decline with age, I was particularly interested in examining RB category learning in older adulthood. Both older adults and younger adults benefitted from pre-training, performing better on the RB category set following pre-training compared to no-pre-training. Age and IQ were associated with RB pre-train performance in older adults and these variables require further investigation in future studies to understand the connection between age, intelligence and category learning abilities. Strategy analyses revealed that older adults performed better in the pre-train condition relative to the control condition because they applied the RB strategy more consistently. RB pre-train accuracy was not associated with executive functioning in older adults, but using the task appropriate RB strategy was associated with better inhibitory control abilities among older adults. RB pre-train accuracy was associated with inhibitory control in younger adults. Furthermore, even following pre-training, it was beneficial for older and younger adults to have strong inhibitory control abilities to complete the hypothesis testing process involved in RB learning. However, given that working memory and set-shifting abilities were not associated with RB performance, suggests that pre-training may have reduced executive function task demands enough, so that older adults with varying executive functioning abilities could perform relatively well on the RB task.

In line with prior aging research, I too found that older adults struggled with RB and NRB category learning (Filoteo & Maddox, 2004; Maddox et al., 2010; Rabi & Minda, 2016; Racine et al., 2006). However, in contrast with the majority of prior research involving more complex RB category sets, I was able to show that older adults also struggled with learning a difficult single-dimensional RB category set which is consistent with the only other study to examine RB category learning in older adults using this paradigm. The findings from Study 1 demonstrated that older adults also struggled with single-dimensional rule learning, confirming that any RB tasks that places heavy demands on executive functions may lead to category learning deficits in older adults. In extension of these findings I also examined NRB learning in older adults, which has yet to be examined using this standardized category learning paradigm. Study 1 findings showed that older adults also struggle with NRB learning. The present findings are consistent with the COVIS model, which posits that humans have an initial bias towards the verbal, RB system. Only once this bias has been overcome, can individuals transition to the nonverbal system to learn NRB categories. In Study 1, older adults were unable to overcome this bias, resulting in poor RB learning because of frequent strategy shifts and poor NRB learning due to a reliance of RB strategies.

Results from a developmental category learning study are also consistent with our findings. Compared to young adults, Huang-Pollock and colleagues (2011) found that children’s performance on a RB categorization task was hindered by their persistent use of a rule based on a more salient, but incorrect stimulus dimension. Older adults in the present study were best fit by a guessing model, however, I propose that although their categorization responses resembled guessing, older adults were actually frequently shifting categorization strategies. While children and older adults both seem to struggle with learning difficult, single-dimensional rules, it appears that older adults were better able to make use of negative feedback, and at least attempt to switch strategies in an effort to improve categorization accuracy. In contrast, due to executive function limitations, children in the Huang-Pollock et al. study may have relied on a suboptimal but salient rule, regardless of feedback. In the NRB task, Huang-Pollock et al. found that, similar to older adults in Study 1 of my thesis, children frequently relied on a RB strategy and had difficulty transitioning to a NRB strategy. Likewise, research using this category learning paradigm has shown that patients with prefrontal lesions are also impaired at both RB and NRB category learning (Schnyer et al., 2009). Given that children, patients with prefrontal lesions, and older adults all have reduced executive function abilities, it makes sense that these population of individuals struggle with category learning.

The finding that older adults in Study 1 relied on a RB strategy when learning both category sets is grounded in prior research showing that older adults tend to use simpler, less cognitively demanding strategies (Mata, Schooler, & Rieskamp, 2007). As shown in Study 1, working memory and set-shifting are important for learning RB categories and switching between systems. If some older adults have reduced working memory and set-shifting abilities, it makes sense that their category learning abilities would be impaired. RB learning follows a hypothesis testing approach, which is faster than the trial-and-error associative process involved in NRB category learning. Additionally RB learning involves the use of verbalizable rules that are easier to communicate, while NRB learning does not lend itself well to formulating verbal rules. For these reasons, it is not particularly surprising that older adults chose to adopt a RB strategy rather than a NRB strategy when learning the NRB category set. An individual categorizing according to a single dimension could achieve up to 70% correct on the NRB category set, so it may have been more adaptive for older adults to apply a RB strategy, even though it is not as effective as a well-applied NRB strategy.

