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A Quantitative Model-Based Approach to Examining Aging Effects on Information-Integration Category Learning

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Information-integration category learning was examined in older and younger adults. Accuracy results indicated that older participants learned less well than younger participants in both linear and nonlinear conditions. Model-based analyses indicated that both groups in the linear condition tended to use information integration but that later in training younger participants were more likely to do so. In contrast, the 2 groups in the nonlinear condition were equally likely to use information integration. Further analysis indicated that younger adults were more accurate than older adults when an information-integration approach was adopted, whereas fewer age-related differences were observed when a rule-based approach was used, suggesting that age can have a negative impact on information-integration category learning processes but less impact on rule-based learning.

Category learning is the cognitive process by which individuals learn to place stimuli into two or more groups.[1] This process is important for day-to-day functioning and represents a fundamental aspect of cognition. Every day we categorize hundreds of times, and throughout our lifetime we are required to learn new categories (Ashby & Maddox, 1998). For example, both children and older adults are required to learn whether certain situations are safe or unsafe, and the nature of these situations will obviously change across the life span. For children such situations might be associated with whether certain objects are sharp or not, whereas for older individuals such situations might be associated with which medications are dangerous or not. Therefore, a fundamentally important question to investigate is whether category learning abilities change with age and, if so, under what conditions are such changes observed.

The specific cognitive processes associated with categorization have been studied extensively in college-age individuals, and several formal models have been developed to account for normal categorization performance (Ashby, 1992a; Ashby & Maddox, 1993; Estes, 1994; Nosofsky, 1992; E. E. Smith & Medin, 1981). In comparison, only a small number of studies have examined categorization in older individuals. Of those studies, most have examined age-related differences in categorizing information that has already been learned. The majority of these studies have used free-sorting paradigms in which participants are asked to sort stimuli into categories based on a self-determined rule. These studies have indicated that older and younger participants tend to focus on different aspects of the stimuli and use different strategies when categorizing under such conditions (Cicirelli, 1976; Denney, 1974a, 1974b; Denney & Denney, 1982; Denney & Lennon, 1972; Hess & Wallsten, 1987; Kogan, 1974; Pearce & Denney, 1984).

A second line of research examining categorization in older adults has focused on the ability to learn new categories. At least two types of category-learning tasks have been examined: observational learning and feedback learning. The most widely used observational learning task is the dot-pattern classification task (e.g., Homa, Sterling, & Trepel, 1981; Posner & Keele, 1968; J. D. Smith & Minda, 2001), and studies that have examined aging effects on this task have indicated that older adults (a) show less learning (Davis, Klebe, Bever, & Spring, 1998; Hess & Slaughter, 1986b), (b) display less familiarity with the category prototype (Hess & Slaughter, 1986a), and (c) show more interference when learning categories that are based on established concepts (Hess, 1982). In contrast, at least two studies have demonstrated no effects of aging on a similar task that requires participants to learn an artificial grammar under observational learning conditions (McGeorge, Crawford, & Kelly, 1997; Salthouse, McGuthry, & Hambrick, 1999). However, category membership in artificial grammar learning is not dependent on prototypical information but rather on a set of rules that dictate the order of letters for each exemplar within the artificial grammar. Given that both the dot-pattern task and the artificial grammar learning task rely on observational learning procedures, it may be that age specifically impacts pro-

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[1] In this article we make the important distinction between those processes involved in learning to categorize and those involved in making categorizations for information that has already been learned. Although there are likely overlapping processes involved in these two aspects of categorization, it is nevertheless important to make this distinction.

totype extraction and does not result in generalized changes in observational category learning.

The second type of task used to investigate age effects on category learning, and the kind used in the current study, are feedback learning tasks. In contrast to observational learning paradigms, participants in feedback learning tasks categorize each new exemplar during training and are provided information regarding the correctness of each response. Categorization tasks that require learning based on trial-by-trial feedback have enjoyed a rich tradition in psychology (e.g., Ashby & Maddox, 1998; Bruner, Goodnow, & Austin, 1956), but unfortunately such tasks have not been used to a large extent to address questions related to aging. Perhaps the task that has been used most to identify age-related changes in category learning is the Wisconsin Card Sorting Test (WCST). This test requires participants to learn to categorize multidimensional stimuli based on a single stimulus dimension (e.g., color) using trial-by-trial feedback provided by the examiner and then to switch dimensions after 10 correct responses. Several studies have demonstrated decreased performance with age on this and similar tasks (Axelrod & Henry, 1992; Hayslip & Sterns, 1979; Kramer, Humphrey, Larish, Logan, & Strayer, 1994). In addition, age-related performance decrements have been observed on feedback learning tasks that require participants to learn to categorize based on artistic styles (Hess & Wallsten, 1987) or certain aspects of social features (Hess, Pullen, & McGee, 1996). Other types of feedback category learning tasks on which older adults tend to perform worse than younger adults are visual discrimination learning tasks (Nehrke, 1973; Offenbach, 1974). Taken together, the majority of studies examining category learning using trial-by-trial feedback tasks indicate that older participants perform more poorly than younger participants.

Although the results of these studies inform us about the conditions under which age-related changes in category learning might occur, there are a few potential shortcomings of these studies. First, those studies that have used the WCST may have tested other cognitive processes not directly related to the ability to attain new categories. Specifically, the WCST requires an individual to not only learn a category but also to switch to a new category, and, as several studies have indicated, age-related changes on the WCST likely occur because of differences in the ability of older adults to switch to a new category (but see Hartman, Bolton, & Fehnel, 2001; Offenbach, 1974). Such perseverative tendencies have often been considered a hallmark of the normal aging process. Second, many past studies of categorization have used tasks that emphasize the semantic aspects of categories. Given the complexities of these types of categories, it is difficult to determine from these studies whether categorization per se changes in aging or whether age-related differences are due to alterations in other cognitive processes.

