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Development of implicit and explicit category learning

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ABSTRACT

We present two studies that examined developmental differences in the implicit and explicit acquisition of category knowledge. College-attending adults consistently outperformed school-age children on two separate information-integration paradigms due to children's more frequent use of an explicit rule-based strategy. Accuracy rates were also higher for adults on a unidimensional rule-based task due to children's more frequent use of the irrelevant dimension to guide their behavior. Results across these two studies suggest that the ability to learn categorization structures may be dependent on a child's ability to inhibit output from the explicit system.

Introduction

Category formation allows people to make adaptive responses across a wide variety of situations and, therefore, is one of the most fundamental decision-making processes needed for survival. According to the COVIS (competition between verbal and implicit systems) model (Ashby, Alfonso-Reese, Turken, & Waldron, 1998), there exist at least two separate, but partially overlapping, categorization systems to guide correct decision making, and both contribute to performance in day-to-day life.

The first system consciously identifies an explicit rule (i.e., if A, then B) or a set of conjunctive rules (i.e., if A and B, then C) through active hypothesis testing and is a form of explicit learning. This system involves a network of late-developing structures that includes the prefrontal and medial temporal cortices, the anterior cingulate cortex, and the head of the caudate (Ashby et al., 1998; Gabrieli, Brewer, Desmond, & Glover, 1997; Schacter & Wagner, 1999). As such, the ability to learn an increasingly complex set of explicit rules over time is dependent on the health and development of these structures to

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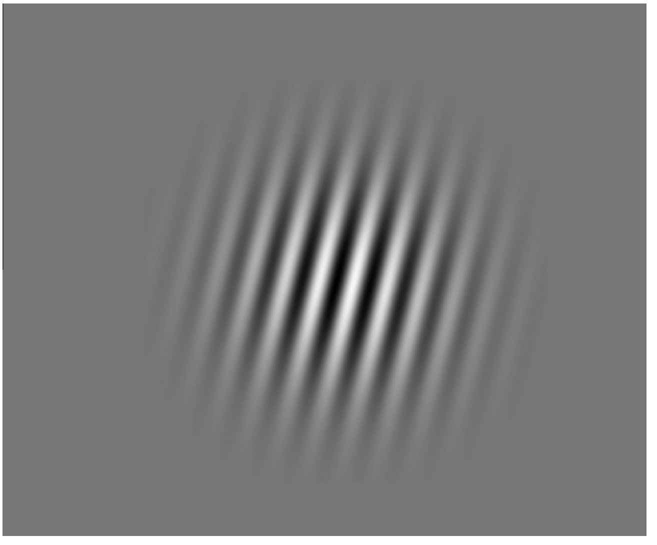

Fig. 1. Example Gabor patch.

represent such rules. The Wisconsin Card Sorting Test (WCST), a task in which participants learn to sort cards by color, number, or shape, would be an example of a task that not only indexes executive flexibility and set shifting but also taps an explicit category learning system.

The second learning system is procedurally based. It is better suited than the explicit system to handle situations in which hundreds, if not thousands, of exemplars exist and for which the relation among them cannot be expressed easily, if at all, using a verbalizable rule-based algorithm (for reviews, see Ashby & Maddox, 2005; Keri, 2003). The implicit system learns not by active hypothesis testing but rather by automatically and gradually recognizing subtle covariations within the environment. The knowledge base that is formed is often not fully accessible to consciousness.

Information-integration category learning tasks are believed to tap the implicit learning system. In these paradigms, participants are asked to sort into two groups, stimuli that are created by randomly sampling from two bivariate normal distributions (e.g., line orientation and spatial frequency [see Fig. 1]). The optimal strategy requires the participant to combine both values prior to the decision stage (Ashby & Ell, 2001; Filoteo, Maddox, Salmon, & Song, 2005). In the current study, we examined the developmental differences in performance when the decisional bound is quadratic in shape (Study 1 [see Fig. 2]) and when it is linear (Study 2 [see Fig. 5]), neither of which can easily be verbally described.

What developmental differences, if any, might be seen for implicit category formation and why? According to the COVIS model, implicit category learning is dependent on a set of frontal–striatal structures, and the posterior caudate in particular, that develops within the first year of life (Ashby & Ell, 2001; Ashby et al., 1998; Nomura et al., 2007; Seger, 2008; Seger & Cincotta, 2005). Therefore, we might expect implicit concept formation to be age invariant (e.g., Reber, 1992). Indeed, the ability to integrate information across two bivariate normal distributions (e.g., speed and direction [Herbranson, Fremouw, & Shimp, 2002]) and to learn complex artificial grammars is present even in pigeons (Herbranson & Shimp, 2003), which lack the cortical input that would support an explicit hypothesis testing learning strategy.

