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Rule-Based and Information-Integration Category Learning in Normal Aging

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Abstract

The basal ganglia and prefrontal cortex play critical roles in category learning. Both regions evidence age-related structural and functional declines. The current study examined rule-based and information-integration category learning in a group of older and younger adults. Rule-based learning is thought to involve explicit, frontally mediated processes, whereas information-integration is thought to involve implicit, striatally mediated processes. As a group, older adults showed rule-based and information-integration deficits. A series of models were applied that provided insights onto the type of strategy used to solve the task. Interestingly, when the analyses focused only on participants who used the task appropriate strategy in the final block of trials, the age-related rule-based deficit disappeared whereas the information-integration deficit remained. For this group of individuals, the final block information-integration deficit was due to less consistent application of the task appropriate strategy by older adults, and over the course of learning these older adults shifted from an explicit hypothesis-testing strategy to the task appropriate strategy later in learning. In addition, the use of the task appropriate strategy was associated with less interference and better inhibitory control for rule-based and information-information learning, whereas use of the task appropriate strategy was associated with greater working memory and better new verbal learning only for the rule-based task. These results suggest that normal aging impacts both forms of category learning and that there are some important similarities and differences in the explanatory locus of these deficits. The data also support a two-component model of information-integration category learning that includes a striatal component that mediated procedural-based learning, and a prefrontal cortical component that mediates the transition from hypothesis-testing to procedural-based strategies. Implications for independent vs. interactive category learning systems are discussed.

Keywords

normal aging; older adults; category learning; striatum; prefrontal cortex; rule-based; information-integration; feedback processing; interactive memory systems

Introduction

The ability to categorize is a fundamental aspect of human cognition. Quick and accurate categorization is involved in every aspect of our day-to-day lives and directly impacts our quality of life. When we decide whether to pass or not pass on a two lane road, to speed up or slow down at a yellow light, or decide to bring an umbrella to work we are categorizing. Quick and efficient categorization is as important later in life, as it is early, and thus an

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understanding of age-related changes in categorization is an important area of scientific inquiry.

There has been a surge of interest in understanding the neurobiological underpinnings of category learning using computational modeling, brain imaging and tests of neurologically damaged patients (for reviews see, Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby & Maddox, 2005; Filoteo & Maddox, 2007; Keri, 2003; Nomura & Reber, 2008; Poldrack & Foerde, 2008; Price, Filoteo, & Maddox, 2009; Seger, 2008). Much of this work tests the basic tenets of a neurobiologically-inspired models of category learning called the Competition between Verbal and Implicit Systems model (COVIS; Ashby, Alfonso-Reese, Turken, & Waldron, 1998). COVIS postulates that the long-term learning of different types of category structures is mediated by different systems that have unique, but interacting neural substrates. Two types of category structures have been studied extensively: rule-based and information-integration (Maddox & Ashby, 2004)[1].

Rule-based tasks are associated with situations in which the rule that maximizes accuracy can be described verbally (Bruner, Goodnow, & Austin, 1956; Shepard, Hovland, & Jenkins, 1961). Rule-based category learning has been shown to be mediated by an explicit, hypothesis-testing system that is highly dependent on the prefrontal cortex (Filoteo et al., 2005; Lombardi et al., 1999; Monchi, Petrides, Petre, Worsley, & Dagher, 2001; Nomura et al., 2007; Schnyer et al., 2009; Seger & Cincotta, 2006). Information-integration tasks, on the other hand, are associated with situations in which the rule that maximizes accuracy can not be described verbally. Rather, accuracy is maximized when information from two or more stimulus dimensions is integrated at some pre-decisional stage, and learning involves incremental acquisition of stimulus-response associations (Ashby & Waldron, 1999). In contrast to rule-based learning, information-integration category learning has been shown to be mediated by an implicit procedural-based learning system that is highly dependent upon the striatum (Aron et al., 2004; Filoteo, Maddox, Salmon, & Song, 2005; Maddox & Filoteo, 2001, 2005; Nomura et al., 2007; Poldrack et al., 2001; Seger, 2008; Seger & Cincotta, 2005). [Throughout this article we use the terms rule-based and information-integration to refer to tasks that an individual attempts to solve, and we use the terms hypothesis-testing and procedural-based learning to refer to "systems/strategies" that can be used in the service of solving these tasks. This distinction is important because an individual can use either of these systems, or some other system, to solve a particular task. In fact, as we show later, it is common for an individual to use the hypothesis-testing system when solving an information-integration task.]

Ell, Marchant and Ivry (2006) examined both rule-based and information-integration category learning in a single group of patients with focal putamen lesions, whereas Schnyer, Maddox, Ell, Davis, Pacheco, and Verfaellie (2009) examined both rule-based and information-integration category learning in a single group of patients with prefrontal cortex lesions. Since COVIS postulates striatal involvement in information-integration category learning and prefrontal involvement in rule-based category learning, the most likely prediction was that Ell et al. would find information-integration, but not rule-based category learning deficits, whereas Schnyer et al. would find rule-based, but not information-integration category learning deficits. Contrary to the predictions from COVIS, Ell et al. found intact information-integration category learning, and an early-training rule-based deficit, and Schnyer et al. found equivalent deficits for both rule-based and information-integration category learning. This pattern suggests that a simple independent systems

[1]Although rule-based and information-integration tasks have been the primary focus, other tasks have been examined and suggest that more than two category learning systems exist (Casale & Ashby, 2008; Reber & Squire, 1999; Zeithamova, Maddox, & Schnyer, 2008)

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approach to category learning is inadequate and instead supports the notion of interacting systems (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby & Ell, 2002; Poldrack & Rodriguez, 2004).

In COVIS there is a competition between the hypothesis-testing and procedural-based learning systems to determine which system dominates responding on each trial. Critically, COVIS assumes an initial bias toward the hypothesis-testing system that must be overcome in information-integration tasks. The Ell et al. findings suggest that putamen damage does not adversely affect this transition, although it does appear to affect early learning of rule-based tasks. The Schnyer et al. findings suggest that prefrontal damage affects rule-based category learning directly, but also affects the transition from hypothesis-testing to procedural-based information-integration category learning.

Rule-based and information-integration category learning rely on effective use of feedback which is at least partially mediated by prefrontal cortex (Cools, Clark, Owen, & Robbins, 2002; Fellows, 2004; Ghods-Sharifi, Haluk, & Floresco, 2008; Haber, Kim, Mailly, & Calzavara, 2006; Monchi, Petrides, Petre, Worsley, & Dagher, 2001; Takahashi et al., 2009). Effective processing of feedback in category learning is essential for testing different verbal rules (as in a rule-based task), and for knowing when or whether to switch strategies to improve performance (as in an information-integration task) (Seger, 2008). A deficit in feedback processing may lead to the use of a task inappropriate strategy, where only a subset of the categories is learned in the rule-based task and the shift from hypothesis-testing to procedural-based strategies is impaired in the information-integration task.

Age-related declines have been observed in rule-based category learning, especially when the tasks are complex and place high demands on cognitive control mechanisms (Filoteo, Maddox, Ing, Zizak, & Song, 2005; Racine, Barch, Braver, & Noelle, 2006; Ridderinkhof, Span, & van der Molen, 2002). Age-related declines have also been observed in information-integration category learning (Filoteo & Maddox, 2004). Given the extensive literature on frontal deficits in older adults (Greenwood, 2000, 2007), the fact that frontal (and striatal) brain regions atrophy with normal aging (Greenwood, 2000, 2007; Grieve, Williams, Paul, Clark, & Gordon, 2007; Gunning-Dixon & Raz, 2003; Raz, 2000; Raz et al., 2003), and the importance of effective feedback processing on rule-based and information-integration learning, it is not surprising that older adults show rule-based and information-integration deficits.