Another potential shortcoming of these past studies is that most focused almost exclusively on measures of accuracy when drawing inferences about the effects of age on performance. Accuracy-based analyses provide a good starting point but tell us little about the specific processes that participants use to solve a category learning problem.[2] It is often the case that qualitatively different processes can yield identical accuracy rates and qualitatively similar processes can yield different accuracy rates. Thus, when age-related differences in accuracy do not emerge, it is still possible that older and younger adults use qualitatively different processes to solve the task. Similarly, when age-related differences in accuracy do emerge, it is still possible that older and younger adults use qualitatively similar processes to solve the task. Although previous studies examining aging effects on free-sorting tasks have addressed this issue to some extent by examining age-related differences in strategy, these possibilities have not been explored in studies using feedback learning tasks. An understanding of the types of processes used to solve a category learning problem requires the application of quantitative models that each instantiate a different response process. This methodology is used in the current study.

The issue of how a participant approaches the task is especially relevant given the growing body of research suggesting that different category learning problems invoke different memory and category learning systems (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby & Ell, 2001, 2002). One important distinction that has been identified is that between rule-based category learning and information-integration category learning. Rule-based category learning tasks are those in which the category structures can be learned by means of some explicit reasoning process. Frequently, the rule that maximizes accuracy (i.e., the optimal rule) is easy to describe verbally (Ashby et al., 1998). In most common applications, only one stimulus dimension is relevant, and the participant's task is to discover this relevant dimension and then to map the different dimensional values to the relevant categories. The most well-known example of a rule-based category learning task is the WCST, in which correct categorization is based on identifying a single stimulus dimension (e.g., color). As stated previously, older adults tend to perform more poorly than younger adults on this task. Because correct categorization on rule-based tasks often depends on a single rule that can be verbalized, learning is said to occur explicitly. Information-integration category learning tasks, on the other hand, are those in which accuracy is maximized only if information from two or more stimulus components (or dimensions) is integrated at some predecisional stage (Ashby & Gott, 1988). Perceptual integration could take many forms, from treating the stimulus as a gestalt to computing a weighted linear combination of the dimensional values.[3] In many cases, the optimal rule in information-integration tasks is difficult or impossible to describe verbally (Ashby et al., 1998).

The majority of studies that have examined age-related differences on feedback learning tasks have focused on rule-based category learning tasks, and to our knowledge only one study has examined both rule-based and information-integration category learning in older and younger adults (Ashby, Noble, Filoteo, Waldron, & Ell, 2003). In that study, Ashby et al. (2003) used a task similar to the WCST. However, instead of administering only a

[2] We use the terms *process* and *approach* when referring to the method that participants used when learning the categories, but the use of these terms should not imply that the participant necessarily used conscious processes when learning the rules.

[3] The use of a conjunctive rule (e.g., "Respond 'A' if the stimulus is small on dimension *x* and small on dimension *y*") is a rule-based process rather than an information-integration process because separate decisions are first made about each dimension (e.g., small or large), and then the outcome of these decisions is combined (i.e., integration is postdecisional, not predecisional).

rule-based condition (i.e., the correct rule was based on a single stimulus dimension), these investigators also included an information-integration condition in which correct categorization was determined by the presence of an arbitrarily weighted combination of features. Ashby et al. (2003) found that the older and younger adults did not differ in terms of the proportion of participants who were able to learn the rule-based categories. In contrast, there was a significant difference between the two groups in the information-integration condition, with a higher proportion of younger adults, compared with older adults, who were able to solve the information-integration problem. These results suggest that, relative to younger adults, older adults have more difficulty learning information-integration category learning tasks but have less difficulty with rule-based tasks. However, when Ashby et al. (2003) examined the number of trials it took the older and younger adults to acquire the categorization rule, older adults performed more poorly than younger adults in both the rule-based and information-integration conditions. Thus, there is some evidence to indicate that older adults perform more poorly than younger adults in both types of categorization tasks, but this conclusion is far from clear.

The purpose of the current study was to further examine information-integration category learning in older and younger adults. In this study, we used the perceptual categorization task (also called the general recognition randomization technique; Ashby & Gott, 1988). This task has been used extensively to study category learning in college-age individuals and patients with various neurological disorders (e.g., Ashby & Gott, 1988; Ashby & Maddox, 1990, 1992; Filoteo, Maddox, & Davis, 2001a, 2001b; Maddox & Bohil, 1998; Maddox & Filoteo, 2001). The perceptual categorization task affords several advantages over previous studies of category learning abilities in older and younger adults. First, it allows the researcher to hold constant a number of important factors, such as nature of the stimuli, type of response and feedback, category distribution parameters, and optimal accuracy, while simultaneously manipulating important variables that might impact category learning differences between older and younger individuals. One important variable that was manipulated in the current study was the linearity of the information-integration categorization rule. Specifically, we examined participants' ability to learn both linear and nonlinear category structures. Linear category structures are those in which category membership is defined by a linear relationship between stimuli attributes, whereas nonlinear category structures are those in which category membership is defined by a nonlinear relationship between stimulus attributes. The stimuli in this study consisted of a single line that varied from trial to trial in length and orientation (Figure 1). Figure 1 depicts the relationship between the stimulus attributes in the linear and the nonlinear conditions. Previous research with younger adults indicates that, compared with nonlinear structures, linear structures are often (but not always) learned faster and result in higher asymptotic performance. As such, it was of interest to determine whether the linearity of the category structures would impact any observed aging differences on an information-integration category-learning task. Because the dimensions of length and orientation are measured in separate physical units (i.e., centimeters and degrees), both the linear and nonlinear optimal categorization rules are difficult (if not impossible) to verbalize. Thus, both rules were highly complex.

A second advantage of using the perceptual categorization task is that a number of formal mathematical models have been developed to analyze data obtained in this task (Ashby, 1992a; Ashby & Maddox, 1993; Maddox & Ashby, 1993). These models have proven invaluable when attempting to determine the type of processes used by a participant, and we take such an approach in the current study. Although we provide more detail about our modeling approach later, it is important to note at this point that we focused on two different approaches that participants might have used to learn the categories: a rule-based approach and an information-integration approach. The model-based approach allows us to determine whether each participant uses the optimal information-integration process, a suboptimal information-integration process, or a qualitatively different process, such as applying a unidimensional or conjunctive rule-based approach that can be verbalized. These model-based analyses allowed us to gain further insight into age-related differences in learning information-integration categorization rules.