Critically, however, the COVIS model proposes that a competition exists between the frontally mediated rule-based system and the subcortically mediated information-integration system, the outcome of which determines which system will dominate the response to any given trial. Both humans and nonhuman primates show a clear bias toward using the explicit system even when the optimal strategy is procedural (Ashby & Maddox, in press; Smith, Beran, Crossley, Bloomer, & Ashby, 2010; but see Smith, Minda, & Washburn, 2004). For humans to adopt an implicit strategy, the bias to use the explicit system must first be inhibited. Indeed, manipulations that improve implicit learning are those that are known to tax the executive processes and to hinder explicit learning (e.g., increasing working memory load [Zeithamova & Maddox, 2006; Zeithamova & Maddox, 2007], the addition of a concurrent task [Waldron & Ashby, 2001], the addition of irrelevant dimensions [Filoteo, Lauritzen, & Maddox, 2010], sleep deprivation [Maddox et al., 2009]). Thus, even though the neuroanatomical structures that subserve implicit learning are present in early life, we might nevertheless observe age differences in performance due to a failure during the transfer stage, which is dependent on intact and mature inhibitory control over the explicit system.

In one study, Minda, Desroches, and Church (2008) compared category learning among 3-, 5-, and 7-year-olds and college-attending adults. As would be expected, 3-year-olds performed significantly worse than the other three age groups on an explicit learning task that was based on a unidimensional categorization rule (i.e., black objects are in category 1 and white objects are in category 2). In contrast, there were no group differences in learning trajectories on a categorization task believed to tap the implicit learning system (i.e., a family resemblance task). These results would suggest that both the implicit associative learning process (which does not involve executive processes) and the transfer stage (which is theorized to involve executive processes) were intact in preschool and early grade school children.

However, no analyses were reported on whether there was a main effect of practice on accuracy in the implicit condition, and visual inspection of the learning trajectories suggests that the limited number of trials ($n = 48$, administered in 6 blocks of 8 stimuli) may have provided insufficient practice to improve the performance for any group, including the college-attending adults. Thus, age differences might have eventually become apparent given additional training. But if additional trials had been provided, a second confound to data interpretation would likely have occurred. Information-integration tasks with few exemplars, such as those used in Minda and colleagues' (2008) study, are solved in a qualitatively different manner from those with many exemplars (Ashby & Ell, 2001). In tasks with only a few repeating exemplars, participants often use simple memorization strategies after approximately 50 trials, bypassing the associative learning mechanisms that the tasks were intended to index (Knowlton, Squire, & Gluck, 1994). Thus, if Minda and colleagues had provided participants with sufficient practice, age differences might have appeared, not because of developmental differences in the ability to acquire implicit knowledge of categories but rather because of developmental differences in the use of memorization strategies.

Regardless, with this example, it becomes clear that to more fully understand category learning in children and why developmental differences might be observed, it is necessary to move beyond examination of accuracy rates alone and to an understanding of the contributing strategies that underlie performance. In the following two studies, we build on Minda and colleagues (2008) to examine developmental differences in implicit and explicit category learning, not only looking for potential age-based differences in performance but also conducting strategy analyses to help explain the developmental differences. Although there exists a large body of work that examines the development of category knowledge and formation during early infancy and preschool (e.g., Ellis & Nelson, 1999; Mareschal & Quinn, 2001), the status of category learning during middle childhood, and implicit categorization specifically, during which time executive processes continue to develop, remains much less well understood.

To best challenge the procedural learning system and the neural structures that subserve it, in Study 1 we chose an information-integration categorization task that used a large number of unique stimuli, provided an extended training period, and followed a nonlinear quadratic rule. Previous research suggests that the requirement to learn a nonlinear decision bound places greater emphasis on striatal involvement than do linear rules (Ashby, Waldron, Lee, & Berkman, 2001; Filoteo, Maddox, Salmon, & Song, 2007). In Study 2, we examined developmental differences on an information-integration categorization task that followed a linear bound and expanded the study to include explicit category learning as a point of comparison.

Study 1

Method

Child participants

Table 1 provides a description of groups. A total of 18 typically developing 8- to 12-year-olds were recruited from local elementary schools and public flyers. All children spoke English as a first language, were attending a regular education classroom, were free of major childhood psychiatric diagnoses (attention deficit hyperactivity disorder, oppositional defiant disorder, conduct disorder, generalized anxiety disorder, and depression) by parental report on the Diagnostic Interview Schedule for Children–Version IV (DISC-IV [Shaffer, Fisher, Lucas, Dulcan, & Schwab-Stone, 2000]), and were not taking any psychoactive medications. Children were of high average intelligence; the average estimated IQ of the childhood sample was 110.28 (76th percentile), as determined by a four-subtest short form of the Wechsler Intelligence Scale for Children-4th edition (WISC-IV [Wechsler, 2003]). Children provided verbal assent and parents provided written consent prior to participation. Children were given a small prize for participating.

Adult participants

A total of 43 college-attending adults (17 men and 26 women, 18–25 years of age) were recruited from the Department of Psychology research participant pool. Most were successful students (grade point average mean = 3.37, SD = 0.46 [on 4-point scale]), and none self-reported taking any psychoactive medications.

Procedure

Experimental procedures were identical for child and adult participants. The task was programmed in Matlab and took approximately 20 min to complete. Participants were asked to categorize 400 unique Gabor patches into one of two groups (Fig. 1). Patches were created by randomly sampling from two bivariate normal distributions of line orientation and spatial frequency in which optimal categorization would be obtained by following a quadratic categorization rule (Fig. 2). Item order was randomized once; each participant viewed the same random order.

