Published in final edited form as:
J Exp Child Psychol. 2011 July ; 109(3): 321–335. doi:10.1016/j.jecp.2011.02.002.

Development of Implicit and Explicit Category Learning

Cynthia L. Huang-Pollock[1], **W. Todd Maddox**[2], and **Sarah L. Karalunas**[1]

[1] Department of Psychology, The Pennsylvania State University, University Park, PA

[2] Department of Psychology and Institute for Neuroscience, University of Texas, Austin

Abstract

We present two studies that examine developmental differences in the implicit and explicit acquisition of category knowledge. College-attending adults consistently outperformed school-aged 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 upon a child's ability to inhibit output from the explicit system.

Keywords

COVIS; category formation; development; implicit learning; explicit learning

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

The first system consciously identifies an explicit rule (i.e. if A then B) or 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, 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 upon the health and development of these structures to represent such rules. The Wisconsin Card Sorting Test, 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 to than the explicit system to handle situations in which hundreds if not thousands of exemplars exist, and for which the relation among them cannot easily (if at all) be expressed using a verbalizable

NIH-PA Author Manuscript
NIH-PA Author Manuscript

rule-based algorithm (for review see: Ashby & Maddox, 2005; Keri, 2003). The implicit system learns not by active hypothesis testing, but 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 Figure 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 examine the developmental differences in performance when the decisional bound is quadratic in shape (Study 1, Figure 2) and when it is linear (Study 2, Figure 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 COVIS, implicit category learning is dependent upon a set of frontal-striatal structures that develops within the first year of life, and the posterior caudate in specific (Ashby, et al., 1998; Ashby & Ell, 2001; Nomura, Maddox, Filoteo, Ing, Gitelman, Parrish, 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), who lack the cortical input that would support an explicit, hypothesis testing learning strategy.

Critically, however, COVIS 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 non-human primates show a clear bias towards 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 which 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, 2005, 2006, 2007), addition of a concurrent task (Waldron & Ashby, 2001), addition of irrelevant dimensions (Filoteo, Lauritzen, & Maddox, 2010), and sleep deprivation (Maddox, Glass, Wolosin, Savarie, Bowen, Matthews, 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 in the transfer stage, which is dependent upon intact and mature inhibitory control over the explicit system.

In one study, Minda, Desroches, & Church (2008) compared category learning among 3, 5, and 7 year old children, and college-attending adults. As would be expected, 3 year old children 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, 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 do not involve executive processes), as well as 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, had additional trials been provided, a second confound to data interpretation would likely have occurred. Information integration tasks with few exemplars such as those used in the Minda et al. (2008) study are solved in a qualitatively different manner than 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, had Minda et al. (2008) 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 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, to an understanding of the contributing strategies that underlie performance. In the following two studies, we build upon Minda et al. (2008) to examine developmental differences in implicit and explicit category learning, looking not only for potential age-based differences in performance, but also conducting strategy analyses to help explain the developmental differences. Although a large body of work exists that examines the development of category knowledge and formation in early infancy and preschool (e.g. Ellis & Nelson, 1999; Mareschal & Quinn, 2001), the status of category learning in middle childhood, and implicit categorization specifically, during which time executive processes continues 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 non-linear quadratic rule. Previous research suggests that the requirement to learn a non-linear decision bound places greater emphasis on striatal involvement than 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. Eighteen typically-developing children aged 8-12 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 parent report on a structured diagnostic interview (Diagnostic Interview Schedule for Children, 4th Edition: 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 (76^{th} percentile), as determined by a 4-subtest short form of the Wechsler Intelligence Scale for Children—IV (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—Forty three college attending adults (17 males, 26 females) aged 18-25 were recruited from the Department of Psychology Research Participant pool. Most were successful students with an average Grade Point Average of 3.37 (SD = 0.46) out of 4.0, 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 minutes to complete. Participants were asked to categorize 400 unique Gabor patches into one of two groups (See Figure 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 (See Figure 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 inter-stimulus interval. All participants were read the following instructions "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 letter "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 5 times." Instructions were repeated as necessary; optional rest periods were offered between blocks of 80 trials.