Method

Participants

Twenty-six younger and 25 older individuals participated in both the linear and nonlinear conditions. The mean age was 19.9 years ($SD = 2.5$) for younger adults and 68.3 years ($SD = 8.4$) for older adults. The male–female ratio was 13:13 for the younger group and 10:15 for the older group, which was not reliably different (Fisher's exact test, $p = .58$). 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 accident, head trauma, and any other neurological condition. The education level of the younger participants ($M = 14.1$ years, $SD = 0.89$) was significantly lower than that of the older participants ($M = 14.9$ years, $SD = 2.0$), $t(49) = 2.0$, $p < .05$.

Stimuli and Stimulus Generation

The stimuli consisted of line segments of varying lengths and orientations (see Figure 1). Stimuli were white and presented on a black background using a PC. Two categories were defined by specifying two bivariate normal distributions. The stimuli were generated before the experiment. Fifty stimuli were sampled randomly from each of the two categories with the constraint that the sample means, variances, and covariances were similar to the category distribution parameters (Table 1). Six random orderings of the 100 stimuli were generated and made up the six 100-trial blocks used in the study. Each random sample was composed of an ordered pair (x, y), and each stimulus was created by converting the x value into a line length (measured in pixels) and the y value (after applying a scaling factor of $\pi/500$) into line orientation. The scaling factor $\pi/500$ was chosen to (approximately) equate the salience of line length and line orientation. The parameters of the two category distributions are displayed in Table 1. In Figure 1, the optimal decision rule maximizes long-run accuracy. The average stimulus line length in the linear condition was 7.5 cm, which subtended a visual angle of about 9.5 degrees from a viewing distance of 45 cm, whereas in the nonlinear condition, the average stimulus line length was 7.75 cm, which subtended a visual angle of about 9.8 degrees.

General Procedure

Six hundred trials were presented for both the linear and nonlinear conditions. At the start of the experiment, participants were told that

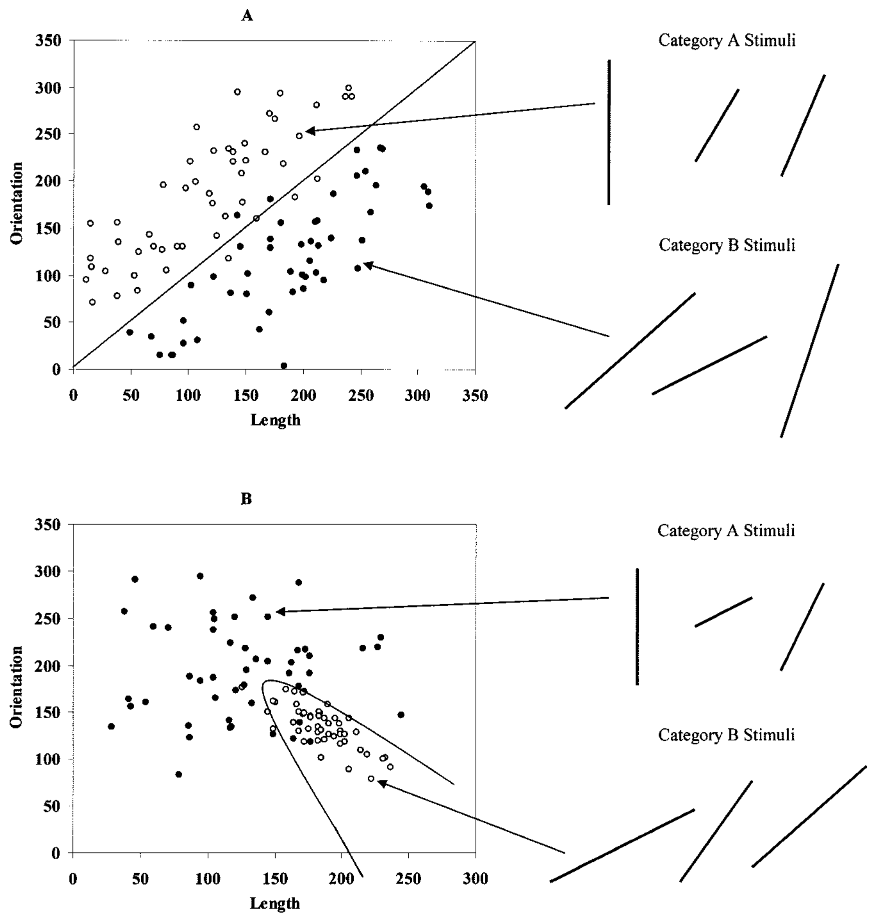

Figure 1. Stimulus distributions for linear (A) and nonlinear (B) conditions and sample stimuli from each category. Arrows link a sample stimulus with its representation in the two-dimensional space. (Note that stimuli are relative to scale in terms of length.) Each point represents a single stimulus. Unfilled circles = Category A stimuli; filled circles = Category B stimuli; *x*-axis = the length of the line; *y*-axis = orientation of the line; solid line (A) = experimenter-defined (optimal) linear category structures; solid quadratic curve (B) = experimenter-defined nonlinear category structures.

they were involved in a study that examined their ability to categorize simple stimuli. A series of stimuli would be presented, and participants would be asked to categorize each as a member of either Category A or Category B. They were also told that at the beginning of the experiment they may feel as though they were guessing, but as the experiment progressed their accuracy would likely increase. Participants indicated their categorization responses by pressing one key for Category A stimuli and another key for Category B stimuli. At the start of each trial, a fixation point was displayed for 1 s and then the stimulus appeared. Immediately after the participant's categorization response, the correct category label was presented on the screen for 1 s along with the word *wrong* if their response was incorrect or *right* if their response was correct. Once feedback was given, the next trial was initiated. Participants were instructed to respond as quickly but as accurately as possible. Each individual participated in both the linear and nonlinear conditions. The order in which the conditions were administered was

Table 1
Category Distribution Parameters for the Linear and Nonlinear Information-Integration Category Structures

	Category A					Category B				
Structure	μ_1	μ_o	σ_1	σ_o	$\mathrm{cov}_{1,o}$	μ_1	μ_o	σ_1	σ_o	$\mathrm{cov}_{1,o}$
Linear	115	185	65	65	3350	185	115	65	65	3350
Nonlinear	185	135	23	23	−393	125	195	51	51	0

Note. Across the table, the statistic column headings refer to mean, standard deviation, and covariance.