Each stimulus remained on the screen until the participant made a keyboard response. Feedback then appeared for 500 ms, followed by a 500-ms interstimulus interval. All participants were read the following instructions by the experimenter:

> You are going to see a circle with lines through it like this [showing printed example of Gabor patch]. Your job is to say whether you think the circle should go in the "A" or "B" pile. If you think it should go in Pile A, press the A button [which was the "Z" with a sticker over it]. If you think it should go in Pile B, press the B button [which was the "?" key with a sticker over it]. The computer will tell you if you are right or wrong. At first, you'll just be guessing. After a while, though, you'll probably start getting a "feeling" or an idea about which pile is the right pile. Go with your feeling. Don't worry about going fast. You're going to play this game five times.

Table 1
Description of groups.

	Males:females	Age (years)	Estimated IQ	Grade point average	% Accuracy		Condition order (RB first:II first)
Study 1					Quad		
Children	7:11	10.14 (1.04)	110.28 (10.17)	–	67	–	–
Adults	17:26	18.61 (0.93)	–	3.37 (0.46)	72	–	–
Study 2					II	RB	
Children	11:11	10.22 (1.00)	106.41 (7.04)	–	59	63	12:10
Adults	14:16	19.23 (1.30)	–	3.30 (0.43)	66	75	16:14

Note: Standard deviations are in parentheses. Quad, quadratic information-integration task; II, linear information-integration categorization task; RB, rule-based task.

Instructions were repeated as necessary; optional rest periods were offered between blocks of 80 trials.

Data analysis

The categorization task generated a two-factor design with one between-participants factor (group, two levels) and one within-participants factor (block, five levels). Based on previous research, we predicted that children would be able to acquire implicit category knowledge in a manner similar to that of adults.

Accuracy-based analyses provide a useful first step, but they tell us little about the decision strategy that participants might use because qualitatively different strategies can yield identical accuracy rates. Therefore, model-based analyses at the individual participant level were conducted. A number of different models were fit to each participant's responses on a block-by-block basis. These models fall into three classes. One class is consistent with rule-based strategies that have been studied extensively (for detailed reviews, see Ashby, 1992; Ashby et al., 1998; Maddox & Ashby, 2004; Maddox, Filoteo, Hejl, & Ing, 2004) and assume that the participant sets decision criteria along one or more stimulus dimensions that partition the stimulus space into verbalizable response regions. Each response region is assigned to a category (e.g., respond "A" if the line is short or respond "A" if the line is short and shallow). The location of each decision criterion is a free parameter.

Three specific rule-based models were applied to the data. The first is the unidimensional frequency model. This model assumes a unidimensional rule along the frequency dimension while ignoring the orientation dimension. The decision criterion along the frequency dimension is a free parameter. The second is the unidimensional orientation model. This model assumes a unidimensional rule along the orientation dimension while ignoring the frequency dimension. The decision criterion along the orientation dimension is a free parameter. The third is the conjunctive rule-based model. This model assumes a decision criterion along the frequency and orientation dimensions that effectively partitions the stimulus space into four response regions. The frequency and orientation decision criteria are free parameters. We examined a number of different category-to-response region assignments, but the one that yielded the best fit was one for which large spatial frequencies and shallow slopes were assigned to Category A, with the other three response regions being assigned to Category B.

A second class is consistent with the assumption that the participant uses an information-integration strategy. The general quadratic classifier was applied in this case. The general quadratic classifier assumes that the participant partitions the stimulus space into two response regions (A and B) using a quadratic decision bound. A third class is the random responder model. This model assumes that the participant guessed or applied different strategies across trials within a block. All rule-based and information-integration models included a "noise" parameter that provided an estimate of the perceptual and criterial noise associated with classification. In all cases, the model parameters were estimated using maximum likelihood procedures (Ashby, 1992; Wickens, 1982) and model comparisons were based on the AIC (Akaike information criterion) statistic that penalizes models for each additional free parameter with AIC = $(2 \times n) + (2L)$, where n equals the number of parameters and L is the maximum likelihood estimate of the data given the model (Akaike, 1974).

Results

Fig. 3 presents performance over time for both age groups. The Group $\times$ Block interaction was not significant, $F(4, 236) = 0.87$, $\eta_p^2 = .02$, $p = .48$, indicating that children and adults were able to learn the categorization task at the same rate. We observed a main effect of group in which adults consistently outperformed children, $F(1, 59) = 7.68$, $\eta_p^2 = .12$, $p = .01$, and a main effect of block in which accuracy improved over time, $F(4, 236) = 9.31$, $\eta_p^2 = .14$, $p < .001$. As can be seen from Fig. 3, accuracy was above chance even for the first block of trials for both children and adults (both $ps < .001$), a result that is not unusual given the large number of trials ($n = 80$) per block.

