Familiarization May Minimize Age-Related Declines in Rule-Based Category Learning

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Abstract

Being able to categorize promotes cognitive economy by reducing the amount of information that an individual needs to remember. This ability is particularly important in older adulthood, when executive functioning abilities are known to decline. Prior research has shown that older adults can learn simple categories quite well but struggle when learning more complex categories which place a demand on executive function resources. The goal of Experiments 1 to 3 were to assess whether familiarizing older adults with complex rule-based or non-rule-based categories prior to beginning a categorization task would minimize age-related categorization deficits. Both rule-based and non-rule-based category learning improved among older adults following pre-training, but the improvements to rule-based learning were more drastic, suggesting that executive functioning plays a heavier role in rule-based category learning. Findings provide a potential solution for improving the category learning abilities of older adults.

Keywords: category learning, executive function, aging, explicit learning, implicit learning

People make categorization decisions on a daily basis to help them organize the world and to consolidate individual memory into functional classes. 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, COVIS (COmpetition between Verbal and Implicit Systems) theory (Ashby et al., 1998; Maddox & Ashby, 2004), assumes that two cognitive systems are involved in learning categories. The verbal system uses executive functioning to learn rule-based (RB) categories that can be described using a verbal rule (e.g., members of family X all have brown eyes). Executive function can be thought of as a set of cognitive abilities supported by the prefrontal cortex, which include working memory updating, inhibitory control, and set-shifting (Miyake, Friedman, Emerson, Witzki, Howerter, & Wager, 2000). The nonverbal system learns non-rule-based (NRB) categories that cannot be described via a verbal rule, but can be learned by attending to overall similarity among items (e.g., 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 reducing/taxing executive functioning abilities impairs performance on RB categories (Zeithamova & Maddox, 2006; Minda & Rabi, 2015), leaving NRB categorization performance unaffected. Such findings suggest that executive functioning is necessary for optimal RB learning and less 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.

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 new

categories. Research has 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).

Our previous research (Rabi & Minda, 2016) relied on a widely used, standardized category set originally created by Shepard, Hovland, and Jenkins (1961) that consisted of several types of RB and NRB categories that varied in complexity. These categories have been used extensively in studies involving a range of populations (e.g., young adults, children, individuals with depression, monkeys). Our results revealed that older adults performed comparably to younger adults when learning Type I categories (single-dimensional rules) but unlike younger adults, older adults found Type II categories (disjunctive, two-dimensional rules) exceedingly difficult to learn. 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.

Rule-Based Category Learning Deficits in Older Adulthood

One general question emerged from the findings of Rabi and Minda (2016): why can't older adults learn these disjunctive categories when they are so easy for younger adults to learn? 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). There are also clues from cognitive neuroscience. Several studies have shown that the same brain regions (i.e., the prefrontal cortex) that mediate executive function, are also recruited during RB category learning and show age-related declines (Bharani et al., 2015;

Nomura & Reber, 2012). Behavioural research examining the effects of aging on working memory supports the idea that increasing rule complexity places a heavier burden on the working memory abilities of older adults relative to younger adults. Several studies have shown that as working memory task complexity increases, the performance of older adults decreases relative to younger adults (Bopp & Verhaeghen, 2005; Oosterman et al., 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 et al., 2012).

Given the evidence that these known deficits in working memory and executive function may prevent older adults from learning disjunctive categories, how might they overcome this constraint? The answer may lie with working memory. Numerous training studies have suggested that older adults are able to improve their working memory performance (Borella et al., 2010; Brehmer, Westerberg, & Bäckman, 2012; Karbach & Verhaeghen, 2014; Richmond et al., 2011). Research has yet to be conducted examining methods of improving categorization performance in older adults. However, a study by Minda, Desroches, and Church (2008) found that children, like older adults, struggled with complex rule learning (including Type II categories). In a second experiment, Minda et al. (2008) reduced the overall task demands with a pre-training task that familiarized children with the categories and the exemplars prior to the learning task. In this pre-training task, participants first learned to name all the features of each exemplar and briefly viewed the exemplars together in the category. It was assumed that this would reduce the task demands by eliminating any initial confusion over what the relevant features were, by providing a simple label for each feature, and by making it clear that there were

only 8 items in total. Results revealed that decreasing the categorization task demands for children resulted in more adult-like performance on the complex RB category set.