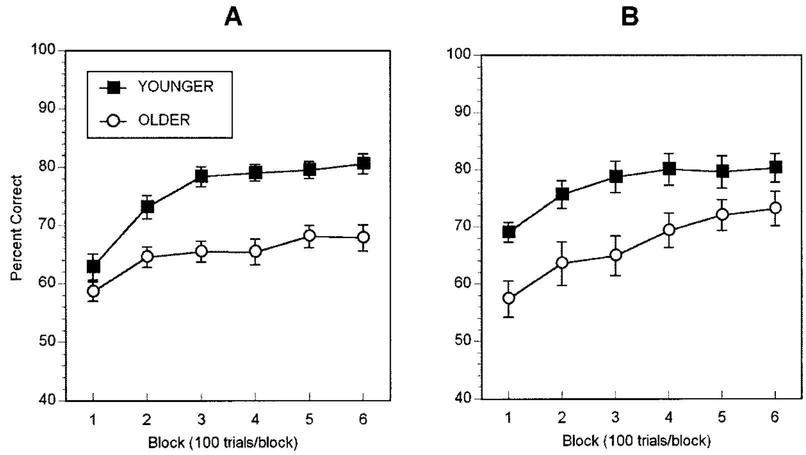

Figure 2. Overall accuracy for linear (A) and nonlinear (B) conditions. Error bars indicate standard errors of the mean.

counterbalanced across participants, and the minimum amount of time between the two conditions was 2 days.

Accuracy Results

Overall learning was examined by contrasting participants' accuracy (percentage correct) across the entire 600 trials in 100-trial blocks using a 2 (group: younger vs. older) × 2 (condition: linear vs. nonlinear) × 6 (Blocks 1–6) mixed-design analysis of variance (ANOVA).[4] These data are depicted in Figure 2 for the linear and nonlinear conditions. Results of this analysis identified a significant three-way interaction between group, condition, and block, $F(5, 245) = 5.07$, $p < .01$. Follow-up ANOVAs were conducted separately for the linear and nonlinear conditions, with group and block as factors. Results from the linear condition revealed a significant Group × Block interaction, $F(5, 245) = 6.29$, $p < .01$, as well as significant main effects of group, $F(1, 49) = 24.12$, $p < .01$, and block, $F(5, 245) = 46.24$, $p < .01$. As can be seen in Figure 2A, the Group × Block interaction was due to the fact that the two groups differed to a larger extent later in training compared with earlier in training. Results from the nonlinear condition also revealed a significant Group × Block interaction, $F(5, 245) = 2.4$, $p < .05$, as well as significant main effects of group, $F(1, 49) = 15.16$, $p < .01$, and block, $F(5, 245) = 39.66$, $p < .01$. However, the nature of the Group × Block interaction was different than that seen in the linear condition. Specifically, in the nonlinear condition, there was a greater difference in accuracy between the younger and older groups early in training compared with later in training.

We also examined the three-way interaction by conducting two separate Condition × Block ANOVAs for each age group. For the younger adults, the interaction between condition and block was significant, $F(5, 125) = 2.92$, $p < .05$, as was the main effect of block, $F(5, 125) = 57.57$, $p < .01$, but there was no significant effect of condition ($F = 1.08$). Similarly, for the older adults, there was a significant Condition × Block interaction, $F(5, 120) = 3.02$, $p < .05$, a significant main effect of block, $F(5, 120) = 33.66$, $p < .01$, but no effect of condition ($F = .84$). Interestingly, the nature of the Condition × Block interactions differed between the younger and older adults. In the younger adults, nonlinear accuracy was better than linear accuracy early in training, whereas for the older adults, nonlinear accuracy was better than linear accuracy later in training.

Model-Based Results

To better characterize the approach used by the participants to learn the categories, we next applied a series of quantitative models to each participants' data in the two conditions. A number of quantitative models of category learning have been developed for application to data collected in the perceptual categorization task (for details see Ashby, 1992a; Filoteo et al., 2001a, 2001b; Maddox & Ashby, 1993; Maddox & Filoteo, 2001; Maddox, Filoteo, Delis, & Salmon, 1996; Maddox, Filoteo, & Huntington, 1998). These decision-bound models are derived from general recognition theory (GRT; Ashby & Townsend, 1986), which is a multivariate generalization of signal-detection theory (e.g., Green & Swets, 1966). The fundamental assumption of GRT is that there is trial-by-trial variability in the perceptual information obtained from every stimulus, no matter what the viewing conditions (Ashby & Lee, 1993). On each trial, it is assumed that the percept can be represented as a point in a multidimensional psychological space. Decision-bound theory assumes each participant partitions the perceptual space into response regions by constructing a decision bound. On each trial, the participant determines which region the percept is in and then emits the associated response. Despite this deterministic decision rule, decision-bound models predict probabilistic responding because of trial-by-trial perceptual and criteria noise.

Application of these models allows for an in-depth examination of the types of response approaches used by the participants that cannot be differentiated based only on accuracy. Both information-integration and rule-based processes were examined (see Ashby, 1992a; Maddox & Ashby, 1993, for a more formal treatment of these models). To model the data, we individually collapsed each participant's responses into the first 300 trials and last 300 trials separately for both the linear and nonlinear conditions. The data were collapsed in this manner for three reasons. First, the overall accuracy results suggested some early and late training differences between the two groups, and collapsing in this manner captured

[4] A preliminary analyses was conducted where the order in which the conditions were administered was included as a factor along with the other factors. As with our previous studies (Filoteo & Maddox, 1999; Maddox et al., 1996), there were no main effects of order in either analysis, and this factor did not interact with any of the other factors.

these effects. Second, the application of the model-based analyses to a larger number of data helped to constrain the models and provided a more conservative estimate of the model fits, which in turn allowed for a more stable comparison of the models across the two age groups. Third, data were collapsed in this manner for ease of data exposition. Each of the following models, when appropriate, was applied to the participants' data in the two conditions.