The Chapter 3 study clearly showed that pre-training led to significant improvements in complex RB learning involving a multi-dimensional, disjunctive rule in both older and younger adults. Aside from the Chapter 3 study, to my knowledge, study 2 of this chapter is the only other study to examine a method for improving RB learning in older adults using pre-training. The findings from these two pre-training studies suggest that pre-training is a useful method for improving both complex single-dimensional and multi-dimensional RB category learning. However, it appears that pre-training differentially assists with RB learning, depending on the type of rule involved. The Chapter 3 study demonstrated that compared to the performance of older adults in the control condition, pre-training considerably improved the RB performance of older adults. Additionally, in contrast to those in the control condition, no older adults consistently relied on single-dimensional rules when learning the RB category set following pre-training. The large majority of older adults in Chapter 3 went from near chance performance in the control condition, to relatively strong RB performance following pre-training. Furthermore, pre-training appeared to assist older adults with identifying the appropriate complex, disjunctive RB strategy. In contrast, in Study 2 of this chapter, pre-training did not significantly change the frequency of older adults using the correct RB strategy, but rather increased the consistency with which older adults applied the correct RB strategy. That is, pre-training in Study 2 led older adults to apply the appropriate RB strategy more consistently, resulting in significantly better RB performance. Furthermore, it appears that pre-training assists with rule identification when older adults are learning a complex, multi-dimensional RB category set, and pre-training assists with rule application/consistency when older adults are learning a complex, single-dimensional category set. Older adults can learn single-dimensional rules, as evidenced by prior research (Rabi & Minda, 2016), but when the single-dimensional RB category set is more difficult, older adults may struggle with applying the appropriate rule, possibly due to temporary lapses in memory (Racine et al., 2006).

Most of the prior aging work has focused solely on identifying category learning deficits in older adults, and now research is needed to better understand methods for reducing these deficits, beyond the two studies discussed in this thesis. Prior category learning research involving younger adults has examined factors that impair RB performance, and recently the attention has switched to examining factors that improve RB performance in younger adults (e.g., Noh, Yan, Bjork, & Maddox, 2016; Miles, Matsuki, and Minda, 2014). Future research should look into whether factors that improve RB performance in younger adults (e.g., blocking exemplars by category during category learning), also provide the same benefits in older adults.

Additionally, in Study 2, the benefits of pre-training were only examined relative to RB learning and not NRB learning. NRB learning is considered more difficult for not only older adults, but younger adults as well (e.g., Huang-Pollock et al., 2011; Morrison et al., Reber, Bharani, & Paller, 2015; Zeithmova & Maddox, 2006). Perfect NRB performance is possible, but this would require a larger set of trials since the implicit associative learning process is quite time consuming (Helie, Waldschmidt, & Ashby, 2010). This is especially the case for older adults, because it appears as though they have a greater initial bias towards the verbal system relative to younger adults, suggesting that they would need more time to perform better. Furthermore, future studies should consider whether lengthening categorization training improves the NRB performance of older adults, and if so, whether a form of pre-training may lead to further improvements in NRB learning. It is plausible that pre-training may enable older adults to rule out RB strategies more quickly, facilitating the switch to the nonverbal system.

Based on the pattern of findings across two studies, it can be concluded that older adults struggle with learning complex, single-dimensional RB categories and these deficits can be reduced by introducing pre-training prior to category learning. Additionally, I showed that NRB category learning is impaired in older adults because they struggle to inhibit output from the dominant, verbal system in favor of the nonverbal system. These findings suggest that any categorization task that taxes executive demands past a certain limit, will lead to category learning deficits in older adults relative to younger adults. Pre-training may have some merit in reducing these deficits, however future research is needed using a range of different pre-training procedures.