Model-based analyses found that children used a verbal rule-based strategy on more blocks of trials, $F(1, 59) = 8.90$, $\eta_p^2 = .13$, $p = .004$, suggesting that they had greater difficulty in abandoning that strategy in favor of an information-integration approach. Use of the correct strategy was directly re-

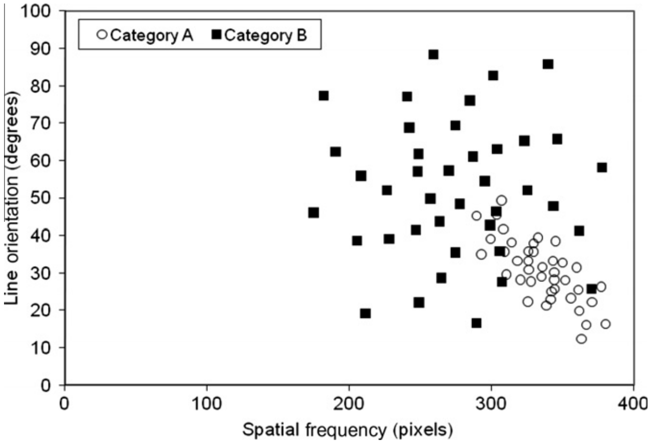

Fig. 2. Scatterplot of stimuli used in Study 1. The optimal decision rule involves information integration and a quadratic decision bound.

lated to performance accuracy. That is, the total number of blocks in which a participant used an information-integration strategy significantly predicted accuracy in Block 5 for both adults (R^2 = .20, t = 3.23, p = .002) and children (R^2 = .28, t = 2.49, p = .02).[1] Performance in Block 5 was fit by either an information-integration or rule-based strategy for all participants (i.e., no participant responded in a random fashion). Fig. 4 presents the model-based data on performance.

Discussion

Category learning is a fundamental process necessary for survival, and the neural structures that support it are functional in infants under 6 months of age (Casey et al., 2004; Quinn, Westerlund, & Nelson, 2006). A previous study of information-integration category formation in school-age children did not find age differences in the implicit acquisition of concepts (Minda et al., 2008). Based on this knowledge, we might have predicted that performance on our task of category learning would be equally developmentally insensitive. However, in Study 1, we found that although children were able to acquire category knowledge at the same rate as adults, they continued to underperform college-attending adults in terms of absolute accuracy throughout the task.

Thus, the fact that the ability to form categories is functional during early life does not preclude it from continuing to develop throughout early and middle childhood, and neither does it require the manner in which items are categorized to remain consistent. For example, during early infancy, category learning is primarily a bottom-up associative process that is dependent on the statistical and probabilistic regularities of an object's perceptual features (French, Mareschal, Mermillod, & Quinn, 2004). However, with development, children acquire the ability to form categories based on higher order attributes (e.g., superordinate similarities such as living vs. nonliving and animal vs. nonanimal). Even when behavioral performance appears to be equivalent to adult levels, the cognitive processes that drive the categorization process continue to develop throughout middle childhood and into early adolescence (Batty & Taylor, 2002).

In the current study, we used model-based analyses to help determine the cause of weaker performance in children. A less interesting finding would have been that random responding accounted for

[1] Because performance following extensive training likely represents a participant's best performance, we conducted these regressions using the fifth and final block of trials as the DV. However, results did not change when the block in which a participant had the highest accuracy was used as the dependent variable. There was also limited variance around age within each group such that age (in months for children to increase potential variance around age) did not predict accuracy or the frequency of information integration or rule-based strategy use. The same analyses were conducted in Study 2 and the same findings emerged.

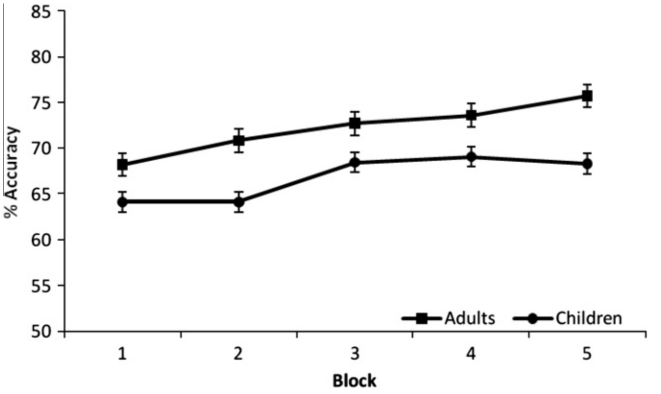

Fig. 3. Performance over time in Study 1.

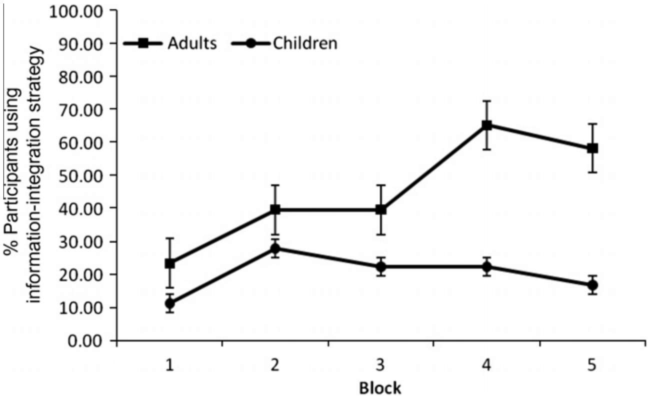

Fig. 4. Model-based performance over blocks of trials for children and adults in Study 1.

children's poorer performance, but this was not the case. Children performed more poorly because they were using a rule-based strategy on more blocks of trials than were adults and had greater difficulty in transitioning to an information-integration approach. Thus, even though the neuroanatomical structures for associative learning are present, accurate performance on this type of categorization task appears to require an ability to inhibit output from the explicit system. Because adult participants increasingly adopted the more optimal information-integration strategy, we may have expected to observe a significant Group × Block interaction on accuracy rates. However, even suboptimal explicit rule use can still yield acceptable levels of accuracy and likely accounts for the lack of a Group × Block interaction on accuracy. It is for this reason that the use of model-based analyses, beyond dependence of accuracy rate alone, is critical to illuminating the process of category learning during development.