The present research attempted to answer the questions above. We examined the ability of older adults and younger adults to learn two very different kinds of category sets, and whether exposure to the stimuli during a pre-training task would enable older adults to improve performance on the RB categories. In the first experiment, we used the same category sets that were used in Rabi and Minda (2016). Experiment 2 and 3 feature larger category sets built about continuously varying dimensions and instantiated as Gabor patch stimuli. To foreshadow, in Experiment 1, we replicated the earlier results of Rabi and Minda (2016) and we also found that the pre-training task enabled the older adults to overcome their difficulty in learning Type II/disjunctive categories. Experiment 2 found that older adults also struggle relative to younger adults on RB distributions of Gabor patch stimuli. And Experiment 3 completed the picture by again showing that the pre-training task can improve performance on RB stimuli in older adults.

Experiment 1

The current study examined whether reducing task demands (via pre-training with the categories and the individual exemplars) would enable older adults to identify and apply complex rules in a similar manner to younger adults. To do this, we conducted three experiments. Experiment 1 used the same categories (Type II disjunctive and Type IV family resemblance) that were used in Rabi and Minda (2016). Both younger adults and older adults were randomly assigned to a category set (Type II or 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 (Figure 1). 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. We 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) and were briefly shown the entire set. 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, and made it clear how large the set size was. By familiarizing participants with the exemplars, we 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 several of reasons. First, prior research has used a similar pre-training paradigm with children (Minda et al., 2008) and the task produced the intended effect. Second, this is an interactive pre-training task in which participants actively describe the stimuli in order 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 we were interested in examining whether reducing task demands would enable older adults to better formulate the rule. That being said, the form of pre-training we 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 individual stimuli and the groups of stimuli as they described them. While the pre-training procedure implemented was meant to encourage RB strategy use, there still exists the possibility that some participants may have relied on memorization strategies during the category learning task.

We expected that pre-training would improve the Type II performance of both younger and older adults by facilitating the hypothesis testing process and reducing the executive function demands of the task. We also expected that pre-training would be more beneficial to Type II learning compared to Type IV learning, since the complex rule-learning involved in Type II appears to involve more executive function resources relative to Type IV.

Method

Participants

Participants included 89 younger adults ($M = 19.0$ years, $SD = 2.0$; 42 males & 47 females) from Western University 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 community centres, exercise groups and an alumni lecture series. Older adults received \$20 for participating in the study. Participants were pre-screened to ensure that they were fluent in English, in good health, and had normal vision. 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 research from Bharani et al., 2015) as determined by the Freiburg Visual Acuity and

Contrast Test (Bach, 2007). The education level of younger adults ($M = 12.3$ years, $SD = 0.6$) was significantly lower ($t(162) = 7.76, p < .001$) than that of older adults ($M = 14.6, SD = 2.6$) because our younger adult sample were still in university. Experiments 1 to 3 were approved by the University of Western Ontario Department of Psychology Research Ethics Board.

Materials

Category Learning Task

Two category learning tasks were chosen from the 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 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.

Cognitive Battery

The alpha span and digit span tasks were used to assess working memory ability. In the alpha span task (Craig, 1986), working memory was assessed by asking participants to repeat a list of words back in alphabetical order. Lists ranged in length from 2 to 8 words. 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. The alpha span score is the total number of points awarded across all presented lists. Details regarding the digit span task can be found in Rabi and Minda (2016).

The Flanker, Simon and Stroop tasks were used to assess inhibitory control. See Rabi and Minda (2016) for inhibition task details.

