

# Category Learning Strategies in Younger and Older Adults: Rule Abstraction and Memorization

Christopher N. Wahlheim and Mark A. McDaniel  
Washington University in St. Louis

Jeri L. Little  
Hillsdale College

Despite the fundamental role of category learning in cognition, few studies have examined how this ability differs between younger and older adults. The present experiment examined possible age differences in category learning strategies and their effects on learning. Participants were trained on a category determined by a disjunctive rule applied to relational features. The utilization of rule- and exemplar-based strategies was indexed by self-reports and transfer performance. Based on self-reported strategies, the frequencies of rule- and exemplar-based learners were not significantly different between age groups, but there was a significantly higher frequency of intermediate learners (i.e., learners not identifying with a reliance on either rule- or exemplar-based strategies) in the older than younger adult group. Training performance was higher for younger than older adults regardless of the strategy utilized, showing that older adults were impaired in their ability to learn the correct rule or to remember exemplar-label associations. Transfer performance converged with strategy reports in showing higher fidelity category representations for younger adults. Younger adults with high working memory capacity were more likely to use an exemplar-based strategy, and older adults with high working memory capacity showed better training performance. Age groups did not differ in their self-reported memory beliefs, and these beliefs did not predict training strategies or performance. Overall, the present results contradict earlier findings that older adults prefer rule- to exemplar-based learning strategies, presumably to compensate for memory deficits.

*Keywords:* aging, category learning, feedback training, strategy, transfer

Categorization is a fundamental aspect of cognitive function that involves organizing knowledge about objects and events into groups based on common features. Everyday examples of categorization can be seen in professional settings, such as when a dermatologist diagnoses a skin disorder, or in recreational settings, such as when a bird watcher identifies the family membership of a bird. This ability allows individuals of all ages to interact with their environment by reducing complexity and the need for constant learning (Bruner, Goodnow, & Austin, 1956). The improved cognitive economy afforded by categorization is especially important for older adults to counteract the variety of cognitive impairments that occur with age (Hartshorne & Germine, 2015; Park, 2000). Although age-related deficits are well established for many

cognitive functions, few studies have examined age differences in the learning of new categories.

The available studies have generally shown that older adults are impaired in their learning of categories for which rules cannot be verbalized (e.g., Filoteo & Maddox, 2004), and model-based analyses have shown that older adults prefer different strategies from younger adults (e.g., Mata, von Helversen, Karlsson, & Cupper, 2012). However, it is unclear whether age-related learning deficits will generalize to complex categories with verbalizable rules, and whether self-reported learning strategies will also differ between age groups. In the present study, we explored these issues by comparing younger and older adults' training performance, transfer performance, and self-reported training and transfer strategies for categories defined by a disjunctive rule applied to relational features. Before presenting our experimental procedures and developing specific hypotheses, we first overview what the existing literature has shown.

The ability to learn new categories has frequently been examined using feedback training procedures in which individuals attempt to categorize exemplars of novel perceptual categories prior to receiving category labels as feedback (e.g., Ashby & Maddox, 1998; Bruner et al., 1956). Returning to the bird watcher example, the benefits of feedback can be seen when a novice's ability to categorize birds is improved by the corrective feedback of an expert. Feedback training procedures have often been used to assess learning strategies because formal mathematical models can be applied to identify how individuals approach the task (e.g., Ashby, 1992). Learning strategies can be assessed using a model-

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Christopher N. Wahlheim and Mark A. McDaniel, Department of Psychological and Brain Sciences, Washington University in St. Louis; Jeri L. Little, Department of Psychology, Hillsdale College.

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Correspondence concerning this article should be addressed to Christopher N. Wahlheim, Department of Psychology, Washington University, One Brookings Drive, St. Louis, MO 63130. E-mail: [cnwahlhe@wustl.edu](mailto:cnwahlhe@wustl.edu)

based approach by fitting models with different underlying assumptions concerning the decisions bounds individuals place between categories, and identifying the model that best fits the data. Most model-based investigations have distinguished between rule-based and information integration approaches to learning perceptual categories. Rule-based strategies reflect an explicit reasoning process used to establish a verbalizable rule that maximizes accuracy, whereas information integration strategies are predecisional and serve to integrate stimulus dimensions when explicit rules are difficult to verbalize (Ashby & Maddox, 2005).

Older adults' learning has been found to be impaired during feedback training when rules were difficult to verbalize (Filoteo & Maddox, 2004), but model-based analyses have shown a reduction in this deficit when rule-based strategies were used (for similar findings, see Ashby, Noble, Filoteo, Waldron, & Ell, 2003; Maddox, Pacheco, Reeves, Zhu, & Schnyer, 2010). Perhaps not coincidentally, older adults have also been shown to prefer rule- to exemplar-based strategies in a multiple-cue categorization task in which the categories of fictional characters were determined by aspects of their hair, nose, ears, and belly (Mata et al., 2012). Exemplar-based strategies are similar to information integration strategies in that they both involve retrieval-based comparisons of current with earlier-presented stimuli. Older adults may use rule-based strategies in these situations to compensate for memory deficits, such as when a bird watcher identifies birds using characteristic features (e.g., beak shape) instead of relying on memory for earlier-seen birds. Consistent with this, Mata, von Helversen, Karlsson, and Cüpper (2012) found a deficit in older adults' training and transfer performance relative to younger adults, and model-based analyses showed that transfer performance was best described by a rule-based model for the majority of older adults and by an exemplar-based model for the majority of younger adults.

The results from the model-based assessments described above suggest that the majority of older adults prefer rule-based learning strategies, presumably because they produce superior performance (at least for older adults). However, despite the elegance of the model-based approach, Donkin, Newell, Kalish, Dunn, and Nosofsky (2015) recommended caution when interpreting these model-fitting analyses because the percentage of individuals classified as preferring a particular strategy varies dramatically depending on the details of model. Of relevance to the present experiment, Donkin et al. (2015) suggested that earlier investigations of information integration category learning did not consider a sufficient range of alternative models, which resulted in an overclassification of individuals as using information integration strategies and an underestimation of individuals who used rule-based strategies. Thus, the extent to which older adults prefer rule-based strategies remains an open issue.

A complementary approach to model-based assessments is a procedure in which categorization of ambiguous transfer items reveals the representational structure of learned categories, thus indicating the type of learning strategies utilized. Previous studies using this procedure with younger adults have shown it to be effective for identifying individual differences in strategy use (e.g., Little & McDaniel, 2015; McDaniel, Cahill, Robbins, & Wiener, 2014; Regehr & Brooks, 1993). The present experiment adopted the procedure developed by Little and McDaniel (2015) to compare younger and older adults' strategy preferences. In their study,

participants received feedback training for two categories of perceptual objects that were determined by a disjunctive rule applied to relational features (an object containing inner and outer shapes belonged to one category if the shapes were the same form *or* color, whereas an object belonged to another category if the form and color of the shapes both differed). Individual differences in the extent to which younger adults relied on rule- or exemplar-based strategies were shown in self-reports of strategy use and transfer performance. An overarching question of importance to theoretical perspectives on cognitive aging is whether older adults will display individual differences akin to those shown by younger adults when faced with a relatively challenging rule-based categorization task. Indeed, age-related deficits have been shown to increase with rule complexity (e.g., Racine, Barch, Braver, & Noelle, 2006), and these might be accompanied by differences in strategy preference (cf. Touron & Hertzog, 2004).