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Chapter 5

5 General Discussion

To date, research involving category learning has centered primarily on examining the categorization performance of younger adults and children. Research involving category learning in older adults is still in its infancy, highlighting the need to better understand how this core cognitive process changes with age. The present research investigated how older adults learn RB and NRB categories, as well as provided insight regarding methods of improving category learning in older adults. The first study demonstrated that older adults, like younger adults, performed quite well when learning an easy, single-dimensional RB category set. In contrast to younger adults, older adults found complex, disjunctive RB categories more difficult to learn than NRB, family-resemblance categories. Furthermore, the complex RB task appeared to be the most difficult for older adults to learn because it placed the heaviest demands on working memory, which is known to decline with healthy aging. The second study was aimed at reducing age-related deficits in category learning. Older adults benefitted from a reduction in the executive functioning demands of the categorization task via pre-training when learning a complex RB task, and to some extent when learning a NRB, family-resemblance category set as well. The third study further explored how task complexity interacted with RB and NRB category learning, by examining more complex single-dimensional RB category learning (relative to the single-dimensional RB category set used in Study 1) and NRB category learning (involving the II category set). Additionally, strategy analyses were conducted to shed light on the approaches older adults took when learning categories relative to younger adults. Findings from Study 3 demonstrated that older adults struggle with learning complex rules which place demands on executive function resources, regardless of the category structure (i.e., single-dimensional vs. multi-dimensional rules). Also, older adults struggle with NRB learning because they have difficulty switching from the verbal system to the nonverbal system, and rely on RB strategies instead of more optimal NRB strategies. The fourth study focused on reducing single-dimensional RB deficits in older adults via pre-training, demonstrating that familiarizing older adults with stimulus dimensions improved single-dimensional RB learning. In contrast to Study 2, where pre-training improvements were a result of better rule identification, in Study 4, pre-training improvements were a result of better rule application.

5.1 Implications for Category Learning in Older Adulthood

Prior research has shown that older adults struggle to learn complex RB categories. More specifically, relative to younger adults, older adults find it difficult to learn conjunctive RB (uses the logical relation ‘and’ to relate stimulus attributes; e.g., large *and* shiny items belong in category A) category sets (e.g., Maddox et al., 2010; Racine et al., 2006). Additionally, Davis and colleagues (2012) have shown that older adults also struggle with learning rule-plus-exception category sets, where older adults performed well on rule-following items, but struggled to learn exception items. Another important form of complex RB category learning, which had not been examined until the current thesis is disjunctive RB learning (uses the logical relation ‘or’ to relate stimulus attributes; e.g., small items *or* shiny items belong in category A). Chapter 2 of this thesis confirmed and extended prior research involving category learning in older adulthood, by showing that older adults also struggle with learning complex rules with a disjunctive rule structure. Increasing rule complexity places greater demands on the maintenance and manipulation processes in working memory, making it difficult for older adults to identify and apply the appropriate rule. Study 1 in Chapter 4 of this thesis demonstrated that older adults struggle with learning single-dimensional rules, when task complexity is increased. That is, prior research by Rabi and Minda (2016/Chapter 2) has shown that older adults can learn simple, single-dimensional rules quite well (e.g., white objects belong in category A), and Study 1 in Chapter 4 confirmed that single-dimensional RB learning is impaired when a more difficult single-dimensional rule structure is used. Furthermore, any RB categorization task (single-dimensional or multi-dimensional), which places demands on executive functions, can result in RB category learning deficits among older adults. The first study in Chapter 4 also demonstrated that older adults relied on guessing more frequently than younger adults, most likely reflecting frequent changes in strategy use. These findings provide support for the COVIS theory of category learning, which assumes that the verbal system is mediated by the prefrontal cortex and relies on executive functions to learn categories that can be defined by a rule. Given that the prefrontal cortex is the brain region most disrupted by healthy aging, which is associated with reduced executive function abilities (Greenwood, 2000; Grieve, Williams, Paul, Clark, & Gordon, 2007), it follows that older adults should find it difficult to learn complex, RB categories. Findings from Bharani and colleagues (2015) support this line of thinking by showing that recruitment of prefrontal resources was associated with better RB performance among older adults. Older adults who successfully learned the RB category set showed larger frontal ERPs compared with younger adults, suggesting that increased neural activity was required to maintain high cognitive function.

Although rather limited, prior research has also shown that older adults struggle with learning NRB categories (Filoteo & Maddox, 2004; Maddox et al., 2010). In line with these findings, Chapter 4 demonstrated that older adults struggled with learning a NRB (information-integration) category set. Additionally, Chapter 2 demonstrated that older adults found NRB (family-resemblance) category learning challenging, but not as challenging as complex RB learning, which places heavier demands on executive functions. The fact that older adults struggle with NRB learning in addition to RB learning, suggests that executive functioning may be important for NRB learning as well. For example, Chapter 4 revealed that older adults struggled to learn the NRB category set, because they relied on a RB strategy. This shows that older adults found it difficult to switch from the dominant, verbal system to the nonverbal system, and instead attempted to use rules to learn the NRB category set. These data also provide support for the COVIS theory of category learning, which assumes that the verbal system is the dominant system used during initial learning. Individuals only switch to the nonverbal system when it is clear that no acceptable rule exists. The current thesis suggests that older adults had difficulties testing possible rules, and continued on with hypothesis testing, rather than switching to the nonverbal system. It is possible that given more trials, older adults may have been able to test enough rules to realize that no acceptable rule existed, and that a NRB strategy needed to be used instead.