A computerized version of the Wisconsin Card Sorting Test (Berg, 1948; adapted from the Psychology Experiment Building Language test Battery, Mueller, 2012), which consists of 64 trials, was used to assess set shifting ability. The 64 card version of this task has been highly correlated with the longer version (perseverative errors $r = .77$, categories completed $r = .86$, Fox et al., 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 and the number of perseverative errors.

Procedure

Session 1

Participants were tested individually across two testing sessions, approximately one week apart. Younger adults were tested in a lab setting and older adults were tested in the lab or in a

quiet room in the senior centre. Participants completed a battery of cognitive tests including the WCST, alpha span task, digit span task, and the WASI.

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 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 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 exemplar, one at a time. Participants were then shown the 4 category B exemplars and asked to name each exemplar one at a time. For the category A exemplars, the experimenter pointed to the first exemplar and said (for example), “This is a big black square, please 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 all 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 experimenter finished saying the last statement, the final display was removed and the participant began the categorization task. It should be noted that while participants in the pre-training condition were familiarized with the category exemplars in the Type II or IV category set, the correct categorization strategy was not given to them. Instead the participant would need to identify the

correct RB strategy on their own using the information they obtained from the pre-training task, or alternatively memorize the categorization stimuli. 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. Stimuli were presented in random order within each block of eight. There were a total of 80 trials (10 blocks total).

Following completion of Type II or IV category set, participants completed the Flanker task, Simon task, and Stroop task.

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. 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 [$F(1, 80) = 5.69, p = .019, \text{partial } \eta^2 = .07$], 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 2, younger adults outperformed older adults across all of

the different category sets and conditions¹. 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 and we examined category learning performance by conducting two separate 3-way ANOVAs: one for older adults and one for younger adults.

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 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 significant².

¹ 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.

² 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.

To further examine the significant category type x condition interaction, Bonferroni corrected pairwise post hoc comparisons were conducted. As shown in Figure 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 [$r = .39, p = .12$], Type IV control [$r = .34, p = .18$], and Type IV pre-training conditions [$r = -.13, p = .57$].

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 [$F(1, 85) = 12.02, p = .001, \text{partial } \eta^2 = .12$], 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 3B). Similar to older adults, it is clear from Figures 2 and 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 ($p = .002$)³.

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

³ 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 ($p < .001$).

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.

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 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 4B). Furthermore, pre-training made older adults perform at a level similar to that of younger adults in the control conditions.

Strategy Analysis

We conducted a strategy analysis to determine whether or not participants used a suboptimal, single-dimensional rule strategy rather than the optimal disjunctive-rule or family resemblance strategies. See Appendix for details of this analysis. As shown in Table 1, for the Type II category set (control and pre-train conditions), no younger adults showed evidence of single-dimensional rule use. 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 were not fit by a single-dimensional rule, suggests that older adults frequently switched their strategies throughout the task. 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 (both 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-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 than two learning blocks⁴. 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 condition⁵.

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

⁴ 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.

⁵ 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.

groups performed similarly (see Table 2). Scores on the executive functioning measures were correlated with average categorization performance across the last five learning blocks for older adults and younger adults separately.

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). 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 performance⁶. 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 between 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

⁶ 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 [$r = -.53, p = .03$].

number of categories completed on the WCST⁷. 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 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 [$r = .37, p = .16$], suggesting that inhibitory control and working memory but not short-term memory (as measured by the forward digit span) may play an important role in complex rule learning among older adults. Type IV control performance was still correlated with forward digit span [$r = .51, p = .032$].

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 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 set⁸.

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

⁷ 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 [$r = -.54, p = .014$].

⁸ 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 [$r = -.49, p = .026$].

(2016) study, in the control conditions, older adults were more successful at learning Type IV categories compared to Type II. Younger adults were more successful at learning Type II categories compared to Type IV. The primary aim of this study was to determine whether pre-training would improve Type II performance relative to baseline. In support of our predictions, we 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 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.

In contrast, 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. Younger adults in the current study significantly benefitted from pre-training during both Type II and Type IV category learning. These findings are comparable to research by Minda et al (2008), showing that familiarizing children with category exemplar improved their RB categorization performance.