The first issue we addressed here was whether younger and older adults would show comparable individual differences in self-reported learning strategies. One possibility is that older adults will prefer rule-based learning to compensate for their episodic memory deficit (for reviews of age-related memory deficits, see Balota, Dolan, & Duchek, 2000; Zacks, Hasher, & Li, 2000). Rule learning may be more appealing to older adults because it summarizes large sets of instances and reduces demands on episodic memory. This preference would be consistent with older adults' reluctance to select retrieval-based strategies in some situations (for a review, see Touron, 2015). However, another possibility is that older adults will be less likely to seek rules when categories are sufficiently complex due to a deficit in cognitive control abilities (for a review, see Braver & West, 2008), required for rule-based learning (e.g., for hypothesis testing). Also, older adults might initially engage hypothesis testing to determine an appropriate rule, but abandon this strategy because the prefrontal cortices that mediate this ability (e.g., Lombardi et al., 1999) decline disproportionately with age (e.g., Greenwood, 2000, 2007). A final possibility is that strategy preferences will not differ between younger and older adults, which could occur for a variety of reasons.

The second issue we addressed was the extent to which older adults would show a deficit in training performance given their choice of learning strategy. As with the first issue, several possibilities seemed theoretically plausible. One possibility is that older adults who prefer a rule-based strategy will show smaller age-related deficits in training performance, especially during early trials, relative to older adults who use an exemplar-based strategy. Consistent with this, model-based analyses have shown that age-related deficits in training performance are diminished when rule-based rather than information integration strategies are applied (e.g., Filoteo & Maddox, 2004). Indeed, rule-based strategies may enhance the economy of categorical representations, thus counteracting older adults' associative memory deficit that impairs learning of object-label associations (cf. Naveh-Benjamin, 2000).

Another possibility is that older adults who use exemplar-based strategies will show smaller training deficits than those who use rule-based strategies. As stated above, prefrontal cortices show disproportionate age-related decline, which could render rule-based strategies ineffective or inefficient. In addition, rule-based learning relies heavily on hypothesis testing which presumably places high demands on cognitive control processes (e.g., see

Kellogg, Robbins, & Bourne, 1978, for cognitive challenges during a rule-based category learning task). Further, both explicit and procedural systems are thought to mediate category learning (e.g., Maddox & Ashby, 2004), and older adults often show intact automatic forms of memory (e.g., Jennings & Jacoby, 1993). Thus, at least one form of memory could serve to spare performance on this task. A final possibility is that all older adult learners will show uniform deficits due to impairments in both cognitive control involved in learning rules and episodic memory involved in acquiring object-label associations.

The third issue we addressed was the extent to which self-reported learning strategies engaged during training predicted categorization responses on transfer objects for younger and older adults. Following Little and McDaniel (2015), a unique feature of the present experiment was that participants categorized objects in both training and transfer phases, and then reported the extent to which they relied on rule-based or exemplar based learning strategies. The transfer phase included ambiguous objects that provided an objective index of the representational structure of categories formed during learning. We expected that younger adults who reported using rule-based strategies would categorize ambiguous transfer objects according to the rule more often than younger adults who reported using an exemplar-based strategy. We thought it possible that older adults would also show this pattern, but to a lesser degree. Older adult rule-abstractors might form incomplete or incorrect rules (e.g., that focus on a single attribute, rather than several attributes) due to difficulties in meeting the cognitive challenges of hypothesis testing, such as sampling from an appropriate hypothesis pool (e.g., Levine, 1975), and remembering the relationship between feedback and previously considered hypotheses (Kellogg et al., 1978). If older adult rule-learners acquire impoverished representations, then this would be evident as a lower probability of categorization according to the rule on ambiguous transfer items relative to younger adults. Converging evidence would be shown by similar age differences in categorization of a set of rule-based transfer items (items that were perceptually dissimilar from training items and thus could only be categorized on the basis of the rule).

Finally, two additional aspects of our investigation bear mention. First, we examined whether working memory capacity predicted training strategies and performance for both age groups. Currently, the existing literature regarding the relationship between working memory and strategy preferences is inconclusive. Craig and Lewandowsky (2012) showed that a working memory construct did not predict preferences for different rule-based strategies in a correlated cues task. In contrast, McDaniel, Cahill, Robbins, and Wiener (2014) found that younger adults with higher working memory capacity on an operation span task (Turner & Engle, 1989) were most likely to display rule learning in a function-learning task. However, Little and McDaniel (2015) found no relationship between operation span performance and self-reported strategies used to learn perceptual categories. Given these mixed findings and that working memory capacity is often lower for older adults (e.g., Park et al., 1996), we reasoned that additional investigation was warranted. Regarding the relationship between working memory capacity and training performance, higher working memory capacity predicts faster learning of rule-based categories for younger adults (DeCaro, Thomas, & Beilock, 2008). Both age groups may show this advantage for high working

memory individuals, as intact cognitive control can enhance hypothesis testing (Dougherty & Hunter, 2003), and remembering in the face of interference (Engle, 2002).

Second, we examined whether participants' beliefs about their memory abilities would predict training strategies. Older adults seem disinclined to rely on memory-based strategies because they believe that their memory abilities have diminished. However, we thought it possible that some older adults would retain a positive belief in their memory abilities, which might result in their preferring an exemplar-based learning strategy. We also examined whether memory beliefs would predict training performance. This would occur if both younger and older adults can accurately monitor their learning (cf. Hertzog & Dunlosky, 2011).

## Method

### Participants

Sixty younger adults (21 men; years of age:  $M = 20.55$ ,  $SD = 2.35$ ) and 60 older adults (17 men; years of age:  $M = 73.85$ ,  $SD = 6.84$ ) participated in the experiment. The younger adults were students at Washington University in St. Louis who received \$10/hr or partial course credit for their participation. The older adults were healthy individuals from the St. Louis community who received \$10/hr for their participation. All participants completed the vocabulary subtest of the Shipley Institute of Living Scale (Shipley, 1986). Vocabulary scores were higher for older adults ( $M = 36.32$ ,  $SD = 2.31$ ) than for younger adults ( $M = 33.53$ ,  $SD = 2.72$ ),  $t(118) = 5.99$ ,  $p < .001$ ,  $d = 1.10$ . Older adults also had more years of education ( $M = 16.12$ ,  $SD = 2.63$ ) than younger adults ( $M = 14.42$ ,  $SD = 2.13$ ),  $t(118) = 3.89$ ,  $p < .001$ ,  $d = .71$ . Participants were tested individually.