Further support for the role of executive functions in RB and NRB category learning comes from Chapters 2, 3, and 4 showing that higher executive function abilities were associated with stronger RB and NRB performance in older adults. That is working memory, inhibitory control, and set-shifting are all important cognitive processes involved in RB and NRB category learning. Even following pre-training, Chapter 3 findings revealed that among older adults, stronger executive functioning abilities were still associated with better RB and NRB categorization performance. These data suggest that having strong executive functioning abilities may have allowed older adults to benefit more from pre-training. The relationship between categorization performance and executive functioning was weaker among younger adults, but still present, suggesting that younger adults had sufficient executive function abilities to perform well on the categorization tasks. These results are in line with cognitive aging theories, which propose that older adults have: difficulty inhibiting irrelevant information (Hasher, Lustig, & Zacks, 2007; Hasher & Zacks, 1988; Milham et al. 2002), reduced processing speed (Salthouse, 1994, 1996) and a smaller working memory capacity (Oberauer, Wendland, & Kliegl, 2003). Executive functions are required to carry out hypothesis testing, inhibit incorrect rules, maintain the current rule in memory, and for switching between category learning systems. Furthermore, age-related declines in executive functioning may help to explain category learning deficits among older adults.

5.2 Implications for the Usefulness of Pre-Training in Category Learning

Older adults show clear deficits when learning RB and NRB categories. Prior research has focused on examining these deficits, but has yet to examine methods of reducing age-related category learning deficits. Chapters 3 and 4 focused on minimizing category learning deficits in older adults, by minimizing task demands via pre-training. Older adults in Chapter 2 greatly struggled with learning complex, disjunctive rules, performing near chance. This low performance signifies that older adults were unable to identify the correct, disjunctive rule during the course of the category learning task. Chapter 3 findings showed that familiarizing older adults with the stimulus dimensions by asking them to verbally describe category exemplars, resulted in improved RB performance relative to a control condition. The NRB performance of older adults also improved following pre-training, but only marginally. These findings signify that while pre-training was helpful in Type IV learning, the benefits to Type II learning were greater. The second study in Chapter 4 examined the effects of pre-training in single-dimensional RB category learning. During pre-training, participants verbally described a set of category exemplars and began the category learning task with easier trials, to jumpstart the hypothesis testing process. Chapter 4 showed that following pre-training, older adults performed significantly better on the RB task relative to control performance. Strategy analyses confirmed that this improvement in RB performance was due to more consistent application of the appropriate RB strategy. Furthermore, the research presented in this thesis is the first to shown that pre-training can have significant benefits for RB category learning in older adults. In multi-dimensional RB learning (e.g., disjunctive rule learning), pre-training enabled older adults to better identify the rule. In contrast, when learning a single-dimensional RB category set, pre-training enabled older adults to better apply the correct rule more consistently. Additionally, Chapter 3 showed that pre-trained older adults performed similar to younger adults in the control condition for both the RB and NRB category learning task. This demonstrates that by reducing executive function task demands via pre-training, older adults are able to perform at a level similar to younger adults, who generally have strong executive functioning abilities. The current findings have important implications for understanding ways of improving older adults' ability to acquire new information. That is, encouraging older adults to describe key features of new items or information, may help familiarize them with the information, and allow them to recall the information more easily. Furthermore, the present findings not only benefit older adults by highlighting a manner in which categories can be learned more easily, but also benefit health care professionals and other professionals who educate older adults, by providing them with suggestions on how to present new information. In line with current pre-training findings, prior research has shown that older adults have a decreased capacity to process multiple pieces of information (Stevens, 2003) and benefit from learning manageable chunks of information. Additionally, research involving medical adherence in older adults, suggests that patient education strategies should be tailored to account for age-related changes in cognitive functioning (Speros, 2009; Zhang, Swartzman, Petrella, Gill, & Minda, 2016). For example, key points should be reinforced, so that the patient will become familiarized with the information and complex information should be broken down into simpler points, as not to overwhelm the patient. Older adults make complex judgments and categorization decisions on a daily basis, whether it involves driving, judgments of personal health status, or financial decision-making. For this reason, it is important to understand why older adults may struggle with learning new information, and how this difficulty can be overcome. The present findings highlight that in relation to category learning, pre-training involving familiarization with concept dimensions can promote better RB category learning.