Information-Integration Models

The optimal model assumes that the decision bound used by the participant are those depicted in Figure 1. In the linear condition, this model assumes a linear decision bound, and in the nonlinear condition, this model assumes a nonlinear decision bound. In the linear condition, the optimal model contains one free parameter that denotes the sum of perceptual and criterion noise (these two sources of noise are nonidentifiable when the decision bound is linear; Ashby & Maddox, 1993). In the nonlinear condition, the optimal model contains one parameter to measure perceptual noise and another to measure criteria noise. A suboptimal information-integration model was also applied to each condition. In the linear condition, the suboptimal model assumes that the participant used a linear decision bound but estimates the slope and intercept from the data. This model contains three parameters: the slope, intercept, and sum of perceptual and criterial noise. In the nonlinear condition, the suboptimal model assumes that the participant used a quadratic (nonlinear) decision bound but estimates the coefficients of the quadratic decision bound from the data. This model contains seven free parameters: five quadratic-bound coefficients, perceptual noise, and criteria noise. The minimum distance classifier was also applied. In the linear condition, the model assumes that the participant constructs two decision bounds to separate the A and B categories. In fitting this model, we assume that there are four units in the length-orientation space: two assigned to Category A and two assigned to Category B. On each trial, the participant determines which unit is closest to the perceptual effect and gives the associated response, which yields two linear decision bounds. Because the location of one of the units can be fixed, and 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., five that determine the location of the units and one that determines noise variance). This model has been found to provide a good computational model of participants' response regions in previous information-integration category learning studies (e.g., Ashby & Waldron, 1999; Waldron & Ashby, 2001; for applications to stimulus identification, see Ashby, Waldron, Lee, & Berkman, 2001; Maddox, 2001, 2002). The same version of the model was applied to the nonlinear data, along with a second version that assumed two units for Category A and three units for Category B.

Rule-Based Models

Two models were compatible with the assumption that participants used an explicit rule-based process. The unidimensional model assumes that participants set a criterion on a single perceptual dimension and then make an explicit decision about the level of the stimulus on that dimension (Ashby & Gott, 1988; Shaw, 1982). For example, in the current experiments, participants might use the rule: "Respond A if the line length is short and B if it is long." A different version of this model assumes participants set a criterion along the orientation dimension rather than the length dimension. The unidimensional models estimate the decision criterion from the data along with the sum of perceptual and criterial noise.

The conjunction model assumes participants use a conjunctive rule in which they make separate decisions about the levels on the two dimensions and then select a response based on the outcome of these two decisions. Two versions of the conjunction model were applied to the linear data. In Version 1, the decision rule was "Respond A if line length is short and orientation is high, otherwise respond B." This model never provided the best account of any participants' data sets and is not discussed further. In Version 2, the decision rule was "Respond B if line length is long and orientation is low, otherwise respond A." One version of the conjunction model was applied to the nonlinear integration data, and the decision rule was "Respond A if line length is long and orientation is low, otherwise respond B." Notice that all of these conjunction rules partition the perceptual space into four regions and assign one region to Category A (or Category B) and the rest to Category B (or Category A). Such a strategy is rule based because information integration is postdecisional and because the rule is easy to describe verbally. The conjunction model contains three parameters: a decision criterion on length, a decision criterion on orientation, and the sum of perceptual and criterial noise.

Model Fits

As stated above, for each participant, each of these models was fit separately to the linear and nonlinear data for the first 300 trials (early training) and the last 300 trials (later training). The model parameters were estimated using maximum likelihood (Ashby, 1992b; Wickens, 1982), and the goodness-of-fit statistic was as follows:

$$\mathrm{AIC} = 2r - 2lnL,$$

where r is the number of free parameters and L is the likelihood of the model given the data (Akaike, 1974; Takane & Shibayama, 1992). Akaike's information criterion (AIC) statistic penalizes a model for extra free parameters in such a way that the smaller the AIC, 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 an AIC value for each model and chooses the model associated with the smallest AIC value.

The frequencies of participants whose data were best fit by the information-integration and rule-based models are displayed in Table 2. These frequencies were compared between groups using Fisher's exact test. Early in training in the linear condition, both younger and older adults' data tended to be best fit by an information-integration model (77% for the younger group and 80% for the older group), and the frequency of this pattern did not differ between the groups ($p = 1.0$). In the later trials of the linear condition, younger participants' data were again best fit by one of the information-integration models (92%), whereas in the older group a smaller number of participants' data sets were best fit by these same models (68%), which did represent a significant difference between the groups ($p < .05$). In the nonlinear condition,

Table 2
Frequencies of Participants' Data Sets That Were Fit Best by the Various Models in the Linear and Nonlinear Conditions Separated by Early (Trials 1–300) and Late (Trials 301–600) Trials

Model	Early		Late	
	Younger	Older	Younger	Older
Linear				
Information integration	20	20	24	17
Rule based	6	5	2	8
Nonlinear				
Information integration	23	22	19	19
Rule based	3	3	7	6

both groups' data sets were best fit by an information-integration model early in training (89% for the younger group and 88% for the older group), and the frequency distribution was not significantly different between the groups ($p = 1.00$). Interestingly, there was a slight decrease later in learning in the frequency at which an information-integration model best fit the two groups' data (73% for the younger group and 76% for the older group), but again these frequencies did not differ between the groups ($p = 1.00$). Thus, in the nonlinear condition, there was not an age-related difference in how the two groups approached the task.

One potential problem with the frequency analyses reported previously is that some participants did not exceed chance performance (>57% for 300 trials) early or later in training in the two conditions. The model-fitting procedure we adopted required that one of the models best fit participants' data regardless of how accurately that participant responded. However, when a participant is performing below chance, the model fitting is basically attempting to account for random responding, and to impose the best model on such data could be misleading. That is, just because one model provides a better fit of the data based on the AIC statistic when accuracy is below chance, it does not necessarily mean that this is the process used by that individual. Thus, to better characterize the nature of participants' response approach and to alleviate any potential confounds that could arise from modeling below-chance performances, we analyzed the frequency counts from the model fits in only those data sets that were above chance in accuracy. Importantly, the results were exactly the same as those reported earlier in that the only time the groups differed in the type of approach they used was later in training in the linear condition. Specifically, early in training in the linear condition, the data sets of the younger group were best fit by an information-integration model 72% (16/22) of the time compared with 71% (12/17) for the older group ($p = 1.0$). Later in training in the linear condition, 92% (23/25) of the younger groups' data sets were best fit by an information-integration model compared with 56% (10/18) for the older groups' data sets ($p < .01$). Early in training in the nonlinear condition, 88% (22/25) of the younger groups' data sets were best fit by an information-integration model compared with 77% (10/13) for the older groups' data sets ($p = .39$). Later in training in the nonlinear condition, 72% (18/25) of the younger groups' data sets were best fit by an information-integration model compared with 73% (16/22) of the older groups' data sets ($p = 1.0$). Thus, the pattern of results described earlier was also observed when participants' data sets were only included when performance was above chance.