We speculate that familiarizing older adults with the category exemplars reduced the working memory demands of the task and allowed the explicit RB system to operate optimally. An alternative explanation is that the pre-training phase encouraged participants to simply memorize the category exemplars. Although we cannot rule out this explanation with complete certainty, we do believe 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 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.

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, we 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. Our 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 allowed older adults to rule out simpler, single-dimensional rules at a faster rate.

While our primary interest was in comparing pre-train to control performance in each age group separately, we noted that younger adults outperformed older adults across all of the study conditions, and for this reason we examined how the pre-train performance of older adults compared to the control performance of younger adults. 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 et al., 2014; Minda & Rabi, 2015). That is, increasing the task/working memory demands will lead to reduced performance when learning RB categories. In comparison, the present findings demonstrate that by reducing task demands (via pre-training), RB performance can be improved. 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 and executive functioning. 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 pre-training task did not eliminate this relationship, suggesting that strong executive functioning abilities may have allowed older adults to benefit more from pre-training. 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. 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. We are limited in drawing conclusions related to Type IV category learning and executive functioning, because while Type IV lends itself most easily to family-resemblance (implicit) based learning, it is also possible to learn Type IV via a complicated rule.

Experiment 2

The limited research that has been done on category learning has focused on examining complex, multi-dimensional 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. In Experiment 2, we used an extremely well studied category learning paradigms for examining RB and NRB category learning. In the task, participants divided Gabor patches 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. 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 insight into the specific strategies individuals use to learn novel categories.

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. We 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. 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 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. By investigating NRB category learning in the current study we 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 was expected that relative to younger adults, older adults would rely on suboptimal rules in the RB condition. With regards to NRB category learning, relative to younger adults, it was 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.

Method

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)⁹. 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 based on the same criterion described in Experiment 1. The education level of younger adults ($M = 12.2$ years, $SD = 0.5$) was significantly lower ($t(113) = 7.05, p < .001$)¹⁰ than that of older adults ($M = 14.5$ years, $SD = 2.6$).

Materials

Category Learning Task

Participants classified sine-wave gratings that varied in spatial frequency and orientation. 80 stimuli were generated for each category set (Ashby 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 5). The resulting category structures for RB and NRB category sets are illustrated in Figure 5. 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

⁹ Of the 64 younger adults, 49 subjects also participated in Experiment 1 and 15 subjects were newly recruited. Of the 55 older adults, 51 subjects also participated in Experiment 1 and 4 subjects were newly recruited to keep the sample size of the conditions relatively equal.

¹⁰ Data regarding education level was not collected from 4 older adults.

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.

Cognitive Battery

We administered the same cognitive battery that was used in Experiment 1.

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 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 NRB 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 6). 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 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 WCST and the alpha span task.

Session 2

Participants completed the Flanker, Simon, 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.

Results

Category Learning Accuracy

The RB and NRB categorization performance of younger adults and older adults was calculated for each 80-trial block. The resulting RB and NRB learning curves are presented in Figure 7. A 2 (age group: older vs. younger) x 2 (category type: RB vs. NRB) 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 NRB 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.

A 2 (age group) x 4 (block) ANOVA was also carried out for NRB categorization performance and revealed a main effect of age group [$F(1, 57) = 27.45, p < .001$, partial $\eta^2 = .325$], suggesting better overall NRB 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 NRB 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 NRB 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.

Computational Modeling

The accuracy-based analyses of the categorization data suggested that older adults struggled relative to younger adults when learning both RB and NRB category sets. While accuracy data are a useful measure of overall categorization performance, it provides little information about the types of decision strategies that participants used to learn the category set. 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. Details regarding the computational modeling procedure can be found in Appendix B.