What is lacking is an examination of rule-based and information-integration category learning within the same group of participants so that task performance on each can be compared directly. We address this shortcoming in this paper. In addition, we use rule-based and information-integration tasks that are equated on the critical variables of optimal accuracy, within- and between-category similarity, and the number of relevant dimensions (Maddox, Filoteo, Hejl, & Ing, 2004). This allows us to be certain that across task performance differences are due specifically to the nature of the optimal decision strategy and not to other uncontrolled factors. In addition, we apply a series of quantitative models that were developed specifically for application to these tasks (Ashby, 1992a; Filoteo & Maddox, 2004; Maddox & Ashby, 1993). These models provide important insights onto the cognitive processes and strategies being utilized by participants to solve each task. Importantly, this information can not be garnered from an examination of performance accuracy alone, as qualitatively different strategies often yield the same performance level. The model-based analyses will be critical for determining the locus of any age-related performance deficits. Finally, multi-domain neuropsychological tests were also administered and provide additional insights onto the locus of performance deficits.

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Experiment

The current study uses category structures that are identical to those used in two recent cognitive neuroscience studies of category learning (Ell, Marchant, & Ivry, 2006; Schnyer et al., 2009). In both studies, the stimulus was a single line whose length and orientation was fixed on each trial but varied across trials. Stimuli were assigned to one of four categories. A scatterplot of the stimuli along with the optimal decision bounds are displayed in Figure 1. Note that the rule-based and information-integration categories are related via a simple rotation in the length-orientation space. Thus, the two tasks are equated on optimal accuracy, within- and between-category similarity, and the number of dimensions relevant to the categorization. In the rule-based task, the accuracy-maximizing strategy was to decide if the line is long or short and if the angle is steep or shallow and to integrate these decisions by applying the following conjunctive rule: respond “A” to short, shallow angle lines, “B” to short, steep angle lines, “C” to long, shallow angle lines, and “D” to long, steep angle lines. For the information-integration task, the categories were created by rotating the rule-based categories 45 degrees counterclockwise. Accuracy maximization involves integrating information about length and orientation, but does not first involve a separate decision along each dimension. Importantly, reasonable performance levels can be achieved by applying verbal rule-based strategies in the information-integration task. In fact, rule-based strategies are often used early in training with information-integration tasks (Ashby, Alfonso-Reese, Turken, & Waldron, 1998). We applied quantitative modeling techniques at the individual participant level to determine the type of strategy (rule-based or information-integration) used by each participant in each condition (details presented below).

Methods

Participants

Thirty-one younger and 28 older individuals participated in both the rule-based and information-integration conditions. Young adults were recruited from the University of Texas community and older adults were recruited from flyers posted in community centers that serve the aging as well as through newspaper advertisements targeted to a local retirement community. The mean age was 19.7 years ($SD = 1.6$; range 18–24) for younger adults and 69.0 years ($SD = 7.0$; range60–81) for older adults. The male–female ratio was 11:20 for the younger group and 9:19 for the older group, which was not reliably different (Fisher’s exact test, $p = .50$). All participants reported normal or corrected-to-normal vision. The older participants were screened rigorously for any history of neurological disorder, psychiatric illness, substance abuse, cerebral vascular event, head trauma, and any other neurological condition. Younger and older adults were administered and matched on the WAIS Vocabulary scale [younger mean = 12.35; older mean = 12.64; $t(57) < 1.0$]. The education level of the younger participants ($M = 14.4$ years, $SD = 1.4$) was significantly lower ($t(57) = 5.19$, $p < .001$) than that of the older participants ($M = 16.96$ years, $SD = 2.4$) but these individuals were still in college so their years of education is not likely to reflect their terminal level.

Written informed consent was obtained from each volunteer prior to the session. The Human Subjects Committee at the University of Texas approved all procedures and all participants were compensated $20 for their participation.

Stimuli and Stimulus Generation

The 100 stimuli used in the rule-based condition were generated by taking 25 random samples from each of four bivariate normal distributions (Maddox, Filoteo, Hejl, & Ing, 2004). The category distribution parameters used to generate the stimuli were taken from

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Maddox et al. (2004) where each category was defined as a bivariate normal distribution with a mean and a variance on each dimension, and by a covariance between dimensions. For the rule-based task, twenty-five random samples (x, y) were drawn from each category distribution, and each sample was used to construct a single line with some length (in pixels) and orientation that was converted to radians by multiplying the sample value by $\pi/500$. The scale factor ($\pi/500$) was selected based upon previous research to approximately equate discriminability along the length and orientation dimensions. The stimuli used in the information-integration task were generated by rotating each of the rule-based stimuli 45° clockwise around a central point located at 150 pixels in length (4° of visual angle) and 54° from horizontal. The order of the 100 stimuli was randomized separately for each block and each participant. Each stimulus was presented on a black background and subtended a visual angle ranging from 0.7° to 7.3° at a viewing distance of approximately 60 cm. The stimuli were generated and presented using the Psychophysics Toolbox extensions for MATLAB (Brainard, 1997; Pelli, 1997). The stimuli were displayed on a laptop LCD with 1024×768 pixel resolution.

Procedure

Each participant completed both tasks in a counterbalanced order with a minimum of one week separating testing sessions. Each session began with a brief set of written and verbal instructions informing the participant that on each trial they would see a single stimulus and would assign it to category A, B, C, or D by pressing the associated response button (characters ‘z’, ‘w’, ‘/’, and ‘p’ were assigned to categories A – D, respectively). Participants were told to be accurate and not worry about speed of responding. After responding, feedback regarding the correctness of the response (correct: green cross; incorrect: red cross) along with the correct category label was presented in the center of the screen for 1 s. A 500ms blank screen ITI was followed by the next trials. In addition to trial-by-trial feedback, feedback was provided at the end of each 100-trial block regarding the participant’s accuracy during that block. The participant was told that there were four equally likely categories and was informed that the best possible accuracy was 95% (i.e., optimal accuracy). Each session consisted of 6 100-trial blocks of trials.

Standardized Neuropsychological Testing of Older Adults

To investigate the relationship between the experimental measures of category learning and measures of episodic memory and various aspects of executive functioning, older adults were administered a selection of standardized neuropsychological tests. Memory performance was evaluated using the Wechsler Memory Scale, Third Edition (WMS-III; Wechsler, 1997) and the California Verbal Learning Test (Delis, Kramer, Kaplan, & Ober, 1987). In the case of the WMS-III, the delayed recall subtest scores from Logical Memory and the delayed free recall subtest of the CVLT were used to measure new episodic learning ability. For assessment of executive functions, older adults completed tests of lexical word generation (FAS; Stuss & Benson, 1986), complex visual scanning and tracking (Trails B; Partington & Leiter, 1949), category formation and set shifting (WCST; Heaton, Chelune, Talley, Kay, & Curtiss, 1993), and salient response inhibition (Stroop Color-Word Test; Stroop, 1935). In the Controlled Oral Word Association (FAS) test, subjects are asked to generate as many different words as possible that begin with a particular letter during a 1 min period and the total number of words generated for all three letters comprises the verbal fluency score. The Trail Making Test – Part B is a visual conceptual and visuomotor tracking task that requires connecting consecutively numbered and lettered circles on a paper work sheet by alternating between the two sequences. Trails B is sensitive to frontal-lobe dysfunction, and it has been proposed that performance is indicative of the subject's ability to shift set and process concurrent stimuli (Lezak, 1995). The Digit Span test consists of two parts, the first requires individuals to repeat back a series of numbers in the exact

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order they were presented, and the second requires them to be repeated in the reverse order. This reflects a person’s working memory ability, also thought to be dependent of the frontal-lobes (Wechsler, 1997). The Wisconsin Card Sorting Test assesses a person's ability to form abstract concepts, utilize feedback, and to shift and maintain set. Scores reflect both the ability to move through cards in an effective manner (total concepts obtained) as well as the ability to disengage from previous concepts (perseverative errors). The Stroop Color–Word Test (Stroop, 1935) measures the ability to inhibit inappropriate responses in the presence of interfering stimuli (Lezak, 1995).