5.3 Relations to Prior Category Learning Research Involving Different Populations

Additional support for the role of executive functions in category learning comes from research involving a range of populations. Developmental research has shown that young children have difficulty learning RB categories relative to adults, because the neural systems that mediate the verbal system are not yet fully developed in early childhood (Huang-Pollock et al., 2011; Minda et al., 2008; Rabi, Miles, & Minda, 2015). Rabi and Minda (2014) examined the relationship between RB category learning and executive functioning in children ranging from age four through adolescence. Results revealed that categorization performance improved with age and stronger working memory and inhibitory control abilities were associated with better RB categorization performance. Huang-Pollock and colleagues (2011) also showed that children struggle with NRB category learning because they rely on RB strategies more frequently than younger adults and have greater difficulty transitioning to a NRB approach. Comparative research has shown that monkeys struggle with RB category learning, because they rely on single-dimensional rules too frequently and fail to learn more complicated rules (Smith et al., 2004). Such categorization performance deficits have been attributed to the fact that monkey’s lack the language and executive function resources needed to represent complex rules and hypotheses succinctly and store them for testing and possible acceptance or rejection. These findings provide support for the results from the current thesis by emphasizing how, across development and across species, reduced executive functioning resources negatively impact category learning abilities, similar to what is found among older adults.

Aside from research involving children and non-human primates, many studies involving younger adults have also examined the importance of executive functioning in category learning. More specifically, studies have investigated how taxing executive function resources negatively influences category learning abilities. For example, research has shown that asking participants to complete a task that engages executive functions while concurrently completing a RB categorization task interferes with RB categorization performance (Filoteo, Lauritzen, & Maddox, 2010; Minda et al., 2008; Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). Similarly, prior to category learning, reducing participants' executive functioning via a resource depletion manipulation interferes with RB category learning (Minda & Rabi, 2015). With regards to NRB category learning, Miles, Matsuki and Minda (2014) found that continuously taxing the executive function resources of younger adults resulted in a decreased likelihood of using a NRB categorization strategy, suggesting that when executive functions were unavailable, the transition to the nonverbal system was hindered. Furthermore, younger adults generally perform quite well on RB and NRB category learning tasks, but when their executive function resources are compromised, their performance begins to resemble that of older adults. In the Miles et al. (2014) study, continuously taxing the executive function resources of younger adults seems to mirror the executive function abilities of older adults. This explains why younger adults struggled to switch from the dominant verbal system to the nonverbal system, similar to what was found in the current thesis. Moreover, pre-training may reduce the executive function demands of the categorization task just enough so that older adults can perform more similarly to younger adults. Taken collectively, these research findings illustrate the executive functioning resources are required by both the verbal and nonverbal system. Also, cognitive and contextual variables that interfere with executive functions have negative effects on category learning abilities.

5.4 Future Directions

While limited research exists on the topic of category learning in older adulthood, progress is being made towards understanding age-related categorization deficits. The current study examined category learning in healthy, active older adults between the ages of 63 and 88. Future research would benefit from examining category learning in a broader sample of older adults (e.g., with varying activity levels), to better understand how category learning abilities change with age and varying backgrounds. Additionally, the age range of older adults in the current study was quite broad. Future research should more closely examine category learning among young-old (ages 60 to 69), middle-old (ages 70 to 79) and old-old (ages 80+) adults. The prefrontal cortex is a brain region known to play an important role in RB learning and transition between categorization systems. Most neuroimaging studies involving category learning have been conducted with younger adults and for this reason, future research would benefit from examining prefrontal activation during both RB and NRB category learning in older adults. Since older adults often struggle with NRB category learning it would be interesting to see whether neuroimaging research could shed light on this finding. Additionally, since the majority of older adults in the Chapter 4 study failed to adopt a NRB strategy in the NRB category learning task, future research should examine methods of facilitating the switch to the nonverbal system among older adults. This may involve giving older adults more training trials, since implicit learning by the nonverbal system is known to take longer than explicit learning by the verbal system. The pre-training procedures used in Chapters 3 and 4 successfully improved the categorization performance of older adults. However, future studies should examine alternative pre-training methods to determine whether categorization performance can be improved using different techniques, which reduce the executive function demands of the task.