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 8. Panel A shows that for both older adults and younger adults, RB category learning improved over time, evidenced by 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 6 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 6 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 NRB category set, Panel B shows that among younger adults, the proportion fit by the optimal NRB model increased over learning blocks, however very few older adults applied a procedural-based NRB strategy across blocks. A χ^2 –test comparing the frequency of optimal NRB 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 NRB condition compared to older adults [$\chi^2(1) = 8.51$, $p = .004$]. As shown in Table 6, aside from using the optimal NRB 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 NRB strategy when learning the NRB category set. The large majority of older adults adopted a rule based on frequency during NRB 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 6, older adults ($M = .40$) applied the optimal NRB 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 NRB 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 NRB 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 NRB 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 NRB task in older adults [$R^2 = .451$, $F(1, 26) = 21.32$, $p < .001$].

Categorization accuracy among task appropriate strategy users

To examine whether older adults' general accuracy deficit in average categorization performance resulted from using a non-task appropriate strategy, we 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 NRB 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 ($M = .74$) [$t(15) = 4.40, p = .001$]¹¹. However, given that only 3 older adults applied an NRB strategy when learning the NRB category set (the majority applied a RB strategy), this small sample of older adults using the appropriate strategy precluded us from drawing strong conclusions.

Executive Functioning

To examine the relationship between RB and NRB category learning and executive functioning, average categorization performance was correlated with the various executive functioning measures in older and younger adults (see Tables 7 and 8)¹². Among older adults, RB performance was correlated with the number of categories completed in the WCST and marginally correlated with backward digit span. When controlling for the age of older adults, RB performance remained significantly correlated with WCST [$r = .48, p = .02$] 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, NRB performance was

¹¹ For both the RB task and the NRB task, results were equally significant when final block categorization performance was examined rather than average categorization performance.

¹² 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 WCST 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. WCST data was missing from 7 older adults.

marginally correlated with backward digit span. After controlling for age, NRB performance was significantly correlated with backward digit span [$r = .41, p = .038$]. The NRB performance of younger adults was correlated with the number of categories completed in the WCST. These findings suggest that working memory and task switching may be important for both RB and NRB category learning.

In addition to accuracy data, we were also interested in the relationship between strategy use and executive functioning. We 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 NRB 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 WCST [$t(21) = 3.6, p = .002$] 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 WCST 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. We 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, we did not compare executive functioning performance and strategy use among older adults in the NRB condition, because only three older adults used the optimal NRB strategy. Among younger adults in the NRB condition, WCST 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: WCST perseveration errors [$M = 5.9$ vs. $M = 6.9$]). No other comparisons were significant.

Discussion

In line with our predictions, younger adults performed significantly better than older adults on both the RB and NRB category learning task. 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 Experiment 2 were best fit by guessing models during the final block of the RB task, we 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. 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 NRB 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. 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), 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 WCST performance. To further explore the relationship between RB category learning and executive functioning in older adults, we 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 WCST 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 for 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. Too 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 WCST 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 WCST 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.

Experiment 3

Experiment 2 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, we were particularly interested in examining whether pre-training similar to what we used in Experiment 1 would reduce RB category learning deficits in older adults in a similar way. 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. For this reason, the focus of Experiment 3 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. RB categorization performance following pre-training in Experiment 3 will be compared to RB performance without pre-training in Experiment 2 (the control condition). 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 practice trials from an easier version of the RB categorization task. Prior work involving RB and NRB category learning in younger adults have shown that NRB category sets are learned best when participants begin with the most difficult items first, whereas RB category sets are learned equally well regardless of which types of items are learned first (Spiering & Ashby, 2008). Other studies involving difficult cognitive tasks have shown that it is best to begin with easy examples and then transition to more difficult examples (Squires, Hunkin, & Parkin, 1997; Wilson, Baddeley, Evans, & Shiel, 1994; Ahissar & Hochstein, 1997). Additionally, cognitive and perceptual training programs with older adults have shown successful task performance when participants tasks adaptively progress in difficulty (Ball, Edwards & Ross, 2013; Berry et al., 2010). Based on the above research, we decided to present participants with easier trials first during the category learning task. 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.