Results

Category Learning Accuracy

Average accuracy in each 100-trial block was subjected to a 2 participant group (older vs. younger) x 2 condition (rule-based vs. information-integration) x 6 block ANOVA. These data are displayed separately for the rule-based and information-integration conditions in Figure 2. The main effects of participant group [$F(1, 57) = 12.18$, $p < .001$, $\eta^2 = .176$], condition [$F(1, 57) = 17.76$, $p < .001$, $\eta^2 = .238$], and block [$F(5, 285) = 159.16$, $p < .001$, $\eta^2 = .736$] were significant and suggested better overall performance for the younger (.80) than the older (.68) adults, better performance in the information-integration condition (.78) than in the rule-based (.70) condition, and a performance improvement with experience. The participant group x block interaction was significant [$F(5, 285) = 2.287$, $p < .05$, $\eta^2 = .039$] and suggests a slightly larger performance deficit for older adults early in learning. The condition x block interaction was also significant [$F(5, 285) = 2.41$, $p < .05$, $\eta^2 = .04$] and suggests that performance reached asymptote around the 3rd or 4th block in the information-integration condition, whereas learning continued in the rule-based condition. The participant group x condition [$F < 1.0$], and the three-way [$F(5, 285) = 1.57$, ns] interactions were non-significant.

Neuropsychological Predictors of Older Adult Performance

Correlations between neuropsychological measures and final block rule-based and information-integration performance were restricted to the older adults and are displayed in Table 1. All neuropsychological measures were converted to Z scores following the publicized normative data, or scoring guidelines, that accompanied each test. For each of the included tests, normative data factored in the subject’s age, so age was not explicitly controlled for in our correlation analysis. A single “interference” composite score was created by combining the WCST perseverative errors and Stroop task interference Z scores (word color) with larger values indicating less vulnerability to interference. In addition, an episodic memory composite score was created by combining the delayed free recall subtest of the CVLT and the delayed recall subtest scores from WMS-III Logical Memory Z scores with larger values indicating greater new verbal learning.

The interference composite measure correlated significantly with final block performance for both the rule-based [$r(26) = .67$, $p < .001$] and information-integration conditions [$r(26) = .65$, $p < .001$]. Both subcomponents correlated with information-integration performance [Stroop: $r(26) = .44$, $p < .05$; WCST: $r(26) = .44$, $p < .05$], whereas only the Stroop subcomponent correlated with rule-based performance [$r(26) = .64$, $p < .001$]. Working memory span (as measured by the total digit span) correlated with rule-based performance [$r(26) = .62$, $p < .001$] and information-integration performance [$r(26) = .42$, $p < .05$]. Finally, the episodic memory composite did not correlate with either rule-based [$r(26) = .18$, ns] or information-integration [$r(26) = .10$, ns] performance. However, the CVLT subcomponent did correlate with rule-based performance [$r(26) = .37$, $p < .05$], but not

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information-integration performance [r(26) = .24, ns]. All other correlations were non-significant.

Model Based Analysis

The category learning data suggest that older adults are less accurate than younger adults in both rule-based and information-integration category learning. Although mean group accuracy is a useful measure, it provides no information about the types of strategies that any individual is using to solve the task as well as the effectiveness of that strategy. As outlined in the Introduction, some hypothesis-testing strategies yield reasonable accuracy rates when applied in the information-integration condition, and can yield performance comparable to that of some procedural-based strategies. Thus, it is critical to determine whether the lower information-integration performance level for older adults is due to an increase in the use of hypothesis-testing or whether it might be in the use of more sub-optimal procedural-based strategies.

In this section, we gain a more detailed understanding of the locus of the rule-based and information-integration performance decrements in our older adults by applying a series of decision bound models to the data (Ashby & Maddox, 1993; Maddox & Ashby, 1993). Because our main interest is in asymptotic performance we focus our analyses on the final block of data. However, we do include a section that examines learning. In addition, because of concerns with modeling aggregate data all models were fit separately for each participant (Estes, 1956; Maddox, 1999; Smith & Minda, 1998).

Each model contains of a set of decision bounds that partition the stimulus space into separate response regions. For example, one hypothesis-testing model might classify lines as short or long depending upon whether they are less than or greater than 200 pixels, and might assign lines as shallow or steep depending upon whether they are less than or greater than 35 degrees. These decisions are then combined to generate categorization responses using the decision rule: short, shallow lines are assigned to category A, short, steep lines are assigned to category B, long, shallow lines are assigned to category C, and long, steep lines are assigned to category D. This model would be applied to a set of data and a measure of “fit” computed. Although somewhat more complex (see Appendix for details), the measure of fit is similar to computing the proportion of the participant’s responses that match with the model’s response. The model fitting algorithm then adjusts the pixel value used to separate short from long lines, and adjusts the orientation value used to separate shallow from steep lines until the values that maximize the correspondence between the participant’s and the model’s responses are achieved.

Different models make different assumptions about the type of strategy that the participant is using. The models allow us to determine whether each participant is using the task-appropriate strategy (i.e., an explicit hypothesis testing strategy in the rule-based condition or an implicit procedural-based learning strategy in the information-integration condition) or a suboptimal strategy to solve the task (i.e., an implicit procedural-based learning strategy in the rule-based condition or an explicit hypothesis testing strategy in the information-integration condition). One class of models is compatible with the assumption that participants used an explicit hypothesis-testing strategy, and a second class is consistent with the assumption that participants used an implicit procedural-based learning strategy. A third class of models is also applied that is consistent with the assumption that participants are testing numerous distinct strategies in a block of trials or are guessing. The details of each model and the model fitting procedure are outlined in the Appendix.

Model Frequencies—The number of participants best fit by each model type is displayed in Table 2. Twenty-seven of the 31 younger adults and 19 of the 28 older adults were using a

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hypothesis-testing strategy in the rule-based condition. Of the remaining 4 younger adults, 3 used a procedural-based learning strategy and one used a guessing strategy. Of the remaining 9 older adults, 6 used a procedural-based learning strategy and 3 used a guessing strategy. A χ^2 test that compared the frequency of hypothesis-testers with those using other strategies (i.e., procedural or guessing) across older and younger adults was marginally significant [$\chi^2(1) = 3.17$, $p = .08$] suggesting that older adults were marginally less likely to use the task appropriate strategy in the rule-based condition.

Twenty-nine of the 31 younger adults and 24 of the 28 older adults were using a procedural-based strategy in the information-integration condition. Both of the remaining younger adults used a hypothesis-testing strategy. Of the remaining 4 older adults, 3 used a hypothesis-testing strategy and 1 used a guessing strategy. A χ^2 test that compared the frequency of procedural-based learners with those using other strategies (i.e., hypothesis-testing or guessing) across older and younger adults was non-significant [$\chi^2(1) < 1.0$, ns] suggesting that older adults were no less likely than younger participants to use the task appropriate strategy.

Final Block Accuracy as a Function of Best Fitting Model—To determine whether the older adult's accuracy deficit in the final block of each task resulted from using a non-task appropriate decision strategy, we examined final block accuracy only for younger and older adults who adopted the task appropriate strategy—that is, only those participants using a hypothesis-testing strategy in the rule-based condition and only those participants using a procedural-based strategy in the information-integration condition. These data are displayed in Figure 3 separately for the rule-based and information-integration tasks. For those individuals using a hypothesis-testing strategy on the rule-based task, younger and older adults performance did not differ [$t(44) < 1.0$] suggesting that those older adults using the task appropriate strategy performed at the same level as younger adults using the task appropriate strategy. For the information-integration task, on the other hand, younger adults (.89) continued to show a performance advantage relative to older adults (.85) [$t(51) = 2.26$, $p < .05$], even though both groups used the appropriate, procedural-based strategy. This suggest that even when older adults are using the task appropriate strategy, they are using one that is more sub-optimal (i.e., yields worse performance)[2].