5.5 Conclusions

The findings of the current studies are compatible with past research showing age-related deficits in RB and NRB category learning and extend this research by showing that older adults struggle with learning disjunctive rules. Additionally strategy analyses findings highlight that older adults tend to use suboptimal rules when learning RB categories and rely on RB strategies when learning NRB categories, likely a result a reduced executive functioning resources. To counteract reduced executive functioning abilities associated with aging, a pre-training procedure was introduced which improved the category learning performance of older adults. This is the first series of studies to examine a method of improving age-related categorization deficits in older adults, demonstrating that declines in categorization performance can be overcome by reducing executive function demands.

5.6 References

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Appendix A: Ethics Approval

Western Research

Research Ethics

Western University Non-Medical Research Ethics Board
NMREB Annual Continuing Ethics Approval Notice

Date: December 15, 2015
Principal Investigator: Dr. John Paul Minda
Department & Institution: Social Science\Psychology,Western University

NMREB File Number: 104859
Study Title: Complex cognition and problem solving in older and younger adults
Sponsor:

NMREB Renewal Due Date & NMREB Expiry Date:
Renewal Due -2016/12/31
Expiry Date -2017/01/30

The Western University Non-Medical Research Ethics Board (NMREB) has reviewed the Continuing Ethics Review (CER) form and is re-issuing approval for the above noted study.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), Part 4 of the Natural Health Product Regulations, the Ontario Freedom of Information and Protection of Privacy Act (FIPPA, 1990), the Ontario Personal Health Information Protection Act (PHIPA, 2004), and the applicable laws and regulations of Ontario.

Members of the NMREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the REB.

The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

Ethics Officer to Contact for Further Information: Erika Basile ___ Nicole Kaniki ___ Grace Kelly ✓ Mina Mekhail ___ Vikki Tran ___

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Western Research

Research Ethics

Western University Non-Medical Research Ethics Board
NMREB Amendment Approval Notice

Principal Investigator: Dr. John Paul Minda
Department & Institution: Social Science\Psychology,Western University

NMREB File Number: 104859
Study Title: Complex cognition and problem solving in older and younger adults
Sponsor:

NMREB Revision Approval Date: January 29, 2015
NMREB Expiry Date: January 30, 2016

Documents Approved and/or Received for Information:

Document Name	Comments	Version Date
Revised Western University Protocol	Revised Western Protocol	
Instruments	Figure displaying the test items that will be used during the third testing session with older adults.	
Recruitment Items	Revised poster for recruiting older adults	
Revised Letter of Information & Consent	Revised letter of information	

The Western University Non-Medical Science Research Ethics Board (NMREB) has reviewed and approved the amendment to the above named study, as of the NMREB Amendment Approval Date noted above.

NMREB approval for this study remains valid until the NMREB Expiry Date noted above, conditional to timely submission and acceptance of NMREB Continuing Ethics Review.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), the Ontario Personal Health Information Protection Act (PHIPA, 2004), and the applicable laws and regulations of Ontario.

Members of the NMREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the REB.

The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

Ethics Officer, on behalf of Riley Hinson, NMREB Chair

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Western Research

Research Ethics

Western University Non-Medical Research Ethics Board
NMREB Amendment Approval Notice

Principal Investigator: Dr. John Paul Minda
Department & Institution: Social Science\Psychology,Western University

NMREB File Number: 104859
Study Title: Complex cognition and problem solving in older and younger adults
Sponsor:

NMREB Revision Approval Date: November 03, 2014
NMREB Expiry Date: August 31, 2015

Documents Approved and/or Received for Information:

Document Name	Comments	Version Date
Revised Study End Date	We are requesting an extension of our study "Complex cognition and problem solving in older and younger adults", until August 31. 2015. Our study expired at the end of August 2014. We have only recently begun data collection (during July and August) and we would like to continue testing participants for another year to reach our target sample size. The approval has been granted from August 31, 2014 to August 31, 2015.	

The Western University Non-Medical Science Research Ethics Board (NMREB) has reviewed and approved the amendment to the above named study, as of the NMREB Amendment Approval Date noted above.

NMREB approval for this study remains valid until the NMREB Expiry Date noted above, conditional to timely submission and acceptance of NMREB Continuing Ethics Review.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), the Ontario Personal Health Information Protection Act (PHIPA, 2004), and the applicable laws and regulations of Ontario.