Method

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)¹³. 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

¹³ Of the 31 younger adults, 26 subjects also participated in the Experiment 1 and 5 subjects were newly recruited. Of the 26 older adults, 25 subjects also participated in the Experiment 1 and 1 subject was newly recruited to keep the sample size of the conditions relatively equal.

in the study. We used the same inclusion criteria as Experiments 1 and 2. The education level of younger adults ($M = 12.3$ years, $SD = 0.74$) was significantly lower ($t(26.7) = 4.47, p < .001$)¹⁴ than that of older adults ($M = 14.9$ years, $SD = 2.8$).

Materials

We administered the same category learning task and cognitive battery that was used in Experiment 2.

Procedure

Session 1

Participants were tested individually across two testing sessions, approximately one week apart. Participants first 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. 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 Experiment 2 except that twenty crystal ball images were presented before the standard 320 trials, which were considered easier to categorize. For these twenty trials, the frequency parameter was altered so that Category A and B stimuli were slightly more distinct from each other along the frequency dimension). As well, variation along the orientation dimension was decreased, so that the orientation dimension

¹⁴ Data regarding education level was not collected from 1 older adult.

was slightly less salient. Eighty stimuli were created using the same protocol as described in Experiment 2, and 20 stimuli were randomly sampled to be used during the beginning 20 trials of the category learning task. Changing the saliency of the frequency and orientation dimensions only applied to the twenty practice stimuli. The remaining 80 stimuli used in the category learning task were the same difficulty as those used in Experiment 2.

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

Session 2

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.

Results

Category Learning Accuracy

Given that declines in executive functioning are associated with normal aging, we 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, we were 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 9. RB pre-training data were compared with RB control data (these data were taken from Experiment 2) 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 ($M = 0.63$) [$F(1, 51) = 4.76, p = .03, \text{partial } \eta^2 = .085$]. A main effect of block was also found, indicating that

categorization accuracy improved over time, [$F(2.5, 129) = 14.28, p < .001$, partial $\eta^2 = .219$; Greenhouse-Geisser corrected]. The group x block interaction was not significant [$F(2.5, 129) = 0.24, p = .84$, partial $\eta^2 = .005$; Greenhouse-Geisser corrected], indicating that older adults in both conditions demonstrated learning across trials.

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 $\eta^2 = .082$], 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 $\eta^2 = .416$; 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 $\eta^2 = .064$; 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 ($M_{pre-train} = .76, M_{control} = .68; p = .007$) and block 2 ($M_{pre-train} = .83, M_{control} = .75, p = .007$) but not during blocks 3 ($M_{pre-train} = .84, M_{control} = .81, p = .32$) and 4 ($M_{pre-train} = .86, M_{control} = .85, p = .57$). 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.

Computational Modeling

We fit decision bound models to each block of each participant's data (for details please see Appendix B). 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 10. 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 9 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 10).

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 [$R^2 = .682, F(1, 24) = 51.55, p < .001$]. 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, we 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.

Executive Functioning

The average categorization accuracy was correlated with the executive functioning performance of older adults and younger adults¹⁵. The correlations between RB performance and executive function scores are presented in Table 11. Among older adults, RB pre-train performance was marginally correlated with alpha span [$r = .39, p = .057$]. No other executive function 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.

We were also interested in examining the relationship between strategy use and executive functioning. We compared the executive functioning performance of participants using task

¹⁵ 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 WCST 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. WCST data was missing from 3 older adults.

appropriate and inappropriate strategies in the RB pre-train task. Age differed significantly across participant's whose data were 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. 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. We 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.

Discussion

Older adults in the pre-train condition performed significantly better on the RB category set relative to older adults in the control condition. 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.

Like Experiment 2, computational modeling was used in Experiment 3 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 suggest 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 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.

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. Experiment 1 demonstrated that in contrast to younger adults, older adults found complex, disjunctive RB categories more difficult to learn than NRB, family-resemblance categories. 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. Experiment 2 further explored how task complexity interacted with RB and NRB category learning, by examining more complex single-dimensional RB category learning and NRB category learning. Additionally, strategy analyses were conducted to shed light on the approaches older adults took when learning categories relative to younger adults. Findings from Experiment 2 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. Experiment 3 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 Experiment 1, where pre-training improvements were a result of better rule identification, in Experiment 3, pre-training improvements were a result of better rule application.