To further analyze the impact of aging on categorization learning, we next examined accuracy rates separately for participants' data sets that were best accounted for by the two classes of models. In doing so, we focused on only those data sets that were above chance for the specific condition (linear or nonlinear) and time (early training or later training) under question. Note that this provides a more stringent test of the accuracy differences between the two groups because of the fact that more data sets from the older group were excluded based on below-chance performance. Figure 3 displays the accuracy rates for each of the groups separated by which class of models best fit their data and whether it was late or early in training. Early in training in the linear condition, the younger adults were more accurate than the older adults when their data sets were best accounted for by either an information-integration model, $t(26) = 2.92$, $p < .01$, or a rule-based model, $t(9) = 3.7$, $p < .01$. In contrast, later in training, younger adults were more accurate than older adults for data sets best fit by an information-integration model, $t(31) = 4.29$, $p < .001$, but age-related accuracy differences were not seen for data sets best fit by a rule-based model, $t(8) = 1.0$, $p > .05$. Turning to the nonlinear condition, there were no differences between the accuracy rates of the younger and older groups whose data sets were best fit by either an information-integration model, $t(30) = 1.69$, $p > .05$, or a rule-based model, $t(4) = 0.30$, $p > .05$, early in training. However, later in training, younger participants whose data were best fit by an information-integration model were more accurate than older participants whose data were best fit by these same models, $t(32) = 3.23$, $p < .01$, whereas there was no difference between the two groups for the data best fit by a rule-based model, $t(11) = 0.75$, $p > .05$. Thus, when examining accuracy based on condition (linear or nonlinear) and time of learning (early or late), younger adults were more accurate than older adults three-quarter times when their data were best fit by an information-integration model, and only one-quarter times when their data were best fit by a rule-based model.[5]

One possible concern with the accuracy results reported previously is the consistency at which participants data sets were best fit by the two classes of models across early and later learning trials. That is, because the accuracy analyses reported previously could be based on different participants early and later in learning, it may be difficult to determine whether accuracy differences truly existed between older and younger participants who adopted either an information-integration or rule-based approach. To correct for this potential confound, we attempted to analyze accuracy differences between the older and younger adults whose data were best fit consistently early and later in training by either an information-

[5] In addition to analyzing accuracy, we also examined reaction times with the hypothesis that rule-based users may have been slower to respond than information-integration users, given the need to verbalize a rule when using a rule-based approach. Results of these analyses, however, failed to support this hypothesis, which is not entirely surprising given that participants were instructed to emphasize accuracy over speed.

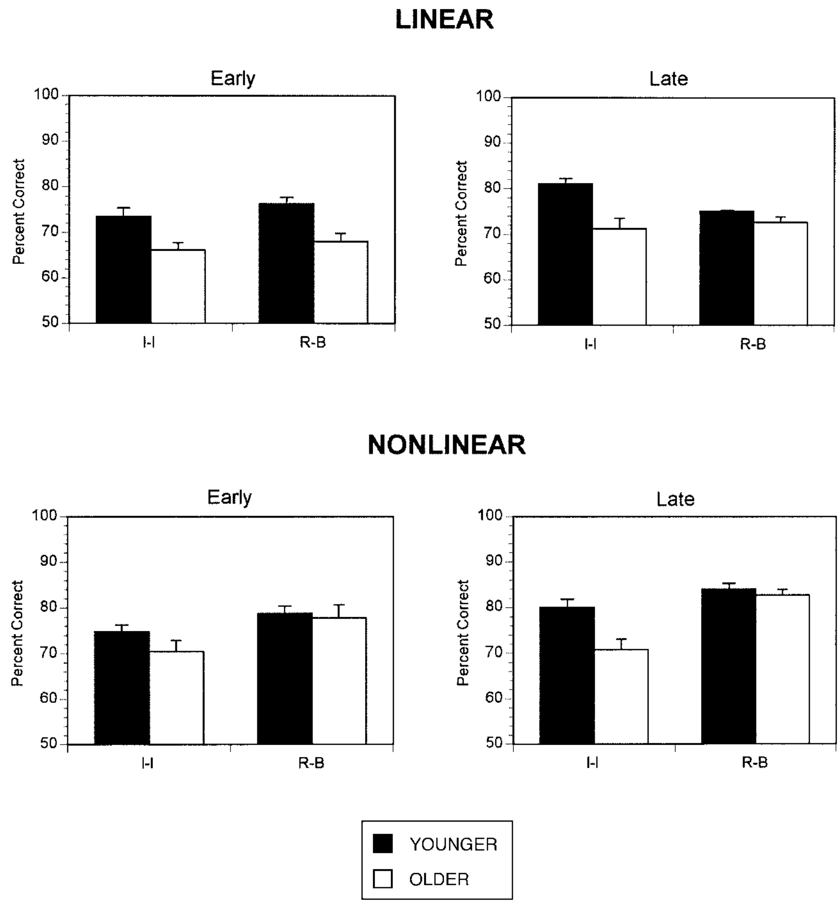

Figure 3. Percentage correct for younger and older participants whose data were best fit by either an information-integration (I-I) or rule-based (R-B) model early and later in training and in the linear and nonlinear conditions. See text for the size of the sample represented in each bar. Error bars indicate standard errors of the mean.