With these considerations in mind, in Study 2 we sought to replicate our findings from Study 1 using a different information-integration task and to extend the scope of the study into explicit learning as a point of comparison. As a controlled and rigorous test of our hypotheses, we chose to use linear decision bounds for both the implicit and explicit conditions. The explicit bound was a linear unidimensional category structure (i.e., rule-based task) based on spatial frequency alone (with line orientation as an irrelevant dimension). For the implicit condition (linear information-integration task), the linear bound was obtained by rotating the unidimensional category structure 45 degrees.

Based on the results from Study 1, we predicted that children would underperform adults on the information-integration task due to difficulty in shifting from a verbal rule-based strategy to an information-integration strategy. For the rule-based task, we predicted that children would underperform adults due to an inability to ignore the irrelevant dimension. As before, we conducted both accuracy- and model-based analyses at the participant level to determine the strategy employed in problem solution. Furthermore, to determine the degree to which category knowledge had become explicit and conscious, we also had participants self-report the type of strategy that they used following task administration.

Study 2

Method

Child participants

A new cohort of 22 typically developing children (11 boys and 11 girls, 9–13 years of age, average age = 10.22 ± 1.00 years) were recruited from local elementary schools and public notices. All spoke English as a first language, were free of parent-reported psychiatric diagnoses according to the DISC-IV, and were not taking any psychoactive medications. Average estimated IQ was 106.41 (66th percentile), as determined by a four-subtest short form of the WISC-IV. Children provided verbal assent and parents provided written consent prior to participation. Children were given a small prize for participating.

Adult participants

A total of 30 college-attending adults (14 men and 16 women, 18–25 years of age, average age = 19.23 years, SD = 1.30) were recruited from the Department of Psychology research participant pool. As with Study 1, most were successful students (grade point average mean = 3.30, SD = 0.43 [on 4-point scale]). No adult self-reported taking any psychoactive medication. Table 1 provides a description of groups.

Procedure

All stimuli and procedures were identical to those of Study 1 with the following exceptions. Participants completed two categorization tasks, the administration order of which was counterbalanced and spaced 1 week apart. The conditions were (a) a linear information-integration task (Fig. 5) and (b) a rule-based categorization task that could be solved through the use of an explicit verbalizable rule along a single dimension (i.e., spatial frequency) (Fig. 6) and was derived from the information-integration task by rotating the stimuli 45 degrees in the spatial frequency orientation space and shrinking the category separation. This approach has a number of strengths, not the least of which is that, unlike classification algorithms based on clustering, within-category coherence is unchanged by the rotation procedure. Notice that the resulting rule-based categories (Fig. 6) are characterized by larger variability along the irrelevant dimension than along the relevant dimension. This should challenge the explicit learning system because accurate performance would require an active inhibition of attention to that dimension. These information-integration and rule-based category structures have been used extensively in previous work (e.g., Maddox, Ashby, Ing, & Pickering, 2004; Zeithamova & Maddox, 2007).

Following the second visit, participants were asked to self-report on the type of strategy, if any, that they used in the task just completed and how often that was successful. Self-report of strategy use was not obtained following the first visit to avoid contaminating the second visit by suggesting that an explicit strategy might be viable.

Counterbalancing

Table 1 provides information on the condition order. Primary results did not vary by condition order. The number of blocks in which a child or an adult adopted a rule-based strategy on the information-integration task did not vary by condition order (both *p*s > .57). Likewise, the number of blocks in which an information-integration strategy was used on the rule-based condition did not vary by condition order for either age group (both *p*s = .77). Accuracy in Block 5 also did not vary by condition

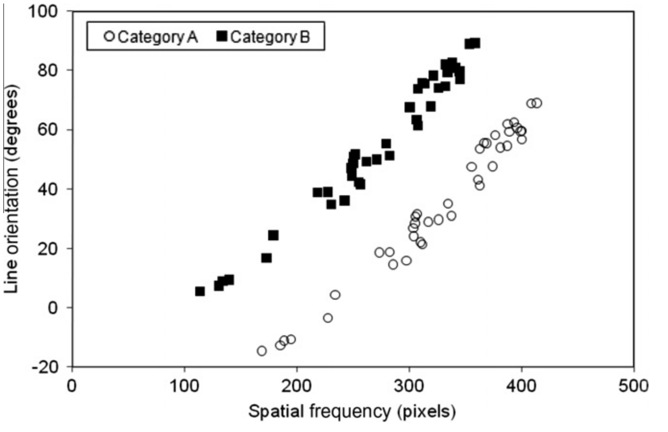

Fig. 5. Scatterplot of stimuli used in Study 2. The optimal decision rule involves information integration and a linear decision bound.