Locus of Final Block Information-Integration Deficit—To provide further insight onto the information-integration performance deficit for older adults using the task appropriate strategy in the final block, we examined two critical model based indices: categorization rule learning and rule application variability (Filoteo, Maddox, & Davis, 2001a, 2001b; Maddox & Filoteo, 2001; Maddox, Filoteo, & Huntington, 1998). As a measure of categorization rule learning we examined the goodness-of-fit of the experimenter-defined (optimal) rule. The smaller the fit, the better the rule describes the data. As a measure of rule application variability, we examined the rule application variability (noise) parameter in the model. The smaller the rule application variability parameter, the more consistently the participant's rule is being applied. The results were clear. A t-test comparing the categorization rule learning index across younger (27.4) and older (33.2) adults who used the task appropriate, procedural-based, strategy was non-significant [$t(51) = 1.48$, ns], whereas a t-test comparing the rule application variability index across the same younger (25.8) and older (37.2) adults was significant [$t(51) = 2.36$, p

[2]Although not displayed in Figure 3, older and younger adults using task inappropriate strategies performed worse than older and younger adults using task appropriate strategies. In addition, older adults using task inappropriate strategies performed numerically worse than younger adults using task inappropriate strategies, but given the small sample sizes, none of these differences reached statistical significance.

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$< .05$], and suggested that older adults were less consistent in the application of their information-integration strategy.

Early Learning in Older and Younger Participants Using the Task Appropriate Strategy in the Final Information-Integration Block—As outlined above, when we focused on older and younger adults who used a procedural-based strategy during the final block in the information-integration condition, we found a small but significant accuracy deficit that was caused by less consistent application of older adults' information-integration strategy. In this section, we examine the time-course of learning for this same subset of participants. In particular, we examine the transition point at which participants switch from the use of hypothesis-testing strategies to the use of procedural-based strategies. We predict that this transition will be later in older than younger adults. As a test of this hypothesis we examined the first block of trials for which a procedural-based strategy provided the best account of data in that block and every block to follow. For older adults this occurred, on average, 2.67 blocks into the session and for younger adults this occurred, on average, 1.24 blocks into the session. This difference was significant [$t(51)=3.791$, $p <.001$] and suggests that older adults were slower to shift from a hypothesis-testing strategy to a procedural-based strategy, although they ultimately adopted the procedural-based strategy by the final block of trials.

Next, we focused on older and younger adults who used a hypothesis-testing strategy during the final block in the rule-based condition. As outlined above, we found no performance difference between these older and younger adults in the final block. However, these older adults were less accurate than their younger counterparts during the first [$t(44) = 3.19$, $p < .01$] and second [$t(44) = 3.92$, $p < .01$] blocks of trials. Because we do not predict, and did not observe, a transition in strategy use in this condition, we examined the decision criterion and rule application variability estimates from the hypothesis-testing model. Interestingly, we found that the accuracy deficit observed in the first and second blocks was due to great variability in the application of the hypothesis testing strategy in the first [$t(44) = 2.18$, $p < .05$] and second [$t(44) = 2.39$, $p < .05$] blocks for older adults.

Taken together, these results suggest that older adults, as a group, showed consistently slower rule-based and information-integration learning than younger adults. However, when the focus was restricted to the (relatively) large proportion of participants in both groups who utilize task appropriate strategies in the final block of trials, the rule-based deficit disappeared, and the information-integration deficit shrunk substantially. Further analyses suggested that the locus of the continued information-integration deficit in the final block of trials was in increased variability in the application of the learned information-integration strategy, and not in the use of the more sub-optimal rule-based strategy. Finally, older adults were also found to shift more slowing away from hypothesis-testing strategies to procedural-based strategies than younger adults in the information-integration condition and were found to show greater variability in the application of their hypothesis-testing strategy than younger adults in the rule-based condition.

In the next section, we attempt to shed more light on older adults rule-based and information-integration category learning performance by examining neuropsychological test performance as a function of whether older adults were classified as using a task appropriate or task inappropriate strategy during the final block of trials.

Older Adults Neuropsychological Performance as a Function of Final Block Strategy

First, we examined whether participant's age differed across best fitting strategy (task appropriate or task inappropriate). For the rule-based task, age differed significantly across participant's whose data was best fit by a task appropriate (67.1 years) or task inappropriate

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(73.0 years) strategy [$t(26) = 2.21$, $p < .05$] suggesting that the older the elderly adults were, the more likely they would be using a task inappropriate strategy. For the information-integration task, on the other hand, age did not differ as a function of strategy [$t(26) = 1.16$, ns].

The neuropsychological performance averages for participants using the task appropriate and task inappropriate strategies are displayed in Table 3. For the rule-based task, the composite measure of interference was significantly larger (implying less interference) for those best fit by a task appropriate strategy than by a task inappropriate strategy [$t(26) = 4.63$, $p < .001$]. The same pattern held for the information-integration task (task appropriate = 1.17; task inappropriate = -.16) [$t(26) = 2.78$, $p < .01$]. The difference was also significant for the Stroop subcomponent for the rule-based [$t(26) = 3.14$, $p < .01$] and information-integration [$t(26) = 2.23$, $p < .05$], but not for the WCST subcomponent ($p > .18$ for both tasks). For the rule-based task, the Total Digit Span Z values were significantly larger (implying better performance) for those best fit by a task appropriate strategy than by a task inappropriate strategy [$t(26) = 2.49$, $p < .05$]. Trails B Z and FAS Z values did not differ as a function of strategy (all t's < 1.0). For the information-integration task, the Total Digit Span Z, Trails B Z and FAS Z values were not affected by strategy (all three t's < 1.0). Finally, for the rule-based task, the episodic memory composite measure was unaffected by strategy [$t(26) = 1.14$, ns], but the CVLT subcomponent was and suggested that new verbal learning was significantly larger for those best fit by a task appropriate strategy than by a task inappropriate strategy [$t(26) = 2.33$, $p < .05$]. For the information-integration task, neither the episodic memory composite, nor the subcomponents were affected by strategy (all three t's < 1.0).

Taken together, these findings suggest that interference and cognitive processes associated with inhibition of non-dominant rules, as measured by the composite of the Stroop interference and the WCST perseveration measures, are relevant to both rule-based and information-integration category learning and that these abilities are predictive of who will and who will not ultimately learn to utilize the task appropriate strategy. On the other hand, measures of working memory (Total Digit Span) and new verbal learning (CVLT) are relevant only to rule-based category learning, and, within that domain, are predictive of who will and who will not ultimately learn to utilize the task appropriate strategy. It is important to note that the number of older adults using a task inappropriate strategy in the information-integration condition was small (only 4 participants). This reduces our statistical power to observe true performance differences. Although this did not preclude us from identifying effects of strategy on interferences/inhibition measures, it might have precluded us from identify effects of working memory and verbal learning.

Components of Rule-Based and Information-Integration Category Learning in Normal Aging

The neuropsychological, accuracy-based, and model-based analyses to this point support a large body of previous work in suggesting that rule-based category learning involves cognitive operations associated with interference, inhibition, working memory and episodic memory (e.g., Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Racine, Barch, Braver, & Noelle, 2006). These analyses also suggest that information-integration category learning involves cognitive operations associated with interference and inhibition, with those likely affecting the ease of the transition from hypothesis-testing to procedural-based strategies, but also involves cognitive operations associated with procedural-based learning directly.