integration model or a rule-based model. As with the accuracy analyses described previously, we only examined those individuals who performed above chance in the conditions under study. For the linear condition, 14 younger and 8 older participants' data sets were best fit consistently by an information-integration model early and later in training, and 0 younger and 4 older participants' data sets were best fit consistently by a rule-based model. For the nonlinear condition, 16 younger and 6 older participants' data sets were best fit consistently by an information-integration model early and later in training, and 1 younger and 2 older participants' data sets were best fit consistently by a rule-based model.[6] Given the number of participants in the various conditions, the accuracy analyses were performed only for consistent information-integration users in the linear and nonlinear conditions. For both of these analyses, 2 (group: younger vs. older) × 6 (Blocks 1–6) mixed-design ANOVAs were conducted. In the linear condition for information-integration users, there was a significant main effect of group, $F(1, 20) = 14.72$, $p < .01$, indicating that younger participants were more accurate than older participants, and a significant effect of block, $F(5, 100) = 29.38$, $p < .01$, indicating that both groups improved their performance across the learning trials. The interaction between group and block was not significant ($F = .53$). In the nonlinear condition for information-integration users, there was only a main effect of block, $F(5, 100) = 18.16$, $p < .01$, which indicated that both groups improved in their accuracy across trials, but there was not a significant effect of group ($F = 1.60$), and the Group × Block interaction was not significant ($F = .68$). These results suggest that, at least for the linear condition, even within participants who consistently used the same approach throughout learning, younger participants were more accurate than older participants when using an information-integration approach to learn the categories.

[6] We also tallied the number of participants in each condition who changed either from an information-integration approach to a rule-based approach or from a rule-based approach to an information-integration approach. In the linear condition, 2 younger adults and 4 older adults switched from an information-integration approach to a rule-based approach, and 6 younger adults and 1 older adult switched from a rule-based to an information-integration approach. In the nonlinear condition, 6 younger adults and 4 older adults switched from an information-integration to a rule-based approach, and 2 younger adults and 1 older adult switched from a rule-based to an information-integration approach.

Self-Report Data

In an attempt to ascertain more information regarding the approach that participants used when learning the categories, a questionnaire was administered to a subgroup of younger ($n = 10$) and older ($n = 9$) participants after completion of the linear and nonlinear conditions. This questionnaire asked participants to explicitly state the rule they used and on what aspects of the stimuli they based their decisions. The majority of participants stated that they based their decision on both the length and the orientation of the line, but participants were rather vague in describing the exact rule they used. Only 3 (1 younger and 2 older) indicated that they were guessing, and for those individuals an information-integration model best fit their data for that condition. However, a few participants stated a specific rule that they used, and their data were also best fit by an information-integration model. Interestingly, 3 older adults indicated that they had attempted to memorize a particular exemplar and use that as a prototype for comparison to the other stimuli. Of these 3 participants' data sets, two were best fit by an information-integration model, and the other was best fit by a rule-based model. In general, the information obtained from the participants' self-reports did not match directly with the model-based results, a finding that has been observed in previous studies that have used similar complex rules (F. Gregory Ashby, personal communication, June 2003).

Discussion

The results from the current study indicated that older adults were less accurate than younger adults at information-integration category learning in both the linear and nonlinear conditions. The model-based analyses enabled us to further determine the nature of these age-related changes by identifying the types of response processes used by participants. The results suggested that, in the linear condition, older and younger participants differed in how they approached the task. Specifically, later in training, younger adults were more likely to use an information-integration approach, whereas older adults were more likely to use a rule-based approach. In contrast, in the nonlinear condition, older and younger participants did not differ in which approach they used to learn the task; both groups were more likely to use an information-integration approach. Importantly, the subgroup analyses derived from our model-based approach indicated that the overall accuracy differences observed between the older and younger adults were primarily seen in individuals who used an information-integration approach, but not in individuals who used a rule-based approach. Each of these findings has important implications for the impact of aging on category learning, and we turn now to a more detailed discussion of these issues.

Aging and Categorization

The first main finding from the current study was that, in terms of overall accuracy, aging can have a detrimental impact on category learning. These results are highly consistent with those studies that have identified such changes in older adults (Ashby et al., 2003; Axelrod & Henry, 1992; Davis et al., 1998; Hayslip & Sterns, 1979; Hess, 1982; Hess et al., 1996; Hess & Slaughter, 1986a, 1986b; Hess & Wallsten, 1987; Kramer et al., 1994) and extend previous work by indicating that these cognitive changes may be seen under information-integration category learning conditions in which the categories are defined by perceptual aspects of the stimuli.

Although the accuracy results identified age-related changes in category learning, they did not help to identify the nature of these changes. However, an examination of the modeling results helped to inform us under which conditions these differences were most evident. First, for both the linear and nonlinear conditions, it appeared that participants were not entirely constrained to use an information-integration process, despite the fact that optimal responding would have resulted in the use of such an approach. However, the likelihood that a participant adopted a particular approach depended on both their age group and on whether the rule was linear or nonlinear. Focusing on the age-related differences, it was clear that older adults were less likely to use an information-integration approach later in learning in the linear condition and instead were more likely to use a rule-based approach. Interestingly, it did not appear that these aging effects in the linear condition were due simply to the fact that the proportion of younger adults using an information-integration approach increased from early to later training trials but that the proportion of older adults using an information-integration approach actually decreased somewhat across early and later training (see Table 2). In addition, in both the linear and nonlinear conditions, 8 younger and 5 older participants switched approaches from early to later in training (whether from an information-integration approach to a rule-based approach or vice versa; see footnote 6). These findings suggest that the age-related differences in frequencies observed later in training were not simply due to the older participants being less flexible in how they approached the task (i.e., that they simply locked onto a certain approach and stayed with it), but that there was somewhat of a tendency for them to switch to using a different approach.

In the nonlinear condition, a somewhat different picture emerged. Specifically, as with the linear condition, both younger and older adults were likely to use an information-integration approach early and later in training. However, unlike the linear condition, the proportion of older and younger participants who used the various approaches did not differ either early or later in learning. These results indicate that, at least within the nonlinear condition, older and younger participants will likely approach the task in a similar way. This finding is somewhat in contrast to the age-related differences observed in previous studies that examined free-sorting tasks. Specifically, when participants are allowed to categorize based on their own rules (i.e., without corrective feedback), older adults tend to categorize items based on how the items function together (e.g., hammer and nail), whereas younger adults sort based on how items are similar (e.g., nail and pin; Denney, 1974a, 1974b; Denney & Denney, 1982; Denney & Lennon, 1972; Pearce & Denney, 1984). These past findings suggest that older and younger adults use a different approach when performing free-sorting categorization tasks. The results from the current study, however, indicated that older and younger adults used similar approaches to learn the categories with a nonlinear relationship but that age-related differences emerged in how accurately the two groups used the various approaches. Although there are other important aspects of the tasks used in these past studies and the current study that might account for these differences (e.g., the use of semantic-based categories in past studies and the use of perceptually based categories in the current study), our findings may indicate that age can impact free-sorting categorization and category learning in fundamentally different ways. It may be that age impacts free-sorting tasks in how older and younger participants approach the task, whereas for category learning tasks, in which acquisition is based on trial-by-trial feedback, age does not differentially impact how a participant approaches the task, but it may impact how accurately an individual can learn the categories. Clearly, more work is needed to identify possible age-related performance differences observed between free-sorting and feedback-based learning, paying particular attention to other important task differences.