### Procedure and Materials

Participants completed a variety of tasks in the following order: (a) training, (b) ambiguous object categorization (transfer), (c) strategy questionnaire, (d) rule object categorization (transfer), (e) memorization object categorization (transfer), (f) memory beliefs questionnaire, (g) computation span, and (h) reading span. The experiment lasted approximately 1–1.5 hrs. Details for these tasks appear below.

**Training.** The training phase used here was modeled from the procedure and materials used by Little and McDaniel (2015). Participants received a feedback learning procedure in which they categorized objects comprised of two colored shapes with one shape inside the other. The complete set of stimuli comprised eight objects with four belonging to each of two categories (one shape inside another) that were unique in their specific color and shape combinations (i.e., 16 unique shape and color combinations; see Figure 1). The categories were determined by a disjunctive rule that related the inner and outer shapes. When objects had inner and outer shapes that matched in either form or color, they belonged to the “Blicker” category. In contrast, when objects had inner and outer shapes that differed in both form and color, they belonged to the “Dax” category. Before beginning the task, participants received the following instructions:

In this first phase of the experiment, you will be presented with objects that belong to one of two categories (Blicker or Dax). Your

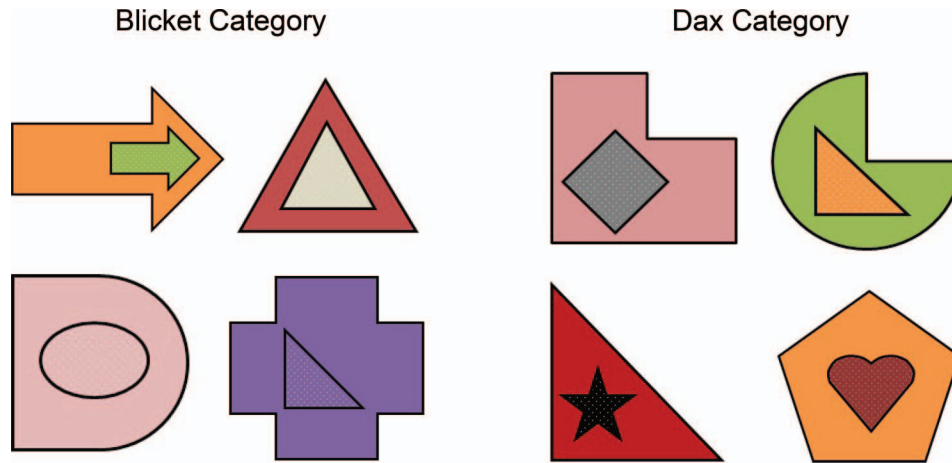


Figure 1. The eight objects above were presented in the category learning phase of the experiment. The four objects on the left represent the Blicket category and include inner and outer shapes that are the same in either color or form. The four objects on the right represent the Dax category and include inner and outer shapes that differ in both color and form. See the online article for the color version of this figure.

task will be to learn the category membership of each object. Choose a category for each object by pressing the LEFT key for “Blicket” and the RIGHT key for “Dax.” At first you will just be guessing, but you will receive feedback about the actual category membership of the objects. Use that feedback to learn the category to which each object belongs. There will be a total of eight objects, and you will have 12 practice trials for each. Continue practicing even after you have learned all the objects.

To ensure that participants understood the instructions, the same experimenter discussed the task with every participant and answered all questions before allowing participants to begin training.

Participants received 12 blocks of training that each comprised eight items (four from each category). For the Blicket category, the form of the inner and outer shapes matched for two objects and the color of the inner and outer shapes matched for the other two objects (Figure 1, left panel). For the Dax category, the form and color of the inner and outer shapes differed for all four objects (Figure 1, right panel). In each training block, objects appeared individually on a computer screen against a white background. Participants were instructed to assign each object to a category by pressing the “S” key with their left index finger for the Blicket category and the “L” key with their right index finger for the Dax category. The keys were marked with a white sticker so that participants knew which keys to press; the letters were not visible. Eight objects appeared in a different predetermined random order for each of the 12 training blocks, with the constraint that no more than two objects from the same category appeared sequentially in any block. The presentation order remained constant across participants so that individual differences could be examined. Objects remained on the screen until participants entered a response. After each response, the correct category label for each object appeared as feedback.

**Ambiguous object categorization (transfer).** Participants categorized eight new ambiguous objects that had the same outer shape and outer color as the training objects, but were rendered a member of the opposing category on the basis of the rule (see

Figure 2). Unlike the training phase, feedback was not provided following each response.

**Strategy questionnaire.** Following categorization of ambiguous objects, participants reported the strategies they used during

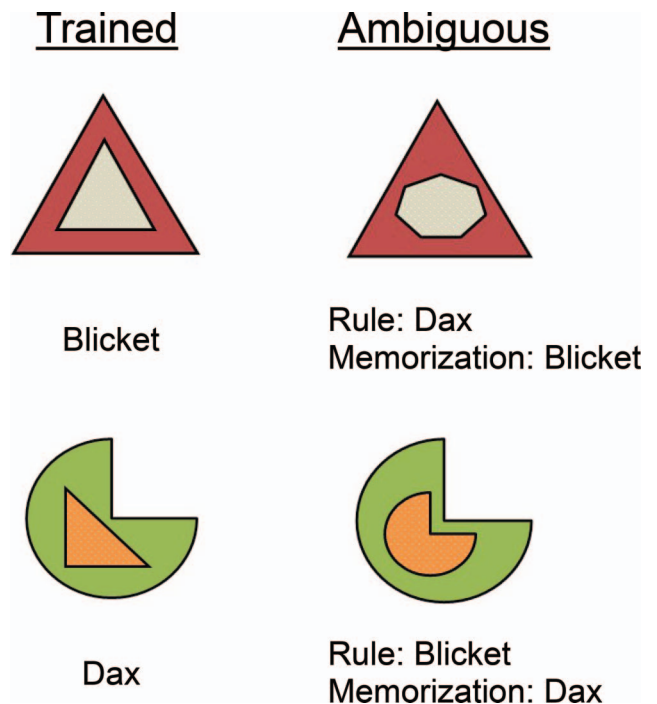


Figure 2. Examples of objects from the training phase (left column) and their respective ambiguous objects from the transfer phase (right column). The ambiguous objects place rule-abstraction and memorization strategies in opposition to one another. Categorization of ambiguous objects on the basis of rules results in assignment to the category opposite that to which the perceptually similar training items belonged. See the online article for the color version of this figure.

the training and transfer phases. Here, participants were first asked to report the strategy they used during the training phase, and they were next asked to report the strategy they used during the transfer phase that involved categorizing ambiguous objects.