As a direct test of these ideas, we conducted stepwise regression analyses in which we entered model type (appropriate or inappropriate), composite interference score and episodic memory score (CVLT) as predictors of final block accuracy. As expected, model type

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emerged as the sole predictor of rule-based performance (β = .88, t(26) = 9.47, $p < .001$), with the interference measure ($p > .25$) and memory score ($p > .50$) failing to capture significant additional variance in the data. Model type emerged as the primary predictor of information-integration performance (β = .53, t(26) = 3.89, $p < .001$), but the interference measure also captured significant additional variance in the data (β = .39, t(26) = 2.86, $p < .01$). The memory score ($p = .11$) failed to capture significant additional variance in the data.

Taken together, the regression analyses suggest that the model does a nice job of capturing all of the relevant cognitive processes associated with rule-based category learning. However, these analyses suggest that there may be two separable components to information-integration category learning. One component is independent of rule-based learning, involves procedural-based processes, and is captured by the procedural-based models. This component is likely mediated by the striatum, or the striatum in interaction with PFC, and is the component most often linked with information-integration learning (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby & Ennis, 2006). The second component overlaps with rule-based learning and involves interference and inhibitory processes. This component is likely associated with the transition and maintenance from hypothesis-testing to procedural-based learning and is mediated by prefrontal cortex (Schnyer et al., 2009).

General Discussion

The current study examined older and younger adults' rule-based and information-integration category learning ability. Older adults were less accurate than younger adults in both conditions. Older adults rule-based and information-integration performance was correlated with less interference, better inhibitory control and greater working memory, whereas older adults rule-based, but not information-integration, performance was correlated with increased verbal learning ability. Model-based analyses suggested a trend toward greater use of task inappropriate strategies for older adults in the rule-based condition, but not in the information-integration condition. In addition, when directly comparing older and younger adults who used the task appropriate strategy, we found no rule-based performance deficit but a continued information-integration deficit. The latter deficit was due to increased variability in the application of the task appropriate strategy for older adults and even those older adults who eventually adopted the task appropriate strategy were slower to transition from hypothesis-testing strategies to procedural-based strategies. In addition, we found that performance on a number of neuropsychological measures differed as a function of strategy. In the rule-based and information-integration conditions, participants who used task appropriate strategies were also those who showed less interference and inhibition on the Stroop and WCST. In the rule-based condition, but not the information-integration condition, participants who used task appropriate strategies were also those who showed better working memory and new verbal learning. Finally, a regression analysis that attempted to predict final block accuracy showed that older adults' rule-based performance was well predicted by appropriateness of the best fitting model whereas older adults' information-integration performance was well predicted by the separate influence of appropriateness of the best fitting model and neuropsychological measures of interference/inhibition. In the remainder of the General Discussion we outline the implications of this work.

Relations to Prior Work on Rule-based and Information-integration Learning in Normal Aging

In a particularly informative study, Racine, Barch, Braver and Noelle (2006) examined age-related changes in rule-based category learning across tasks that differed in rule complexity. They found no performance deficit for older adults when the rule was simple, but found a

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large performance deficit when the rule was complex (for related findings see Ashby, Noble, Filoteo, Waldron, & Ell, 2003; Filoteo, Maddox, Ing, Zizak, & Song, 2005) Further analyses suggested that the critical explanatory factor was the need for enhanced cognitive control (Braver et al., 2001). Specifically, they found that the demand for cognitive control increased as the complexity of the rule increased and that this was associated with an increased age-related deficit. The present findings converge nicely with Racine et al. in that we found a rule-based deficit in a complex conjunctive rule-based task. At the same time, we extend this work by showing that the rule-based deficit disappears when we focus exclusively on older and younger adults who learn the task appropriate strategy, and we show that those older adults who use the task appropriate strategy show less interference and better inhibitory control, as well as larger working memory spans and better new verbal learning as measured by standard neuropsychological test batteries. Inhibitory control and working memory are two domains that have been tied to executive functioning and the prefrontal cortex and have been shown to decline with normal aging (Berman et al., 1995; Greenwood, 2000, 2007; Grieve, Williams, Paul, Clark, & Gordon, 2007; Stuss & Knight, 2002).

Filoteo and Maddox (2004) found age-related declines in two-category linear and non-linear information-integration categorization. They also found the deficit to remain when they focused only on those using a task appropriate strategy. Our findings converge with those of Filoteo and Maddox and extend them to a 4-category information-integration task. The fact that a performance deficit remains even when we focus on participants using the task appropriate strategy converges with Filoteo and Maddox, but also suggests some important changes in striatal function with normal aging. As outlined briefly in the Introduction, striatal brain volumes have been shown to decline with healthy aging (Raz et al., 2003) and these might partially explain the continued performance deficit for participants using the task appropriate strategy. Although this result is suggestive of a causal role for striatal atrophy in the age-related information-integration deficit, it is important to note that structural and functional declines in executive function and related frontal brain regions can not be ruled out (Berman et al., 1995; Grieve, Williams, Paul, Clark, & Gordon, 2007). In fact, structural and functional changes are seen across the brain, and any of these could (at least partially) explain the observed results (Greenwood, 2000). Clearly more work is needed to fully understand the role of the striatum in cognitive aging.

The current study also shows that those older adults who use the task appropriate, procedural-based strategy in the information-integration task show less interference and better inhibitory control, but show no differences in working memory span or new verbal learning. The lack of a relationship between working memory and new verbal learning in information-integration categorization, but the presence of these relationships in rule-based categorization suggests that working memory and new verbal learning are important for testing and rejecting/accepting verbal categorization strategies, but may not be important for the transition from hypothesis-testing to procedural-based learning. This is a subtle but important finding that suggests a critical difference between rule-based and information-integration category learning and their relation to working memory and episodic memory.

Prefrontal Contributions to Category Learning in Normal Aging

One of the most important contributions of the current work was that we examined rule-based and information-integration category learning in the same group of older and younger adults using tasks equated on optimal accuracy, within- and between-category similarity, and the number of relevant dimensions. Not only does this allow us to make stronger claims about age-related performance changes across rule-based and information-integration category learning, but it also allows us to examine the association between critical neuropsychological factors and category learning across both types of tasks. A critical

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finding from this study was that rule-based and information-integration participants who used the task appropriate strategy—that is, who showed more efficient use of the hypothesis-testing system in the rule-based task and an effective transition from the hypothesis-testing to the procedural-based system in the information-integration task--revealed less interference and enhanced ability to inhibit on the Stroop and WCST.

This pattern of category learning performance as well as the pattern of correlates with neuropsychological measures is quite similar to those observed with prefrontal lesion patients who were faced with the exact same category learning tasks. Prefrontal patients were impaired at rule-based and information-integration category learning. In addition, those who used task inappropriate strategies in both conditions showed greater interference and worse inhibition (as measured by the WCST) and evidenced lesions in a fairly localized region of ventral medial prefrontal cortex. Given the similarity in performance profile across the current normal aging study and the Schnyer et al. prefrontal patient study, it seems reasonable to suggest that prefrontal cortical changes associated with aging might be responsible for the category learning deficits seen here.

Despite the differences between the neurobiology of the hypothesis-testing and procedural-based learning systems, both systems rely on effective feedback processing (Maddox & Ashby, 2004) and research clearly indicates that the response to feedback relies, at least in part, on specific regions of the prefrontal cortex. Ventral prefrontal cortex has been implicated in feedback based learning (Cools, Clark, Owen, & Robbins, 2002; Fellows, 2004; Haber, Kim, Mailly, & Calzavara, 2006); in particular, when feedback reflects information about expected outcomes, violations of expectations, and when strategy shifts are in order (Ghods-Sharifi, Haluk, & Floresco, 2008; Monchi, Petrides, Petre, Worsley, & Dagher, 2001; Takahashi et al., 2009).