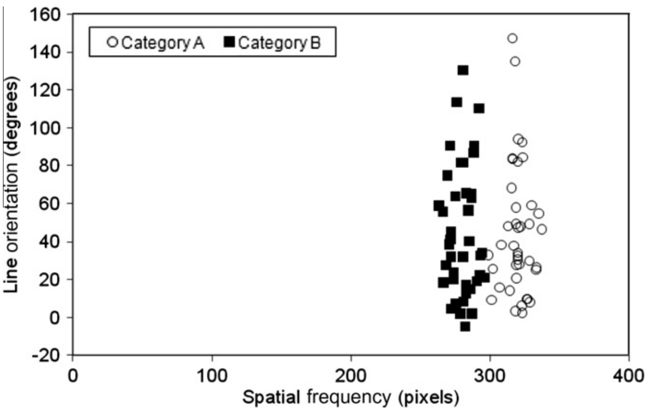

Fig. 6. Scatterplot of stimuli used in Study 2. The optimal decision strategy involves a unidimensional rule.

order for children in either task (all *p*s > .20). For adults, accuracy in Block 5 for the rule-based condition did not vary by condition order ($p = .53$), but accuracy for the information-integration condition was higher if it was preceded by the rule-based condition, $F(1, 28) = 4.26$, $p = .05$.

Data analysis

Each categorization task generated a two-factor design with one between-participants factor (group, two levels) and one within-participants factor (block, five levels). Based on the results from Study 1, we expected to find a main effect of group for both the information-integration and rule-based categorization tasks (i.e., children underperforming adults). We also expected that strategy use would predict performance accuracy on both the information-integration and rule-based tasks.

To the information-integration data, we fit a general linear classifier that assumed a linear decision bound that allowed the slope and intercept to be free parameters. We also fit the two unidimensional models and the conjunctive model outlined in Study 1 to the data. To the rule-based data, we fit the general linear classifier and the unidimensional frequency model. We also fit a unidimensional orientation model to the data. This is a model that assumes that the participant used a unidimensional rule but one along the irrelevant orientation dimension. We also fit the random responder model. All models were fit using maximum likelihood procedures and the AIC.

Results

Fig. 7 presents performance over time for both age groups. In the rule-based task, we observed a main effect of group in which adults consistently outperformed children, $F(1, 50) = 12.48$, $\eta_p^2 = .20$, $p = .001$, and a main effect of block in which performance improved over time, $F(4, 200) = 35.94$, $\eta_p^2 = .42$, $p < .001$. Main effects were qualified by a significant Group × Block interaction, $F(4, 200) = 3.64$, $\eta_p^2 = .07$, $p = .007$. Visual inspection suggested that adults learned at a steeper trajectory than children, and this was confirmed in a one-way analysis of variance (ANOVA) of the slope (adult mean change per block = 5.1%, child mean change per block = 2.6%), $F(1, 50) = 6.58$, $\eta_p^2 = .12$, $p = .01$.

Model-based analyses suggested that the reason why children performed more poorly is because they tended to base their judgments along the irrelevant dimension (i.e., line orientation) over more blocks of trials than adults, $F(1, 50) = 8.43$, $\eta_p^2 = .14$, $p = .05$ (Fig. 8). Correct strategy use was associated with performance; the number of blocks in which the correct sorting rule was used significantly predicted Block 5 accuracy for children ($R^2 = .46$, $t = 4.14$, $p = .001$) and approached significance for adults ($R^2 = .11$, $t = 1.89$, $p = .07$). In Block 5, only 1 participant (a child) was best fit by the random responder model. All other participants used a rule-based (relevant or irrelevant dimension) or information-integration approach. By the end of the task, 6 of 10 children (and 9 of 14 adults) self-reported that they were using a strategy based on the relevant dimension (i.e., spatial frequency).

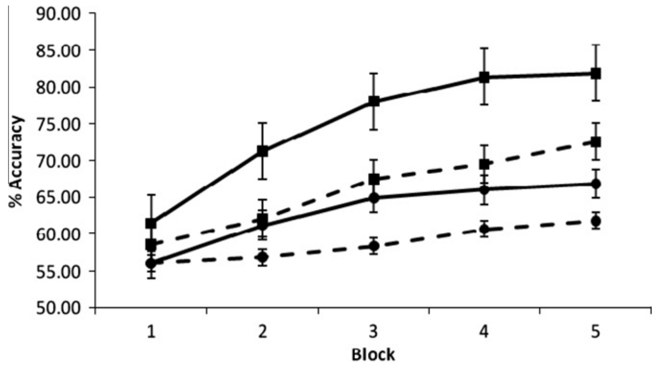

Fig. 7. Accuracy over blocks of trials for linear information-integration and rule-based tasks. Solid line: rule based; dashed line: information integration; squares: adults; circles: children.

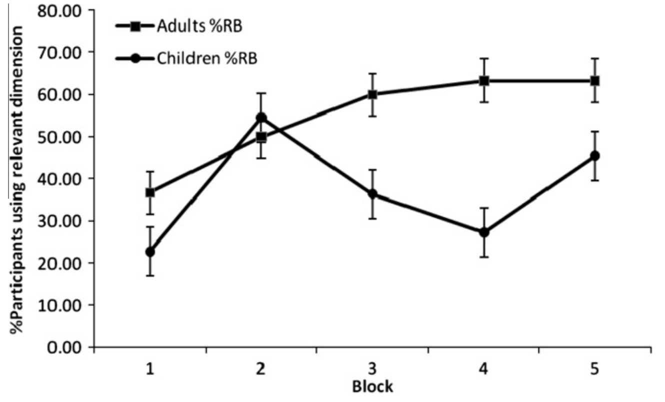

Fig. 8. Percentages of participants using relevant dimension on rule-based (RB) task in Study 2.