For training strategies, participants were instructed to think back to the training phase and remember whether they were more focused on trying to memorize objects or on establishing a rule. To reduce the possibility of biasing participants' reports to a specific strategy, no further description of what constituted the use of either strategy was offered. Participants made their ratings on a Likert scale ranging from 1 (*memorization strategy*) to 7 (*rule-establishing strategy*). Participants were instructed to give an extreme rating only if they used one strategy exclusively throughout training or to give an intermediate rating to indicate the extent to which they used one strategy more than another. Participants were instructed to give the absolute intermediate rating (4) if they used both strategies equally or were uncertain about their strategy.

For transfer strategies, participants were instructed to think back to the immediately preceding phase and to make ratings similar to those they made for the training phase. The primary difference between the questionnaires for each phase was that the memorization strategy on the transfer task was framed in terms of categorizing on the basis of the similarity between ambiguous objects and training objects. Specifically, participants were instructed to indicate the extent to which they used the similarity between the outer shape of "new" objects in the transfer phase and the "old" objects in the training phase to categorize ambiguous transfer objects. Consistent with the question about training strategies, no further description of what constituted the use of either strategy was offered to reduce the possibility of biasing participants' responses. It was also emphasized that extreme ratings should be

given when only one strategy was used, intermediate ratings should be given to indicate the extent to which one strategy was used more often, and a rating of "4" should be given when both strategies were used equally or when participants were uncertain about which strategy they used.

After participants rated their strategies, they were queried about their specific understanding of the rules that differentiated the two categories. First, they were asked to explain the rule that they used to categorize objects if they established one. If they could not articulate a perfect rule but tried to establish one, they were asked to explain the best rule they came up with. Finally, if they stated a rule, they were asked to report whether they established it during the training or transfer phase.

**Rule-favored and memory-favored object categorization (transfer).** The rule object categorization task comprised a set of new objects with inner and outer shapes that were perceptually dissimilar from objects presented in earlier phases (Figure 3, left panel). Participants did not receive feedback after categorizing these objects. Half the objects followed the rule from the Blicket category and the other half followed the rule from the Dax category. The memory object categorization task comprised a final set of new objects that included only the outer shape of training objects with their original color (Figure 3, right panel). Participants also categorized these objects without the provision of feedback. Half the objects included the outer shape from the Blicket category and the other half included the outer shape from the Dax category.

**Memory beliefs questionnaire.** Participants completed a short form of the Metamemory in Adulthood Questionnaire (MIA; Dixon, Hultsch, & Hertzog, 1988) that included 42 items. This form included all the items for the capacity factor (17 items) and the locus factor (nine items). The capacity factor is thought to

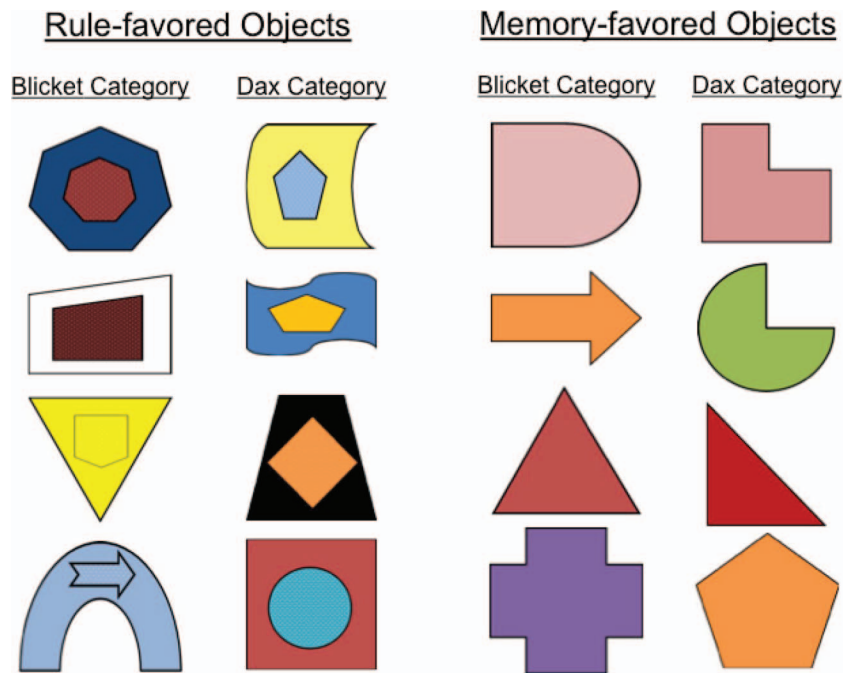


Figure 3. Novel objects used to assess rule-abstraction (left columns) and memory for categories of training objects (right columns). See the online article for the color version of this figure.

measure beliefs regarding one's memory capacity, and the locus factor is thought to measure beliefs regarding one's perceived sense of control over memory skills. Four items from each of the achievement, anxiety, strategy, and task factors were also interspersed throughout the questionnaire to make relationships among items from the target factors less obvious to participants. The filler items are not considered further.

**Computation span.** In the computation span task (Conway et al., 2005), participants were shown math problems that included a solution that was correct for some items (e.g., Is  $5 + 4 = 9$ ?) and incorrect for other items (e.g.,  $7 + 2 = 5$ ?). Participants were instructed to: (a) verify the accuracy of the solution by saying "Yes" for correct solutions and "No" for incorrect solutions, and (b) remember the second number of each problem. Participants received blocks of three sets of math problems. The first block of math problems included three sets of one problem. The number of math problems per set increased by one problem on each subsequent block with the maximum number of problems per set being seven. Participants received increasingly larger sets when they could correctly recall the second number of all the problems in at least two of the three sets in a block. Participants were also required to have solved the math problems correctly to continue in the task. Participants solved the math problems aloud and recalled the second number from each when the message "RECALL" appeared following presentation of the problems.

**Reading span.** In the reading span task (Daneman & Carpenter, 1980), participants were shown individually presented sentences and were given two tasks. The first task was to read each sentence aloud (e.g., The bird that has keen insight for hunting is the canary) and indicate whether it was true or false (e.g., false). The second task was to recall the last word of each sentence. As in the computation span task, there were blocks of three sets of sentences that started with one sentence per set and increased by one sentence per set across blocks, up to a maximum of seven sentences per set. After the last sentence in each set, participants recalled the last word of each sentence when prompted by a string of question marks (???). Participants received increasingly larger sets until they could no longer correctly indicate sentence truth and recall the last word from all sentences in a set for at least two sets in a block.

## Results

### Strategy Utilization

Younger adults showed high consistency in their self-reported ratings of training and transfer strategies,  $r(58) = .75, p < .001$ , which was similar in magnitude to that reported by Little and McDaniel (2015). In contrast, older adults showed lower consistency in their training and transfer strategies,  $r(58) = .49, p < .001$ , as compared with younger adults,  $z = 2.33, p = .02$ . Given that we were primarily interested in differences in categorization based on training strategies, we focus subsequent analyses only on training strategy ratings.