Age-related declines in feedback processing have been observed across a number of studies and are likely due (at least in part) to structural and functional changes in prefrontal cortex with normal aging. For example, age-related declines have been observed in experience based decision making tasks such as the Iowa Gambling Task (Deakin, Aitken, Robbins, & Sahakian, 2004; Denburg, Tranel, & Bechara, 2005; Fein, McGillivray, & Finn, 2007). Older adults also exhibit deficits in stimulus-reward association learning tasks where associations between actions and their outcomes must be learned and reversed during learning (e.g., Mell et al., 2005).

Feedback serves somewhat different purposes in the hypothesis-testing and procedural-based learning systems. In the procedural-based learning system, feedback facilitates dopamine-mediated reinforcement learning when unexpected rewards trigger dopamine release into cortico-striatal synapses thereby strengthening their connections and supporting information-integration category learning (Ashby & Ennis, 2006; Ashby, Ennis, & Spiering, 2007; Schultz, 1998). In rule-based and information-integration category learning, feedback helps guide rule selection and strategy shifting (Maddox, Love, Glass, & Filoteo, 2008; Seger, 2008). For example, in rule-based learning, optimal performance requires trying different types of rule strategies (i.e. unidimensional versus conjunctive rules) and dropping ineffective approaches in response to feedback. Feedback processing is critical to learning the complex conjunctive rule used in this experiment and a deficit in the ability to respond to feedback may lead to the use of a task inappropriate strategy, where only a subset of the categories is actually learned. Interestingly, a careful examination of the response patterns for the 9 of 28 older adults who used a task inappropriate strategy in the rule-based task suggests that at least one category was not learned in every case. Specifically, final block accuracy for the most poorly learned category averaged 75% for the older adults who used a task appropriate strategy and averaged 27% for the older adults who used a task

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inappropriate strategy ($p < .05$). In information-integration learning, optimal performance requires a global shift from verbal hypothesis-testing to the more implicit procedural-based learning (Seger, 2008). It is this ability to shift from hypothesis-testing to rule-based strategies that might be impaired in some of our older participants. In support of this hypothesis, of the 4 older adults who used a used a task inappropriate strategy 3 used a hypothesis-testing strategy and 1 guessed.

Working memory and new verbal learning measures differed across participants using task appropriate and task inappropriate strategies for rule-based, but not information-integration performance. These findings converges nicely with prior research showing a direct link between working memory and rule-based category learning (Filoteo, Lauritzen, & Maddox, in press; Maddox, Ashby, Ing, & Pickering, 2004; Waldron & Ashby, 2001; Zeithamova & Maddox, 2006, 2007), as well as links between rule-based category learning and the medial temporal lobes (Nomura et al., 2007; Nomura & Reber, 2008). Importantly, and in line with these findings, working memory and rule implementation have been shown to rely on overlapping dorsal lateral prefrontal regions (Stuss & Knight, 2002).

Components of Rule-Based and Information-Integration Category Learning in Normal Aging

Another contribution of the current work is that we tested the notion that both rule-based and information-integration category learning involve cognitive operations associated with interference, inhibition, working memory and episodic memory (e.g., Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Racine, Barch, Braver, & Noelle, 2006). In addition, information-integration also involves cognitive operations associated with procedural-based learning. We conducted regression analyses that suggested that the hypothesis-testing model does a nice job of capturing all of the relevant cognitive processes associated with rule-based category learning, whereas the procedural-based model and a separate interference/ inhibition module is needed to capture information-integration category learning.

Based on our reading of the literature, this is the first study of its kind to explicitly identify two separable components of information-integration category learning. In that sense this work makes an important contribution to category learning theory, in general, and normal aging, in particular. Future theoretical work on the cognitive neuroscience of category learning needs to better formalize these two components, and the current data provide some insights on the neural locus (prefrontal and striatal) and cognitive operations associated with each component. Importantly, these data support the notion of independent systems mediating rule-based and information-integration category learning, but at the same time suggest some clear overlap and interactions at the systems level. The debate between independent and interacting category learning systems is ongoing (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby & Ell, 2002; Poldrack & Foerde, 2008; Poldrack & Rodriguez, 2004) and these data suggest that both notions have some validity.

Conclusions

The current study examined rule-based and information-integration category learning in a group of older and younger adults. As a group, older adults showed rule-based and information-integration deficits. Older adults' rule-based and information-integration performance was correlated with neuropsychological measures of interference and inhibition, whereas neuropsychological measures of working memory and new verbal learning were correlated only with rule-based performance. A series of models were applied that provided insights onto the type of strategy used to solve the task. Interestingly, when the analyses focused only on participants who used the task appropriate strategy, the age-related rule-based deficit disappeared whereas the information-integration deficit remained (albeit at

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a smaller level). The latter deficit was the result of increased noise in the decision process. In addition, older adults were slower to transition from a hypothesis-testing strategy to a procedural-based strategy. The use of the task appropriate strategy was associated with less interference and better inhibitory control for rule-based and information-information learning, whereas use of the task appropriate strategy was associated with greater working memory and better new verbal learning only for the rule-based task. Regression analyses suggested that information-integration learning involves two separate components: one procedural-based that is captured by the computational models and is likely mediated by the striatum, and one that involves interference and inhibitory control and is mediated by the prefrontal cortex.

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Appendix

Three different classes of decision bound models were fit to the final block of data from each participant. In this Appendix, we describe the models that were fit to each participant's responses. We organize this section around the two category structures since every model was not applied to data from every condition.

Rule-Based Condition

Hypothesis-Testing Models

Four models were compatible with the assumption that participants used an explicit hypothesis-testing strategy. The optimal model assumes that the participant sets a criterion on the length dimension, sets a criterion on the orientation dimension, and integrates that information post-decisionally. The model assumes that these decision criteria are those that maximize accuracy (i.e., the decision bounds shown in Figure 1). The optimal model uses the following decision rule: Respond A if the line length is short and the orientation is shallow, Respond B if the line length is short and the orientation is steep, Respond C if the line length is long and the orientation is shallow, Respond D if the line length is long and the orientation is steep. This model has one free parameter: the variance of internal (perceptual and criterial) noise (i.e., σ^2). Three additional hypothesis-testing models that used the same decision rule were tested. The sub-optimal-length model assumes that the participant used the optimal decision criterion along the orientation dimension, but used a sub-optimal decision criterion along the length dimension. The sub-optimal-orientation model assumes that the participant used the optimal decision criterion along the length dimension, but used a sub-optimal decision criterion along the orientation dimension. These two models contain two free parameters (i.e., one criterion and the noise variance). The sub-optimal-length-orientation model assumes that the participant used a sub-optimal decision criterion along the length dimension and a sub-optimal decision criterion along the orientation dimension. This model contains three free parameters (i.e., two decision criteria and the noise variance).

Procedural-Based Models

One procedural-based model was fit to the data. The Striatal Pattern Classifier (SPC; Ashby & Waldron, 1999) assumes that there are four "units" in the length-orientation space. On each trial the participant determines which unit is closest to the perceptual effect and gives the associated response. When fitting the SPC to the rule-based condition data, we assume that that each category has one associated unit. This model results in four "minimum-distance-based" decision bounds Because the location of one of the units can be fixed and

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since a uniform expansion of contraction of the space will not affect the location of the resulting (minimum distance) decision bounds, the model contains six free parameters (i.e., 5 that determine the location of the units, and one noise variance). This model has been found to provide a good computational model of participants response regions in previous information-integration category learning studies (Ashby & Waldron, 1999; Ashby, Waldron, Lee, & Berkman, 2001; Maddox, 2001, 2002). In addition, the assumptions of this model have strong neurobiological plausibility.

Random-Responder Models

One model assumes that the participant responds A, B, C, or D with probability .25 for each stimulus. This model has no free parameters. A second model estimates the probability of responding A, B, C, and D from the data with the constraint that these probabilities sum to one. This model has three free parameters.