In the linear information-integration condition, we observed a main effect of group in which adults maintained higher accuracy rates than children, $F(1, 50) = 7.72$, $\eta_p^2 = .13$, $p = .008$, and a main effect of block, $F(4, 200) = 16.75$, $\eta_p^2 = .25$, $p < .001$. Main effects were qualified by a significant Group × Block interaction, $F(4, 200) = 2.91$, $\eta_p^2 = .06$, $p = .02$. Visual inspection suggested that adults learned at a steeper trajectory than children, and this was confirmed in a one-way ANOVA of the slope (adult mean change per block = 3.5%, child mean change per block = 1.5%), $F(1, 50) = 5.42$, $\eta_p^2 = .10$, $p = .02$.

Model-based analyses found that frequently adopting an information-integration strategy predicted higher accuracy in Block 5 for adults ($R^2 = .26$, $t = 3.14$, $p = .004$). For children, the frequency with which either a rule-based or information-integration strategy was adopted did not predict greater accuracy in Block 5 (rule based: $R^2 = .09$, $t = 1.39$, $p = .18$; information integration: $R^2 = .02$, $t = 0.18$, $p = .86$). However, frequent use of a rule-based strategy was positively associated with overall accuracy (i.e., average performance across blocks) on the information-integration task ($R^2 = .20$, $t = 2.22$, $p = .04$). Indeed, 10 of 12 children (vs. 5 of 16 adults) articulated basing their decisions on spatial frequency alone. The other 2 children either reported basing their decisions on line angle alone or did not report any strategy use. Performance in Block 5 was fit by either a rule-based or information-integration strategy for all but 4 participants (2 adults and 2 children), whose responses were best captured by the random responder model. Fig. 9 presents model-based performance on the linear information-integration condition.

Discussion

In Study 1, we found that children were unable to abandon explicit rules for information-integration rules and that this lack of ability to shift strategies predicted performance accuracy in Block 5 of a quadratic information-integration categorization task. In Study 2, we sought to replicate and extend those findings using two linear categorization tasks: one information-integration paradigm that indexed the procedural implicit system and one rule-based paradigm that indexed the explicit learning system.

As expected for an explicit learning task, adults outperformed children in absolute accuracy and in the rate by which they were able to learn the unidimensional categorization rule. This finding is consistent with the developmental literature that finds that the use of unidimensional rules is mediated by the explicit learning system, which in turn is dependent on the developmental status of the executive functions (Bunge, 2004; Bunge & Zelazo, 2006). Model-based analyses suggested that children's performance was hindered by the persistent use of the irrelevant dimension (i.e., line orientation) to base their judgment. In contrast, adults were better able to inhibit the irrelevant dimension, and this directly led to improved performance.

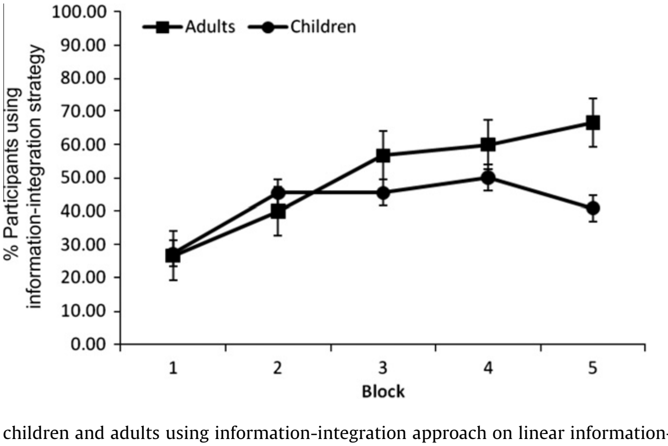

Fig. 9. Percentages of children and adults using information-integration approach on linear information-integration task over blocks of trials in Study 2.

In the linear information-integration task, adults outperformed children in both their absolute accuracy and the rate by which they were able to learn the categorization rule. Despite training over 400 trials, in neither Study 1 nor Study 2 did children ever approach the degree of accuracy that adults displayed. Poorer performance in Study 1 for children was due to an inability to shift from using a primarily rule-based approach to using an information-integration approach, and this was again found for Study 2. In fact, by the end of the task, 10 of 12 children (vs. 5 of 16 adults) self-reported using solely a rule-based approach; no child reported the simultaneous use of both dimensions. Model-based analyses found that for adults, frequent use of an information-integration strategy predicted better performance. In contrast, for children, frequent use of a unidimensional approach was significantly and positively associated with overall accuracy. Thus, in the absence of being able to identify the correct information-integration sorting rule, the ability to identify and consistently use any strategic rule, even if less efficient, was the adaptive approach.

General discussion

Over the course of two studies, we found consistent evidence in two information-integration paradigms that age-related differences in performance were due to the inability of high-functioning school-age children to transition from a rule-based strategy to an information-integration strategy.