Members of the NMREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the REB.

The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

Ethics Officer, on behalf of Riley Hinson, NMREB Chair

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Western Research

Research Ethics

Use of Human Participants - Initial Ethics Approval Notice

Principal Investigator: Dr. John Paul Minda
File Number: 104859
Review Level: Delegated
Protocol Title: Complex cognition and problem solving in older and younger adults
Department & Institution: Social Science\Psychology, Western University
Sponsor:
Ethics Approval Date: January 30, 2014 **Expiry Date:** August 31, 2014

Documents Reviewed & Approved & Documents Received for Information:

Document Name	Comments	Version Date
Western University Protocol		2014/01/02
Instruments	Appendix C.	2014/01/11
Recruitment Items	Poster for older adults.	2014/01/11
Other	Appendix A.	2014/01/11
Other	Appendix B	2014/01/11
Recruitment Items	Poster for all Western students (Includes younger and older adults)	2014/01/11
Letter of Information & Consent	Consent form.	2014/01/11
Revised Letter of Information & Consent	LOI for paid young adults REVISED	2014/01/11
Revised Letter of Information & Consent	LOI for paid older adults REVISED	2014/01/11
Revised Letter of Information & Consent	LOI for participant pool subjects REVISED	2014/01/11
Response to Board Recommendations	Changes to Ethics Form	2014/01/11
Other	Debriefing Form	2014/01/11
Recruitment Items	SONA blurb REVISED to include duration of study and number of research credits to be earned.	2014/01/27

This is to notify you that The University of Western Ontario Research Ethics Board for Non-Medical Research Involving Human Subjects (NMREB) which is organized and operates according to the Tri-Council Policy Statement: Ethical Conduct of Research Involving Humans and the applicable laws and regulations of Ontario has granted approval to the above named research study on the approval date noted above.

This approval shall remain valid until the expiry date noted above assuming timely and acceptable responses to the NMREB's periodic requests for surveillance and monitoring information.

Members of the NMREB who are named as investigators in research studies, or declare a conflict of interest, do not participate in discussions related to, nor vote on, such studies when they are presented to the NMREB.

The Chair of the NMREB is Dr. Riley Hinson. The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

Signature

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Curriculum Vitae

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EDUCATION

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2010-2012 The University of Western Ontario, London, Canada
M.Sc. Psychology

2005-2010 The University of Western Ontario, London, Canada
Honours B.Sc. Psychology

PUBLICATIONS

Rabi, R. & Minda J. P. (2016). Category learning in older adulthood: A study of the Shepard, Hovland, and Jenkins (1961) tasks. *Psychology and Aging, 31*(2), 185-197.

Minda J. P. & **Rabi, R**. (2015). Ego depletion interferes with rule-defined category learning but not non-rule-defined category learning. *Frontiers in Psychology, 6, 35. doi: 10.3389/fp- syg.2015.00035.*

Rabi, R., Miles, S. J., & Minda, J.P. (2014). Learning categories via rules and similarity: Comparing adults and children. *Journal of Experimental Child Psychology, 131*, 149-169.

Rabi, R., & Minda, J. P. (2014). Perceptual category learning: Similarity and differences between children and adults. In P. Bello, M. Guarini, M. McShane, & B. Scassellati (Eds.), *Proceedings of the 36th Annual Conference of the Cognitive Science Society.* Austin, TX: Cognitive Science Society.

Rabi, R. & Minda J. P. (2014). Rule-based category learning in children: The role of age and executive functioning. *PLoS ONE 9(1): e85316. doi:10.1371/journal.pone.0085316.*

Nadler, R. T., **Rabi, R.**, & Minda, J. P. (2010). Better mood and better performance: Learning rule-described categories is enhanced by positive mood. *Psychological Science. 21*, 1770-1776.

AWARDS

2015-2016	Province of Ontario Graduate Scholarship
2012-2015	Natural Science and Engineering Research Council (NSERC) Canada Graduate Scholarship, Doctoral
2011-2012	Natural Science and Engineering Research Council (NSERC) Canada Graduate Scholarship, Masters
2010-2011	Queen Elizabeth II Graduate Scholarship in Science and Technology
2009 & 2010	Natural Science and Engineering Research Council (NSERC) Undergraduate Student Research Award

RELEVANT WORK EXPERIENCE

2010-2016	Graduate Teaching Assistant The University of Western Ontario, London, Canada