To address the issue of whether younger and older adults showed consistent individual differences in learning strategies, we compared the frequencies of self-reported strategies between age groups. Table 1 displays the frequency of participants who reported using each training strategy. The 23 younger adults and 19

Table 1  
*Frequencies of Training Strategies Reported by Younger and Older Adults*

Age group	Training strategy		
	Rule-abstractor	Memorizer	Intermediate
Younger	32	23	5
Older	21	19	20

older adults who gave ratings of 1, 2, or 3 were classified as *memorizers* and the 32 younger adults and 21 older adults who gave ratings of 5, 6, or 7 were classified as *rule-abstractors*. For the younger adult *rule-abstractors*, 30 (out of 32) participants reported acquiring a rule during training; 18 participants were able to completely articulate the rule, and five others were able to articulate a partial rule (i.e., they provided information about the match/mismatch between either color or form but not both). For the older adult *rule-abstractors*, 13 (out of 21) participants reported acquiring a rule during training; two participants were able to completely articulate the rule, and one other was able to articulate a partial rule. Five younger adults and 20 older adults gave a rating of 4 and were classified as *intermediate*. Comparison of training strategy frequencies for younger and older adults revealed a significant association between age group and strategy,  $\chi^2(2) = 11.66, p = .003$ . More older than younger adults reported an intermediate training strategy,  $\chi^2(1) = 9.00, p = .003$ , whereas there were no age differences in the frequencies of rule-abstractors,  $\chi^2(1) = 2.28, p = .13$ , or memorizers,  $\chi^2(1) = 0.38, p = .54$ .

### Analysis Plan for Training and Transfer Performance

In the following analyses of training and transfer performance, younger and older adults' category learning was compared as a function of strategy group. However, given that there were only five younger-adult intermediate learners, this group was not included in any of the factorial analyses. Thus, initial comparisons between younger and older adults only included rule-abstractors and memorizers; follow-up comparisons were then conducted within the older adult group that included rule-abstractors, memorizers, and intermediate learners. Additional analyses were conducted when necessary to address specific issues concerning age differences in category learning.

### Training Performance

Training performance was computed as the probability of correct categorization across all trials (Table 2, left columns). Possible age differences in training performance were examined by comparing performance for younger and older adults in the manner outlined above. A 2(Age: Younger vs. Older)  $\times$  2(Strategy: Rule-abstractor vs. Memorizer) ANOVA revealed a significant effect of Age showing that performance was higher for younger ( $M = .84, SD = .10$ ) than older ( $M = .67, SD = .13$ ) adults,  $F(1, 114) = 47.50, p < .001, \eta_p^2 = .34$ . There was a marginal effect of strategy showing a trend toward performance being higher for rule-abstractors ( $M = .80, SD = .15$ ) than memorizers ( $M = .74, SD = .13$ ),  $F(1, 91) = 3.26, p = .07, \eta_p^2 = .04$ . The Age  $\times$  Strategy interaction was not significant,  $F(1, 91) = 2.66, p = .11, \eta_p^2 = .03$ .

Table 2  
Mean Training Performance and Reaction Times (ms) as a Function of Age and Training Strategy

Training strategy	Accuracy		Reaction time	
	Younger	Older	Younger	Older
Rule-abstractor	.88 (.04)	.68 (.05)	1,172 (153)	2,283 (461)
Memorizer	.80 (.05)	.67 (.06)	1,362 (251)	2,632 (642)
Intermediate	.80 (.11)	.62 (.05)	1,367 (697)	2,678 (586)

Note. Reaction times were trimmed to exclude observations greater than three standard deviations above the mean, which resulted in removal of approximately 2% of all observations. Margins of error for 95% confidence intervals are displayed in parentheses.

A follow-up comparison of younger adult rule-abstractors and memorizers revealed that performance was significantly better for rule-abstractors,  $t(53) = 3.11$ ,  $p = .003$ ,  $d = 0.80$ . In contrast, a comparison of older adults in all three strategy groups revealed no differences,  $F(2, 57) = 1.36$ ,  $p = .27$ ,  $\eta_p^2 = .05$ . These results clearly showed that older adults had a learning deficit no matter which strategy they adopted. However, in terms of learning the categorizations of training items, rule-abbreviation was a more effective strategy than memorization for younger adults.

Possible age differences in reaction times (RTs) were examined next (Table 2, right columns). A  $2(\text{Age: Younger vs. Older}) \times 2(\text{Strategy: Rule-Abstractor vs. Memorizer})$  ANOVA revealed a significant effect of age showing that younger adults ( $M = 1,251$  ms,  $SD = 499$  ms) made their decisions more quickly than older adults ( $M = 2,449$ ,  $SD = 1,173$ ),  $F(1, 91) = 45.07$ ,  $p < .001$ ,  $\eta_p^2 = .33$ . Neither the effect of Strategy nor the Age  $\times$  Strategy interaction was significant, *largest*  $F(1, 91) = 2.31$ ,  $p = .13$ ,  $\eta_p^2 = .03$ . A follow-up comparison of younger adult rule-abstractors and memorizers revealed no difference in RTs,  $t(53) = -1.41$ ,  $p =$

.17,  $d = -.38$ , and a follow-up comparison of older adults in all three strategy groups also revealed no differences,  $F(2, 57) = 0.66$ ,  $p = .52$ ,  $\eta_p^2 = .02$ . These results showed that older adults deliberated longer on their decisions; thus, considered in conjunction with older adults' deficit in training performance, there was no evidence of a speed-accuracy trade-off.

The relationship between training strategies and performance was further examined by comparing rates of learning across training blocks (learning curves; Figure 4) for both age groups. As in the analyses above, younger adult intermediate learners were excluded from these analyses because of the small sample size. An initial  $2(\text{Age: Younger vs. Older}) \times 2(\text{Strategy: Rule-Abstractor vs. Memorizer}) \times 12(\text{Block: 1-12})$  ANOVA revealed a significant Strategy  $\times$  Block interaction,  $F(11, 1001) = 2.15$ ,  $p = .02$ ,  $\eta_p^2 = .02$ . To interpret this interaction, separate  $2(\text{Age: Younger vs. Older}) \times 12(\text{Block: 1-12})$  ANOVAs were conducted within rule-abstractor and memorizer strategy groups, and separate  $2(\text{Strategy: Rule-Abstractor vs. Memorizer}) \times 12(\text{Block: 1-12})$  ANOVAs were conducted within age groups. There were significant Age  $\times$  Block interactions for both rule-abstractors and memorizers, *smallest*  $F(11, 440) = 1.82$ ,  $p = .049$ ,  $\eta_p^2 = .04$ , showing that younger adults learned faster than older adults. There was also a significant Strategy  $\times$  Block interaction for younger adults,  $F(11, 583) = 1.84$ ,  $p < .045$ ,  $\eta_p^2 = .03$ , but not for older adults,  $F(11, 418) = 1.08$ ,  $p = .38$ ,  $\eta_p^2 = .03$ , showing that younger adult rule-abstractors learned faster than memorizers, but learning rates did not differ between older adult rule-abstractors and memorizers.