Data Analysis—The categorization task generated a 2 factor design with one between subjects factor (Group, 2 levels), and one within subjects factor (Block, 5 levels). Based on previous research, we predict that children will be able to acquire implicit category knowledge in a similar manner to 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. Model based analyses at the individual participant level were therefore 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 which 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. One 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 a 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 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. The third is 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 statistic that penalizes models for each additional free parameter with AIC = (2*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

Figure 3 presents performance over time for both age groups. The Group × Block interaction was not significant, $F(4,236)=0.87$, $\eta_p^2=0.02$, $p=0.48$, indicating that children and adults were able to learn the categorization task at the same rate. A main effect of Group was observed, in which adults consistently outperformed children, $F(1,59)=7.68$, $\eta_p^2=0.12$, $p=0.01$, as was a main effect of Block, in which accuracy improved over time, $F(4,236)=9.31$, $\eta_p^2=0.14$, $p<0.001$. As can be seen from the figure, accuracy was above chance even for the first block of trials for both children and adults (both $p < 0.001$), which 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, $F(1,59)=8.90$,$\eta_p^2=0.13$, $p = 0.004$, suggesting they had greater difficulty abandoning that strategy in favor of an information integration approach. Utilization of the correct strategy was directly related to performance accuracy. That is, the total number of blocks in which a participant utilized an information integration strategy significantly predicted accuracy in Block 5 for both adults, $R^2 = 0.20$, $t = 3.23$, $p = 0.002$, and children, $R^2 = 0.28$, $t = 2.49$, $p = 0.02$.[1] Performance in Block 5 was fit by either a rule-based or information integration strategy for all participants (i.e. no participant responded in a random fashion). Figure 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, Davidson, Hara, Thomas, Martinez, Galvan, et al., 2004; Quinn, Westerlund, & Nelson, 2006). A previous study of information integration category formation in school aged children did not find age differences in the implicit acquisition of concepts (Minda, et al., 2008). Based on this knowledge, we might have predicted performance on our task of category learning would be

[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.

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 underperformed college attending adults in terms of absolute accuracy throughout the task.

Thus, the fact that the ability to form categories is functional in 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, in early infancy, category learning is primarily a bottom-up associative process that is dependent upon 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. non-living or animal vs. non-animal). Even when behavioral performance appears to be equivalent to adult levels, the cognitive processes which drive the categorization process continues 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 children's poorer performance, but this was not the case. Children performed more poorly because they were utilizing a rule-based strategy on more blocks of trials than adults, and had greater difficulty 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 account 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 in 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 by 45°.

Based on the results from Study 1, we predicted that children would underperform adults on the information integration task due to difficulty 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 accuracy-based as well as 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

Child Participants

A new cohort of 22 typically developing children (11 boys, 11 girls) aged 9-13 (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 based on a 4-subtest short form was 106.41(66th percentile), as determined by a 4-subtest short form of the Wechsler Intelligence Scale for Children—IV (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

Thirty college attending adults (14 males, 16 females) aged 18-25 (Average = 19.23 years, SD = 1.30) were recruited from the Department of Psychology Research Participant pool. As with Study 1, most were successful students with an average Grade Point Average of 3.30 (SD = 0.43) out of 4.0. 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 a week apart. The conditions were: (a) a linear information integration task (see Figure 5) and (b) a rule-based (rule based) categorization task that could be solved through the use of an explicit verbalizable rule along a single dimension (i.e. spatial frequency; See Figure 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 (Figure 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 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 adult adopted a rule-based strategy on the information integration task did not vary by condition order (both $p > 0.57$). 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 $p = 0.77$). Accuracy in Block 5 also did not vary by condition order for children in either task (all $p > 0.20$). For adults, accuracy in Block 5 for the rule-based condition did not vary by condition order ($p = 0.53$), but accuracy for the information integration condition was higher if it was preceded by the rule-based condition, $F(1,28) = 4.26$, $p = 0.05$.

Data Analysis

Each categorization task generated a 2 factor design with one between subjects factor (Group, 2 levels), and one within subjects factor (Block, 5 levels). Based on the results from Study 1, we expect to find a main effect of Group for both the information integration as well as the rule-based categorization tasks (i.e. children underperforming adults). We also expect that strategy use will 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 AIC.

Results

Figure 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, $F(1,50)=12.48, \eta_p^2=0.20$, $p= 0.001$, and a main effect of Block, $F(4,200)=35.94$, $\eta_p^2=0.42$, $p< 0.001$, in which performance improved over time. Main effects were qualified by a significant the Group × Block interaction, $F(4,200)=3.64$, $\eta_p^2=0.07, p = 0.007$. Visual inspection suggested that adults learned at a steeper trajectory than children, which was confirmed in a one-way ANOVA of the slope (adult mean change per block = 5.1%, child mean change per block = 2.6%), $F(1,50)=6.58$, $\eta_p^2=0.12$, $p = 0.01$.