Our results are consistent with the COVIS model, which posits that in humans an initial bias toward the rule-based system must be overcome for successful performance to occur on an implicit category learning paradigm. Results from a recent study of normal aging are also consistent with our findings. Comparing healthy older and younger adults, Maddox, Pacheco, Reeves, Zhu, and Schnyer (2010) found age-related declines in both rule-based and information-integration category learning. In the rule-based task, older adults were more likely to guess or switch strategies frequently, often failing to identify the correct strategy. In the information-integration task, older adults were less likely to shift from rule-based to information-integration strategies. In that study, measures of interference/inhibition (Stroop interference and perseveration in the WCST) were correlated with performance in both tasks. Maddox and colleagues argued that the Stroop and WCST tap cognitive processes that are important for shifting strategies, whether it be from one verbal rule to another (as in rule-based learning) or from rule-based to information-integration strategies (as in information-integration learning). Future research should test these hypotheses in children.

Why would such a bias toward rule-based learning exist, especially given the early developmental trajectory of the associative learning processes? We speculate that such a bias exists because rule-based learning follows a rational hypothesis testing approach that leads to all-or-none mastery. Thus, rule-based learning is ultimately faster than the incremental trial-and-error associative process of implicit learning. Explicit rules (e.g., sort by color, not by shape) are also easier to communicate to others than the complex and difficult-to-verbalize rules extracted during the process of implicit learning. It may be that these characteristics are sufficiently advantageous to result in an explicit bias despite the early development of implicit learning systems.

The ability to transition or switch from a rule-based strategy to an information-integration strategy relies on the effective use of feedback that is at least partially mediated by the 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) and the ventral medial prefrontal cortex in particular (Schnyer et al., 2009). Effective processing of feedback in category learning is essential for testing different verbal rules (as in a rule-based task) and also for building the body of implicit knowledge that will help to make the transition from the initial bias toward rule-based strategy use (as in an information-integration task) (Seger, 2008). Weakness in feedback processing may lead to poor performance in either task.

That children were dependent on verbally mediated strategies should not, however, be categorically viewed as maladaptive. In Study 2, high overall accuracy rate was associated with the ability to identify and consistently adopt a rule-based strategy even if it is ultimately less effective than the more accurate information-integration approach. Thus, successful performance is related not only to the flexibility of the problem-solving approach but also to the ability to identify a functional strategy in a more basic sense.

Our results are inconsistent with recent work by Minda and colleagues (2008), who found evidence for age invariance on their family resemblance categorization task designed to index a more associative style of learning. The differences between the current study and Minda and colleagues' study may be an artifact of task specifics and in particular a shortened learning period that may have prevented age effects from being observed. (In support of this possibility, we note that in Minda et al.'s Experiment 3, they first familiarized children to the exemplars of the stimuli prior to the onset of training, and with that manipulation they did observe significant age differences in the family resemblance task.) The lack of an age effect in Minda and colleagues' primary experiment may also be because the family resemblance task used in their study can be solved by using a simple unidimensional rule with a single stored exception (e.g., all black objects and the large white triangle are in category 1, all white objects and the small black square are in category 2). To determine whether participants were in fact following such a rule rather than an information-integration approach, it would have been necessary to identify how accurate participants were on rule-following stimuli versus non-rule-following stimuli, an analysis that is rarely conducted for these types of tasks. The current study builds on that work by directly examining the strategies that underlie performance on two information-integration categorization tasks that contain a large number of stimuli, the categorization rule of which is difficult or impossible to verbalize.

The difference in results across these two studies might also be explained if the relationship between information-integration learning and age is nonlinear. Children in Minda and colleagues' (2008) study were younger (5- to 7-year-olds) than those enrolled in the current study (primarily 9- to 11-year-olds). It may be that younger children are able to perform quite well on information-integration tasks because the frontal system is less well developed and so they do not experience the initial bias toward the rule-based system as proposed in the COVIS model and, therefore, do not need to overcome that bias. The liability that nascent executive processes counterintuitively confer on the performance of older versus younger children has also been observed in other cognitive processes, including the development of selective attention (Huang-Pollock, Carr, & Nigg, 2002). Given the rapid rate of neuronal development throughout childhood and the inherent heterogeneity in developmental status of children, in particular when children in a broad age range are grouped together, future studies of information-integration categorization should include a large longitudinal sample or a broader range of child ages binned into smaller cross-sectional groups.

With respect to the rule-based task, children underperformed adults because they persistently used the irrelevant dimension to make their category judgments, whereas adults were able to inhibit that dimension to their benefit. This pattern of performance is not entirely surprising given that explicit learning is specifically theorized to be dependent on executive functionality (Bunge, 2004; Bunge & Zelazo, 2006).

Conclusion

Over the course of two studies in school-age children and college-attending adults, we found evidence of developmental variance in performance on the acquisition of implicit category knowledge. Model-based analyses suggested that the developmental differences in performance are due to children's inability to inhibit output from the verbal system. Few studies exist on the development of explicit and implicit category learning during middle childhood. The current study, which mapped the performance of typically developing children, is an important first step to use of the COVIS model and paradigm to study important childhood outcomes, potentially including psychiatric disorders with basal ganglia involvement.

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