Information-Integration Condition

Hypothesis-Testing Models

Three models were compatible with the assumption that participants used an explicit hypothesis-testing strategy to solve the information-integration category learning problem. The assumptions of the hypothesis-testing(1) model are identical to those from the sub-optimal-length-orientation model (described above) and assume that the participant sets a decision criterion along the length dimension, a decision criterion along the orientation dimension, and uses the same post-decisional integration rule outlined above. The hypothesis-testing(2) model instantiates an “extreme values” type of decision rule. This model assumes that the participant sets two criteria along the length dimension that partitions the length dimension into short, medium and long line lengths. The model assumes that the participant responds A if the length is short, B if the length is intermediate and the orientation is steep, C if the length intermediate and the orientation is shallow, and D if the length is long,. The hypothesis-testing(3) model is similar, but it assumes that the participant sets two criteria along the orientation dimension that partitions the orientation dimension into shallow, intermediate, and steep line orientations. The model assumes that the participant responds A if the orientation is intermediate and the length is short, B if the orientation is steep, C if the orientation is shallow, and D if the orientation is intermediate and the length is long. Both of these models contain 3 free parameters (2 criteria and one noise).

Procedural-Based Models

The optimal model assumes that the participant used the optimal decision bounds (see Figure 1) and contains the single noise parameter. The SPC was also applied to the data under the same assumptions used when applying the model to the rule-based condition.

Random-Responder Models

The same models outlined above were applied.

Model Fits

The relevant models were fit separately to the final block of data for each participant. The model parameters were estimated using maximum likelihood (Ashby, 1992b; Wickens, 1982) and the goodness-of-fit statistic was

$$BIC = r\,ln(N) - 2lnL,$$

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where r is the number of free parameters, N is the number of trials being fit (100) and L is the likelihood of the model given the data (Akaike, 1974; Takane & Shibayama, 1992). The BIC statistic penalizes a model for extra free parameters in such a way that the smaller the BIC, the closer a model is to the "true model," regardless of the number of free parameters. Thus, to find the best model among a given set of competitors, one simply computes a BIC value for each model, and chooses the model associated with the smallest BIC value.

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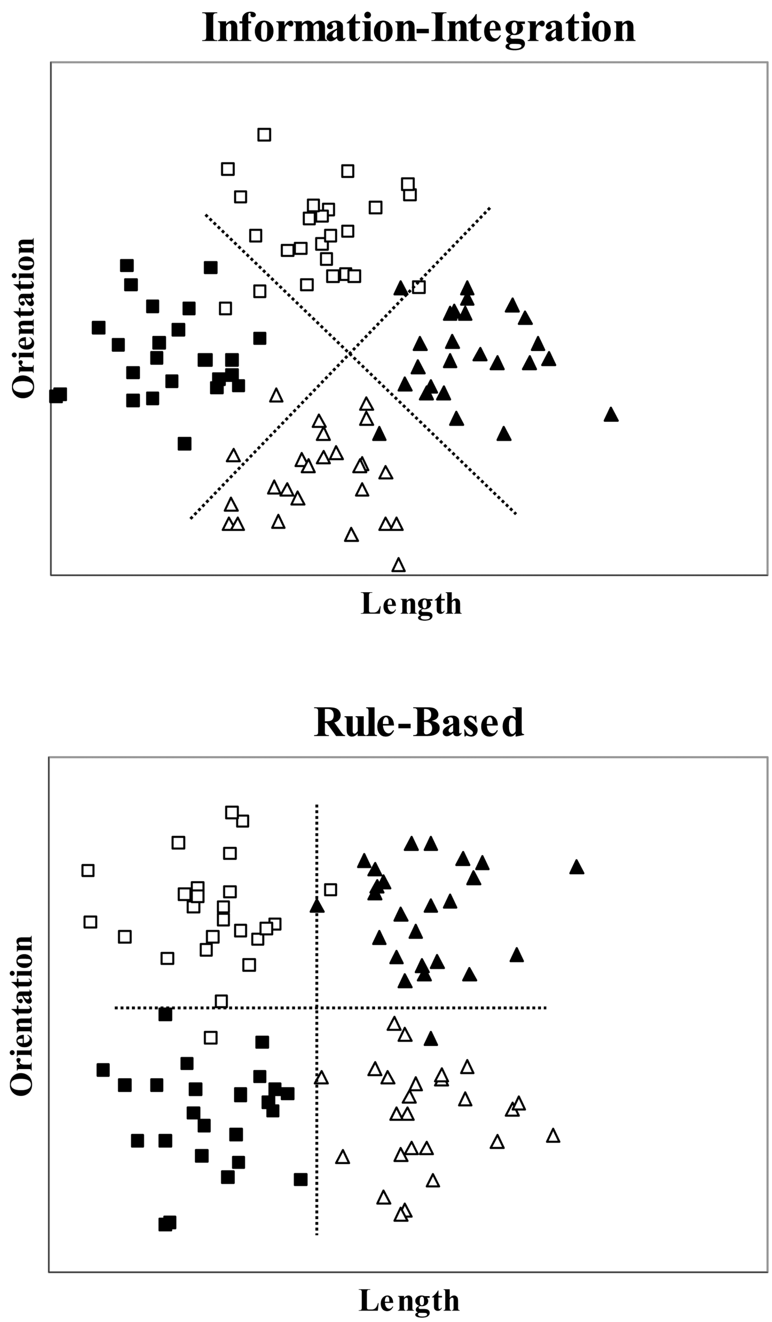

Figure 1.

Scatterplots of the stimuli in length-orientation space in the information-integration (top panel) and rule-based (bottom panel) tasks. Each point in the scatterplot represents a single stimulus. Category A exemplars are denoted by filled squares, B by open squares, C by open triangles, and D by filled triangles. The solid lines are the optimal decision boundaries.

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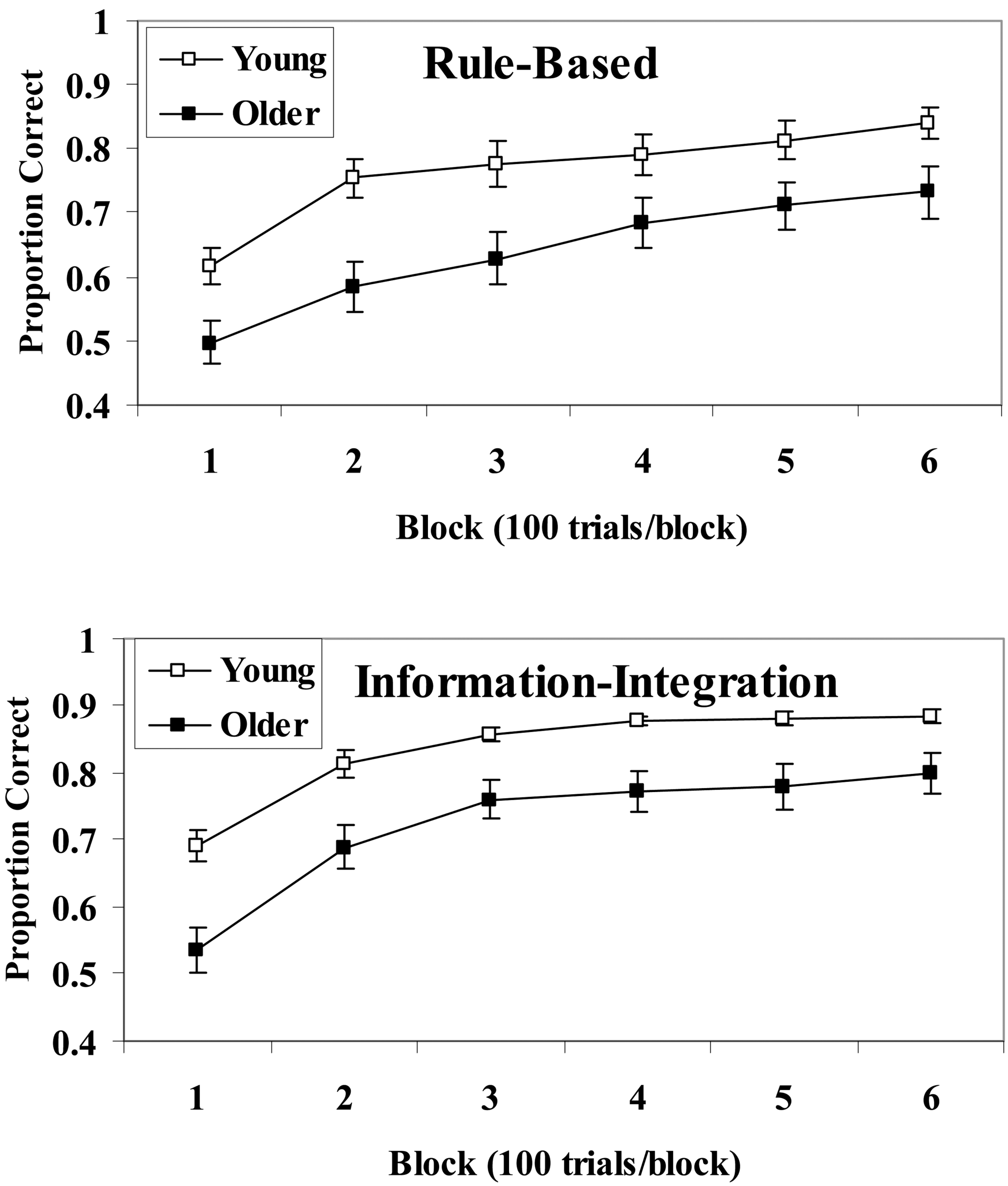