Follow-up  $t$  tests examining performance differences between adjacent training blocks confirmed these interpretations. Younger adult rule-abstractors showed significant increases in performance from Blocks 1 to 2, 2 to 3, and 3 to 4, *smallest*  $t(31) = 3.10$ ,  $p = .004$ ,  $d = 0.55$ , whereas younger adult memorizers showed significant performance increases from Blocks 1 to 2 and 2 to 3, *smallest*  $t(22) = 2.98$ ,  $p = .007$ ,  $d = 0.63$ . In contrast, older adult

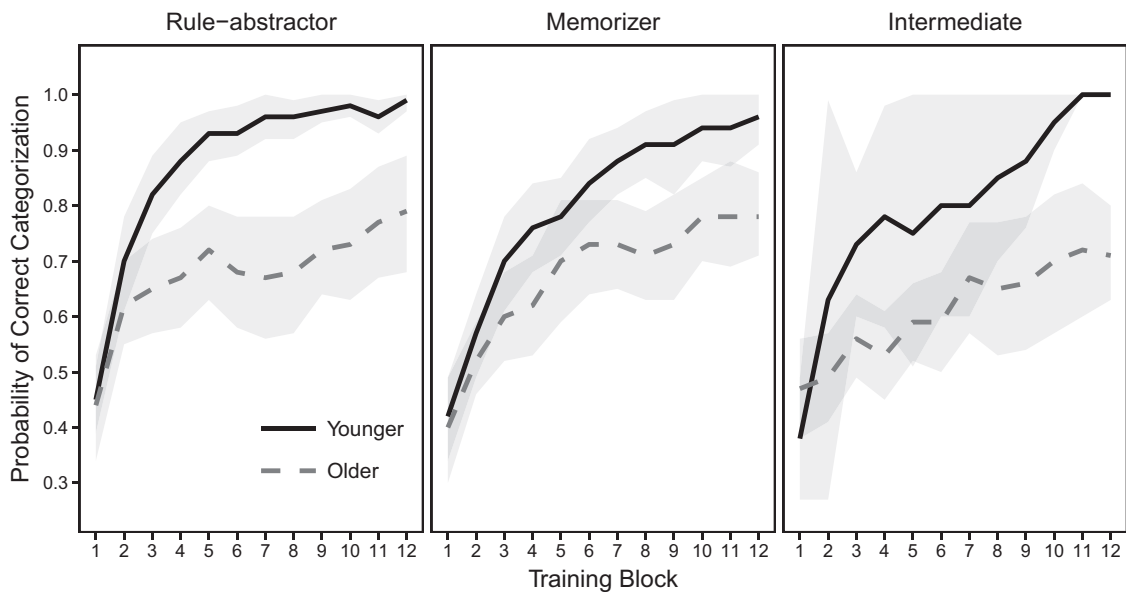


Figure 4. Probability of correct categorization across training blocks as a function of age and self-reported training strategy. Error bands are 95% confidence intervals.

rule-abstractors and memorizers only showed significant increases from Block 1 to 2, *smallest*  $t(18) = 2.47, p = .02, d = 0.58$ .

Finally, a 3(Strategy: Rule-Abstractor vs. Memorizer vs. Intermediate)  $\times$  12(Block) ANOVA conducted only for older adults revealed no significant Strategy  $\times$  Block interaction,  $F(22, 627) = 1.17, p = .27, \eta_p^2 = .04$ , showing that learning rates did not differ across strategy groups. An exploratory analysis was also conducted to examine whether formal education improved the ability to learn categories. Despite this intuitive notion, there was not a significant correlation between years of education and overall training performance for younger,  $r(58) = -.17, p = .20$ , or older,  $r(58) = .22, p = .10$ , adults.

## Transfer Performance

**Ambiguous objects.** Rule-based categorization of ambiguous objects is displayed in the left panel of Figure 5. Categorization performance was computed by dividing the number of objects categorized according to the correct rule by the total number of objects. Performance of 1.00 occurred when all objects were categorized according to correct the rule, whereas performance of 0.00 occurred when no object was categorized according to the correct rule (i.e., instead categorized on the basis of perceptual similarity).

A 2(Age: Younger vs. Older)  $\times$  2(Strategy: Rule-Abstractor vs. Memorizer) ANOVA revealed an effect of strategy showing that categorization according to the correct rule (collapsed across age groups) was higher for rule-abstractors ( $M = .56, SD = .36$ ) than memorizers ( $M = .20, SD = .24$ ),  $F(1, 91) = 26.64, p < .001, \eta_p^2 = .23$ . Follow up  $t$  tests showed that categorization (according to the rule) was significantly higher for rule-abstractors than memorizers within both age groups, *smallest*  $t(38) = 2.84, p = .007, d = .90$ . There was also a marginal Age  $\times$  Strategy interaction,  $F(1, 91) = 3.28, p = .07, \eta_p^2 = .04$ , suggesting that the difference between rule-abstractors and memorizers was greater for younger than older adults. Follow-up  $t$  tests comparing rule-abstractors' performance to chance (.50) showed that rule-based categorization

was marginally above chance for younger adults ( $M = .63, SD = .40$ ),  $t(31) = 1.85, p = .07, d = .33$ , and numerically below chance for older adults ( $M = .44, SD = .26$ ),  $t(20) = -1.01, p = .32, d = -.22$ . In addition, rule-based categorization for memorizers in both age groups was significantly below chance, *smallest*  $t(18) = -5.55, p < .001, d = -2.62$ . Together, these results suggest that older adult rule-abstractors learned incomplete rules to some extent, and they did not learn the correct rule as often as younger adult rule-abstractors. Finally, rule-based categorization was marginally greater for older adult intermediate learners than memorizers,  $t(37) = 1.83, p = .08, d = 0.57$ , but did not differ between intermediate learners and rule-abstractors,  $t(39) = 1.21, p = .23, d = 0.38$ , suggesting that intermediate learners may have used a mixture of learning strategies.

**Rule-favored objects.** The extent to which younger and older adults differed in their use of a rule-based learning strategy was also examined by comparing categorization according to the correct rule for rule-favored objects (Figure 5, middle panel). A 2(Age: Younger vs. Older)  $\times$  2(Strategy: Rule-Abstractor vs. Memorizer) ANOVA revealed that rule-based categorization was significantly greater for younger ( $M = .74, SD = .20$ ) than older ( $M = .51, SD = .21$ ) adults,  $F(1, 91) = 30.01, p < .001, \eta_p^2 = .25$ , and that that rule-based categorization (collapsed across age groups) was significantly greater for rule-abstractors ( $M = .71, SD = .24$ ) than memorizers ( $M = .56, SD = .20$ ),  $F(1, 91) = 9.93, p = .002, \eta_p^2 = .10$ . However, follow up  $t$  tests showed that the advantage for rule-abstractors over memorizers was significant for younger adults,  $t(53) = 3.65, p = .001, d = 1.00$ , but not for older adults,  $t(38) = 1.21, p = .27, d = .36$ , which was again consistent with the idea that older adult rule-abstractors did not learn the correct rule as often younger adult rule-abstractors. Nevertheless, the Age  $\times$  Strategy interaction was not significant,  $F(1, 91) = 1.71, p = .19, \eta_p^2 = .02$ . The comparison of older adults across all strategy conditions revealed no differences,  $F(2, 57) = 0.77, p = .47, \eta_p^2 = .03$ .