Perhaps the most important findings from the current study came from comparing the accuracy rates for older and younger participants who used either an information-integration or a rule-based approach (see Figure 3). In general, when participants adopted an information-integration approach, younger participants tended to be more accurate than older participants both in the linear and nonlinear conditions. In contrast, age-related accuracy differences did not consistently emerge for those participants who used a rule-based approach (except early in learning in the nonlinear condition). Although these latter analyses are based on small sample sizes and, therefore, should be interpreted with caution, it is very clear from Figure 3 that later in learning (when accuracy is greatest) age-related accuracy differences in information-integration users were readily apparent, whereas age-related accuracy differences in rule-based users were not. Taken together, these results suggest that the cognitive processes associated with information-integration category learning may be impacted to a greater extent in normal aging than those processes involved in rule-based learning. Further, these results are consistent with the findings from Ashby et al. (2003), who also examined information-integration and rule-based learning processes in younger and older adults. In their experiment, participants were administered two different category learning tasks: one in which optimal responding required information-integration processes and another in which optimal responding required rule-based processes. The main finding from their study was that a disproportionately larger number of older adults were unable to learn the task that emphasized information-integration processes, but a proportionate number of older and younger adults were able to learn the task that emphasized rule-based processes. Although in the current study we did not use a task in which rule-based learning was optimal, we nevertheless were able to demonstrate that older adults have more difficulty using an information-integration approach when learning to categorize but that age-related differences are not as apparent when participants use a rule-based approach. Thus, both the current study and the study by Ashby et al. (2003) provide evidence for an age-related decrement in learning under information-integration conditions.[7]

Relationship to Age-Related Memory Changes

There is now a general consensus among researchers that memory is not a unified construct but rather consists of several different processes. One distinction that has been drawn is that between declarative memory, which is involved in the ability to learn and recall explicit (or conscious) memories, and nondeclarative (or implicit) memory, which is a collection of processes that are involved in unconscious learning (Schacter, 1987; Squire, 1992). The distinction that has been drawn between implicit and explicit forms of memory has also influenced our understanding of how memory changes as a result of age. Age appears to have its most consistent effect on explicit memory in that older individuals tend to perform more poorly than younger individuals on such tasks (Salthouse, 1994). In contrast to the readily apparent age effects on explicit memory, the evidence for the effects of aging on various tests of implicit memory is inconsistent. For example, performance advantages have been shown for younger adults in some implicit memory tasks (Gomez, 2002; Ryan, Ostergaard, Norton, & Johnson, 2001; Russo & Parkin, 1993; Small, Hultsch, & Masson, 1995; Salthouse et al., 1999) but not others (Anshel, 1978; Davis, Trussell, & Klebe, 2001; Durkin, Prescott, Furchtgott, Cantor, & Powell, 1995; Friedman, Snodgrass, & Ritter, 1994; Java, 1992; McNay & Willingham, 1998; Pilotti & Beyer, 2002; Schacter, Cooper, & Valdiserri, 1992). However, consistent age-related changes have been observed on implicit tasks that emphasize the learning of new associations under procedural learning conditions (Curran, 1997; Harrington & Haaland, 1992; Howard & Howard, 1997, 2001), suggesting that age may have a consistent impact on procedural learning.

Information-integration approaches to category learning are widely believed to require procedural learning for at least two reasons. First, patients with severe declarative memory deficits are normal on information-integration category-learning tasks (Filoteo et al., 2001a), and those with damage to brain regions known to be involved in procedural learning (i.e., the basal ganglia) are impaired on such tasks (Filoteo et al., 2001a; Maddox & Filoteo, 2001). Second, studies with normal participants have shown that information-integration category learning processes (a) place a greater demand on feedback training (Ashby, Maddox, and Bohil, 2002), (b) emphasize the temporal proximity of feedback to the categorization response (Maddox, Ashby, & Bohil, in press), (c) can be impacted by changes in stimulus–response mappings (Ashby, Ell, & Waldron, in press), and (d) are not impacted by increases in working memory requirements (Maddox, Filoteo, Hejl, & Ing, in press; Waldron & Ashby, 2001). Given that feedback training and stimulus response mappings are believed to play an important role in procedural-based learning (Willingham, Wells, Farrell, & Stemwedel, 2000), whereas working memory is believed to place less of an emphasis on procedural-based learning (Willingham, Greenberg, & Thomas, 1997), these previous results are consistent with the notion that information-integration category learning relies on some form of an implicit or procedural-based learning system. Thus, it appears that normal aging can impact implicit memory processes of the type required for category learning under information-integration conditions. How such aging effects are related to other implicit memory tasks remains to be seen and should be the focus of future research. Nevertheless, what the current study does suggest is that aging can differentially impact one type of

[7] This is not to say that older adults will never have more difficulty with tasks that emphasize rule-based processes. In fact, it is very likely that age-related changes would emerge under other conditions, such as when attentional demands are increased. Thus, given this possibility, and the small sample sizes that were used to examine rule-based category learning processes in the current study, future research will need to be conducted to better determine the presence of any age-related effects on rule-based category learning.

category learning process (information integration) more so than other types of category learning processes (rule based).

Conclusions

Older and younger adults differed in their ability to solve information-integration category learning tasks. Quantitative model-based analyses suggested that, in general, older and younger participants used similar approaches when learning the task, but the younger participants were more accurate in category learning when making use of an information-integration approach. Such differences are likely due to age-related alterations in implicit processing.

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