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. Experiments 1-3 focused on understanding and minimizing category learning deficits in older adults, by minimizing task demands via pre-training. Older adults in Experiment 1 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. 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. Experiments 2 and 3 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. 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 paper 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.

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, 2017). 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.

Conclusions

The findings of Experiments 1 to 3 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.

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Tables

Table 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%

Table 2: Executive functioning performance of younger and older adults.

	<u>Younger Adults</u>		<u>Older Adults</u>	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
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
WCST Categories Completed	4.1	0.8	3.1	1.3
WCST Perseveration Errors	7.1	2.3	9.5	4.6

Table 3: Correlations between cognitive tests and categorization performance in 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
WCST Categories Completed	.416	.354	.391	.415†
WCST 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 4: Correlations between cognitive tests and categorization performance in 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
WCST Categories Completed	-.198	.183	.004	-.420
WCST 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: ** $p < .01$, * $p < .05$.

Table 5: Distribution parameters for rule-based and non-rule-based sets.

Category Structure	μ_f	μ_o	σ_f^2	σ_o^2	$cov_{f,o}$
Rule-based					
Cat. A	280	125	75	9,000	0
Cat. B	320	125	75	9,000	0
Non-rule-based					
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.

Table 6: Number of participants fit by each class of decision bound models.

Category	Model							
	<u>Frequency</u>		<u>Orientation</u>		<u>NRB</u>		<u>Random</u>	
	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
NRB								
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.

Table 7: Correlations between cognitive tests and categorization performance in older adults.

	RB	NRB
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
WCST Categories Completed	.462*	.150
WCST Perseveration Errors	-.233	-.282

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

Table 8: Correlations between cognitive tests and categorization performance in younger adults.

	RB	NRB
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
WCST Categories Completed	-.070	.366*
WCST Perseveration Errors	.003	-.058

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

Table 9: Number of older adults fit by each class of decision bound models

Category	Model							
	<u>Frequency</u>		<u>Orientation</u>		<u>NRB</u>		<u>Random</u>	
	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 10: Number of younger adults fit by each class of decision bound models

Category	Model							
	<u>Frequency</u>		<u>Orientation</u>		<u>NRB</u>		<u>Random</u>	
	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.

Table 11: Correlations between rule-based pre-train performance and cognitive tests in 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
WCST Categories Completed	.123	.159
WCST Perseveration Errors	.188	-.286

Note. Executive functioning measures were correlated with average categorization performance.

Two-tailed t-tests: [†] $p < .06$.

Figures

Figure 1: Two category learning tasks from Shepard, Hovland, and Jenkins (1961), Type II is considered a hard/complex RB category set, where two features indicate category membership, and participants can achieve perfect performance using a disjunctive rule. Type IV is family resemblance category set and all three features are used to indicate category membership. 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. The Type IV category set is considered harder to learn than the Type II category set.

Figure 2: Average categorization performance of younger adults and older adults across 10 learning blocks. Error bars denote the standard error of the mean.

Figure 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.

Figure 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.

Figure 5: (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 non-rule-based category set.

Figure 6: An example of a correct trial in the categorization task. Feedback was presented after each response (“correct” or “incorrect”).

Figure 7: Categorization performance of younger adults and older adults across learning blocks in (A) the RB category set and (B) the NRB category set. Error bars denote the standard error of the mean.

Figure 8: 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 NRB category set.

Figure 9: 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.

Figure 10: 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.

Appendix A: Strategy Analysis

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.

It is important to examine strategy use because 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 and in Rabi & Minda (2016) when examining SHJ learning in older adults.

Appendix B: Computational Modeling used in Studies 2 and 3

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 NRB 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. We 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 NRB category set, the two-dimensional information-integration model was the optimal model.