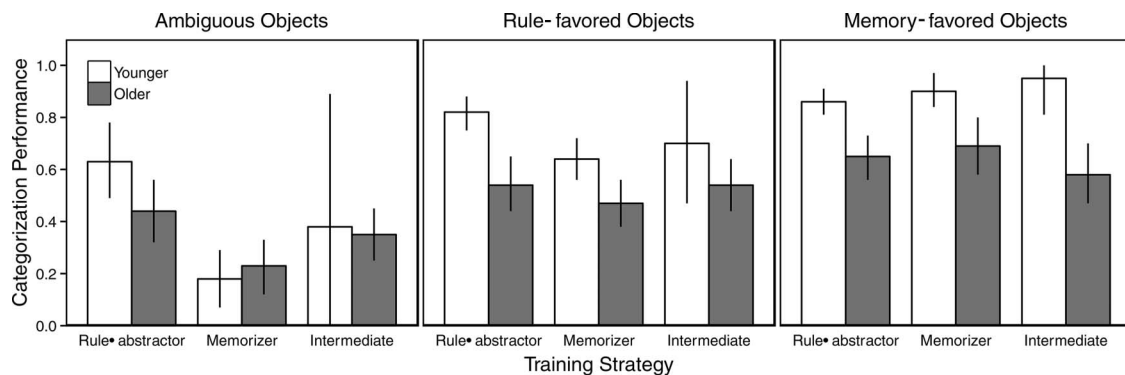


Figure 5. Categorization performance on the transfer tasks. Performance on “Ambiguous Objects” (left panel) and “Rule-favored Objects” (middle panel) reflect probabilities of categorization according to the correct rule. For Ambiguous Objects, performance of 1.00 would reflect perfect categorization according to the correct rule, and performance of .00 would reflect perfect categorization according to memory for similar perceptual stimulus features. Performance on “Memory-favored Objects” (right panel) reflects probabilities of correct categorization based on memory for objects that were perceptually similar to those presented in the training phase. Chance performance on all measures was .50. Error bars are 95% confidence intervals.



**Memory-favored objects.** Age differences in episodic memory were examined by comparing categorization of memory-based objects according to their similarity with training objects (Figure 5, right panel). A 2(Age: Younger vs. Older)  $\times$  2(Strategy: Rule-Abstractor vs. Memorizer) ANOVA revealed a significant effect of age showing that similarity-based categorization was greater for younger ( $M = .88$ ,  $SD = .15$ ) than older ( $M = .66$ ,  $SD = .20$ ) adults,  $F(1, 91) = 35.16$ ,  $p < .001$ ,  $\eta_p^2 = .28$ . Neither the effect of strategy nor the Age  $\times$  Strategy interaction was significant, *largest*  $F(1, 91) = 1.32$ ,  $p = .25$ ,  $\eta_p^2 = .01$ . These results showed that older adults had an episodic memory deficit.

### Working Memory Capacity

The reading and computation span tasks were both scored by computing the average number of total items correctly recalled in each. A composite working memory score was then computed by averaging the total number of correctly recalled items across reading and computation span tasks. Younger adults recalled more total items on average ( $M = 9.43$ ,  $SD = 2.19$ ) than older adults, ( $M = 7.09$ ,  $SD = 2.51$ ),  $t(118) = 5.42$ ,  $p < .001$ ,  $d = .99$ , indicating that younger adults had a higher working memory capacity.

The extent to which working memory capacity predicted training strategies and performance was examined by standardizing working memory scores across the entire sample and correlating them with training strategy ratings (1 = *memorizer* to 7 = *rule-abstractor*) and overall training performance. Younger adults with higher working memory capacity were more likely to utilize a memorization strategy as shown by a significant negative correlation between working memory capacity and strategy rating,  $r(58) = -.33$ ,  $p = .01$ . In contrast, older adults' working memory capacity did not predict their training strategy,  $r(58) = .16$ ,  $p = .24$ . These correlations were significantly different,  $z = -2.69$ ,  $p = .004$ . Younger adults' working memory capacity did not predict their training performance,  $r(58) = .03$ ,  $p = .82$ , whereas older adults with higher working memory capacity showed better training performance,  $r(58) = .35$ ,  $p = .006$ . These correlations were significantly different,  $z = -1.79$ ,  $p = .04$ .

### Metamemory in Adulthood Questionnaire

Despite finding an age-related deficit in episodic memory in categorization of memory-favored transfer objects, younger and older adults did not differ in their self-assessments of memory ability. Ratings for capacity items did not differ between younger adults ( $M = 3.38$ ,  $SD = 0.51$ ) and older adults ( $M = 3.40$ ,  $SD = 0.56$ ),  $t(118) = -.19$ ,  $p = .85$ ,  $d = -0.03$ . Ratings on locus items also did not differ between younger adults ( $M = 2.99$ ,  $SD = .55$ ) and older adults ( $M = 3.07$ ,  $SD = .50$ ) adults,  $t(118) = -.76$ ,  $p = .45$ ,  $d = -0.14$ . Memory beliefs did not predict training strategies or performance for either age group. Capacity and locus ratings were standardized within each age group and then correlated with training strategy ratings and overall training performance for all participants. Capacity scores did not predict strategies for younger adults,  $r(58) < .01$ ,  $p = .99$ , or older adults,  $r(58) = .14$ ,  $p = .28$ , nor did they predict performance for younger adults,  $r(58) = -.16$ ,  $p = .24$ , or older adults,  $r(58) = -.11$ ,  $p = .42$ . Locus scores did not predict strategies for younger adults,  $r(58) = -.05$ ,  $p = .69$ , or

older adults,  $r(58) = .07$ ,  $p = .57$ , nor did they predict performance for younger adults,  $r(58) = -.20$ ,  $p = .12$ , or older adults,  $r(58) = -.07$ ,  $p = .59$ .

### Discussion

The present experiment revealed several results that informed issues regarding age differences in category learning and the strategies used to accomplish such learning. First, younger and older adults reported similar use of rule- and exemplar-based learning strategies during training, but unlike younger adults, a substantial number of older adults identified themselves as using strategies that were neither completely rule nor exemplar based (an "intermediate" strategy). Second, overall training performance was higher for younger than older adults, regardless of the strategy adopted by older adults. Third, categorization of ambiguous transfer objects according to the correct rule was greater for rule-abstractors than memorizers, and this difference tended to be greater for younger than older adults. Fourth, younger adults with higher working memory capacity preferred memorization, whereas working memory capacity did not predict strategy use for older adults. In contrast, younger adults' working memory capacity did not predict overall training performance, whereas older adults with higher working memory capacity showed better training performance. Finally, self-reported memory abilities did not differ for younger and older adults, and these abilities did not predict training strategies or performance. We discuss each of these findings in more detail below.