Figure 2.
Rule-based (top panel) and information-integration (bottom panel) accuracy rates for younger and older adults in each of the 6 100-trial blocks. Error bars are standard error of the mean.

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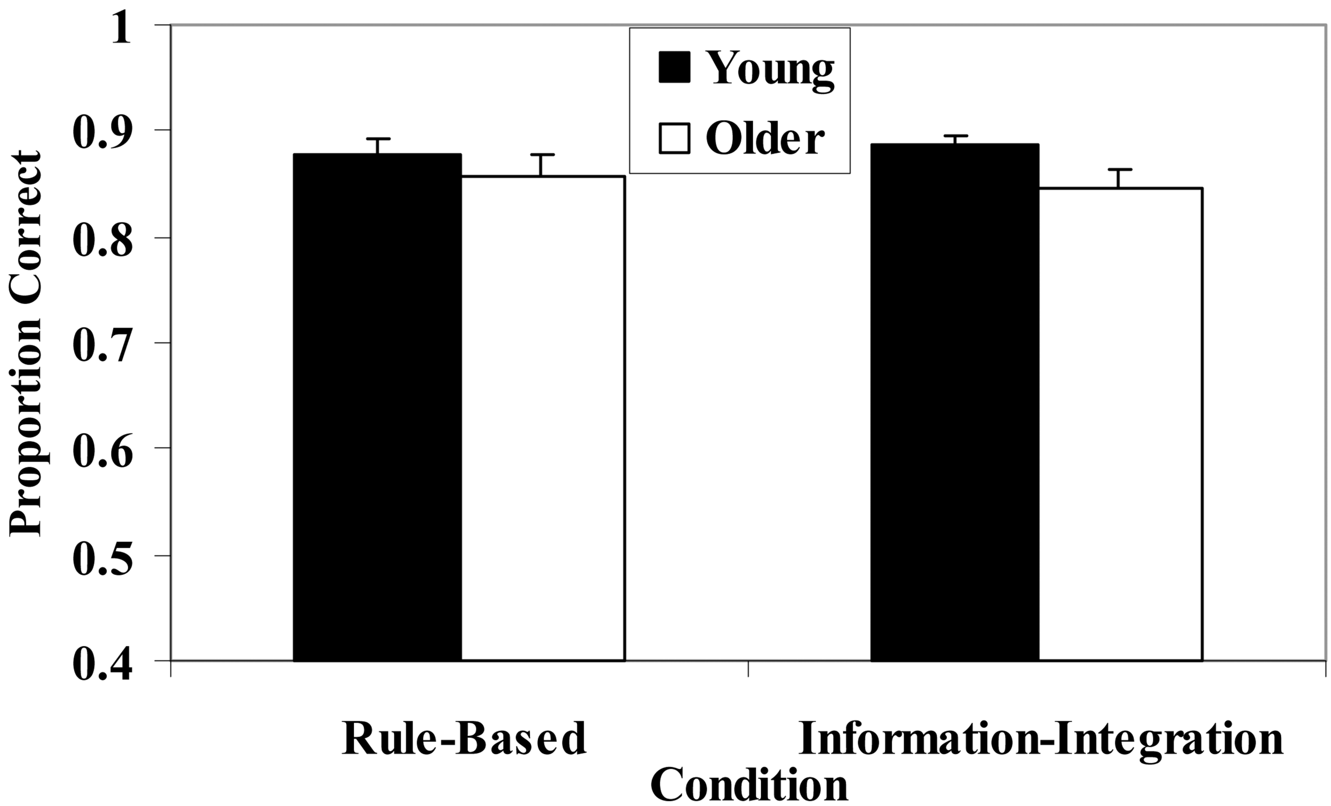

Figure 3.
Rule-based and information-integration accuracy rates for younger and older adults who used the task appropriate strategy (hypothesis-testing in the rule-based condition or procedural-based learning in the information-integration condition) in the final 100-trial block. Error bars are standard error of the mean.

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Table 1

Correlations Between Final Block Rule-Based and Information-Integration Performance and a Number of Neuropsychological Tests for Older Adults.

Measure	Rule-Based	Information-Integration
Stroop interference Z	.64**	0.44*
WCST perseverations Z	0.13	0.44*
Stroop/WCST_composite Z	0.67**	0.65**
Trails B Z	−0.13	−0.13
FAS Z	0.05	0.01
Total Digit Span Z	0.62**	0.42*
CVLT long delay free std	0.37*	0.24
WMS log mem 30 min recall Z	0.03	−0.03
CVLT/WMS composite Z	0.18	0.10

* $p<.05$,

** $p<.01$

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Table 2

Number of Participants Classified as using a Hypothesis-testing, Procedural-based or Guessing Strategy During the Final Block by Participant Group and Condition

Rule-Based Condition			
	Hypothesis-Testing	**Procedural-Based**	**Guessing**
Young	27	3	1
Older	19	6	3

Information-Integration Condition			
	Procedural-Based	**Hypothesis-Testing**	**Guessing**
Young	29	2	0
Older	24	3	1

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Table 3

Average Neuropsychological Test Performance as a Function of Task Appropriateness for the Rule-Based and Information-Integration Conditions

Measure	Rule-Based		Information-Integration	
	Task Appropriate	Task Inappropriate	Task Appropriate	Task Inappropriate
Stroop interference Z	1.93	.36**	1.65	.05*
WCST perseverations Z	.61	−.02	.53	−.38
Stroop/WCST_composite Z	1.38	.02**	1.13	−.16**
Trails B Z	−.52	−.43	−.47	−.64
FAS Z	.15	.49	.24	.41
Total Digit Span Z	1.18	.16*	.88	.70
CVLT long delay free std	1.00	.39*	.81	.75
WMS log mem 30 min recall Z	.99	.94	.90	1.40
CVLT/WMS composite Z	1.00	.67	.86	1.08

*p<.05,

**p<.01 = significant t-tests across task appropriate and task inappropriate values.