Recent studies examining age differences in category learning strategies have used model-based approaches to show that older adults prefer rule- to memory-based strategies, with this preference being greater when materials support rule use (e.g., Filoteo & Maddox, 2004; Mata et al., 2012). The present experiment extended this by examining age differences in self-reported strategies used to learn complex categories with clearly verbalizable rules. Contrary to previous findings, older adults did not show a preference for rule- over exemplar-based learning strategies, and there was a substantial frequency of older adult intermediate learners. This was likely the result of older adults being impaired in their ability to learn the correct rule, but may also have in part been due to older adults' impaired ability to accurately reflect on their strategy use.

Closer examination of older adults' strategy reports was consistent with both possibilities. Older adults' descriptions of the strategies they employed during learning largely corresponded with their strategy ratings, but a minority of older adults showed impairment in their ability to accurately reflect on their strategies. Of the 21 older adults who indicated using a rule-abstraction strategy (a rating of 5–7), 14 explicitly stated a rule or reported trying to find a rule, and only one stated exclusive reliance on memorization (the remaining participants gave ambiguous responses). By contrast, of the 19 older adults who indicated memorization (a rating of 1–3), five reported exclusive reliance on memorization (all providing ratings of 1–2), and five reported resorting to memorization after failing to find a rule (cf. Smith & Minda, 1998). Finally, of the 19 older adults who reported a memorization strategy, seven reported a rule (or attempts at a rule) without mention of memorization, but five out of those seven provided ratings of 3, and none of these individuals reported the correct rule.

Taken together, these findings show that although some older adults had difficulty reflecting on their strategies, most were able to do so, despite the fact nearly every older adult did not learn the correct rule.

The finding that older adults were largely unable to learn the correct rule in the service of remediating their learning deficit is also consistent with findings showing that older adults' impairment in category learning increases with the complexity of categories (Racine et al., 2006). For example, Davis, Love, and Maddox (2012) showed that older adults were not impaired in their ability to categorize exemplars using a rule that was based on a single stimulus dimension. However, older adults' learning is consistently impaired when the correct rule is difficult to verbalize, as with information integration categories (e.g., Filoteo & Maddox, 2004). The present study showed that a verbalizable disjunctive rule applied to relational features was sufficiently complex as to impair older adults' learning. This occurred despite the fact that the categories included a small number of exemplars, feedback was provided, and there was extensive training. This finding is consistent with recent results showing that the greater difficulty of learning categories defined by a disjunctive versus a one-dimensional rule is exaggerated for older relative to younger adults (Rabi & Minda, 2016).

Transfer performance also revealed the consequences of older adults' inability to learn the correct rule. Categorization of transfer objects according to the rule was greater for rule-abstractors than memorizers, but older adults showed a smaller difference between these groups. This suggested that older adult rule-abstractors attempted to utilize rules, but those rules were mostly incomplete. This finding is also consistent with the perspective that older adults are impaired in their ability to execute strategies (Dunlosky & Hertzog, 1998). These results suggest that the fidelity of rule-based representations was higher for younger than older adults. Also noteworthy was that intermediate learners showed middling performance relative to rule-abstractors and memorizers, suggesting that intermediate learners used a mixture of rule- and exemplar-based learning strategies.

It seems reasonable that strategy preferences and consequent training performance would also depend on individual differences in related cognitive abilities. For example, the ability to use cognitive control to actively maintain representations of earlier-tested hypotheses or earlier-learned associations could influence these outcomes. Yet, an earlier study using the same object types as in the present experiment did not find a relationship between working memory and training strategies for younger adults (Little & McDaniel, 2015). Contrary to this, the present experiment showed that younger adults with higher working memory preferred memorization strategies. One possible explanation for the discrepancy between studies is that more objects were included in each block of the Little and McDaniel (2015) study (12) than in the present study (eight). In line with this possibility, set size has been shown to influence strategy selection, with larger sizes increasing the likelihood of rule-based strategies relative to smaller sizes (Little & McDaniel, 2013). The preference for memorization with increased working memory in the present study seems reasonable, as refreshing current object-label associations until they appear again in the following training block could facilitate learning.

However, younger adults' working memory did not predict training performance. This may have resulted from the offsetting

effects of individuals with higher working memory utilizing a less optimal strategy (memorization) and lower working memory individuals utilizing a more optimal strategy (rule-abstraction). For the older adults, working memory ability did not predict training strategies, but higher working memory predicted better training performance. This might be the result of high working memory older adults being generally better at maintaining either rule- or exemplar-based representations.

It also seems reasonable that strategy preferences and consequent training performance would depend on individuals' beliefs about their memory ability. Mata et al. (2012) suggested that age differences in strategy preferences might be the consequence of differences in both actual and perceived abilities. As an example, older adults who experience more memory failures in everyday tasks are more reluctant to rely on retrieval-based strategies (Frank, Touron, & Browne, 2013, as cited by Touron, 2015). However, in contrast to the literature showing that older adults typically have lower self-efficacy regarding their memory abilities as compared to younger adults (Hertzog & Hulstsch, 2000), memory beliefs did not differ between age groups in the present experiment. This occurred despite the fact that older adults demonstrated an episodic memory deficit, as evidenced in transfer performance on the memory-favored items (cf. Crumley, Stetler, & Horhota, 2014). This lack of an age difference in memory beliefs could have resulted from the selection of a highly educated healthy older adult sample. This also might have contributed to the discrepancy between the present results showing that older adults did not have a clear strategy preference, and earlier results showing that older adults preferred rule-based strategies. Older adults in the present experiment who viewed their memory to be intact might have been less reluctant to use retrieval-based strategies. Finally, the explanation for why memory beliefs did not predict training strategies or performance within age groups is not immediately clear. Perhaps strategy choices were based more on stimulus features than evaluations of ability, with performance resulting from the strategies deployed.

In conclusion, older adults showed impaired learning of categories defined by a disjunctive rule applied to relational features. This impairment likely reflected deficits in episodic memory and the ability to learn the correct rule. Older adults did not prefer rule- to exemplar-based strategies, which may have reflected the belief that their memory is largely intact. The high frequency of older adult intermediate learners suggests that older adults are more likely to vacillate among strategies during learning, which could reflect abandonment of a rule-based strategy. Taken with recent cautions for interpreting model-based analyses of individual differences in category learning strategies (Donkin et al., 2015), the present results suggest that a reexamination of previous conclusions about age differences in these strategies may be warranted. One potentially informative avenue is to examine the generalizability of older adults' strategy preferences shown here by sampling from populations with more variability in perceived cognitive function. The frequency of everyday memory failures and the complexity of categories may both contribute to differences in strategy preferences between younger and older adults.

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