Model-based analyses suggested that the reason 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, $F(1,50)=8.43$, $\eta_p^2=0.14, p = 0.05$ (see Figure 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, $R^2 = 0.46$, $t = 4.14$, $p = 0.001$, and approached significance for adults, $R^2 = 0.11$, $t = 1.89$, $p = 0.07$. In block 5, only one participant (child) was best fit by the random responder model. All other participants utilized a rule-based (relevant or irrelevant dimension) or information integration approach. By the end of the task, six out of ten children (and nine out of fourteen adults) self-reported that they were using a strategy based on the relevant dimension (spatial frequency).

In the linear information integration condition, we observed a main effect of Group in which adults maintained higher accuracy rates than children, $F(1,50)=7.72$, $\eta_p^2=0.13, p = 0.008$, and a main effect of Block, $F(4,200)=16.75, \eta_p^2=0.25, p < 0.001$. Main effects were qualified by a significant Group × Block interaction, $F(4,200)=2.91$, $\eta_p^2=0.06$, $p = 0.02$. Visual inspection suggested that adults learned at a steeper trajectory than children, which was confirmed in a one-way ANOVA of the slope (adult mean change per block = 3.5%, child mean change per block = 1.5%), $F(1,50)=5.42, \eta_p^2=0.10$, $p = 0.02$.

Model-based analyses found that frequently adopting an information integration strategy predicted higher accuracy in Block 5 for adults, $R^2 = 0.26$, $t = 3.14$, $p = 0.004$. For children, neither the frequency with which a rule based nor an information integration strategy was adopted predicted greater accuracy in Block 5 (rule based: $R^2 = 0.09$, $t = 1.39$, $p = 0.18$; information integration: $R^2 = 0.02$, $t = 0.18$, $p = 0.86$). 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, $R^2 = 0.20$, $t = 2.22$, $p = 0.04$. Indeed, 10 out of 12 children (vs. 5 out of 16 adults) articulated basing their decisions on spatial frequency alone. The other two children reported either basing their decision on line angle alone, or did not report any strategy use. Performance in Block 5 was fit by either an information integration or rule-based strategy for all but four participants (two adults, two children), whose responses were best captured by the random responder model. Figure 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 out performed 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 the use of unidimensional rules is mediated by the explicit learning system, which in turn is dependent upon 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, which directly led to improved performance.

In the linear information integration task, adults outperformed children in both their absolute accuracy as well as 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 an information integration approach, and this was again found for Study 2. In fact, by the end of the task 10 out of 12 children (vs. 5 out of 16 adults) self reported solely using 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 utilization 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-aged 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 towards 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 et al. (2010) 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 towards 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 which 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 are the complex and difficult to verbalize rules extracted during the process of implicit learning. It may be that these characteristics are sufficiently advantageous which results in an explicit bias, despite the early development of implicit learning systems.

The ability to transition or switch from a rule-based to information-integration strategy relies on the effective use of feedback which is at least partially mediated by prefrontal cortex (Cools, Clark, Owen, & Robbins, 2002; Fellows, 2004; Ghods-Sharifi, Haluk, & Floresco, 2008; Haber, Kim, Mailly, & Calzavara, 2006; Monchi, Petrides, Petre, Worsley, & Dagher, 2001; Takahashi, Roesch, Stainaker, Haney, Caiu, Taylor, et al., 2009), and the ventral medial prefrontal cortex in particular (Schnyer, Maddox, Ell, Davis, Pacheco, & Verfaellie, 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 make the transition from the initial bias towards 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 upon verbally mediated strategies should not be categorically viewed as maladaptive, however. In Study 2, high overall accuracy rate was associated with the ability to identify and consistently adopt a rule based strategy, even if ultimately less effective than the more accurate information integration approach. Thus, successful performance is not only related to the flexibility of 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, 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 et al. (2008) 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 Experiment 3, Minda et al. (2008) first familiarized children to the exemplars of the stimuli prior to the onset of training, and with that manipulation, did observe significant age differences in the family resemblance task). The lack of an age effect in their primary experiment may also be because the family resemblance task used in Minda et al (2008) 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 vs. non-rule following stimuli, an analysis that is rarely conducted for these types of tasks. The current study builds

NIH-PA Author Manuscript

NIH-PA Author Manuscript

upon that work by directly examining the strategies that underlie performance on two information integration categorization tasks which 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 the Minda et al. (2008) study were younger (5-7 years) than those enrolled in the current study (primarily in the 9-11 age range). 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 towards the rule-based system as proposed in COVIS, and therefore do not need to overcome that bias. The liability that nascent executive processes counterintuitively confer on the performance of older vs. younger children has also been observed in other cognitive process 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, particularly when a broad age range of children 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, but adults were able to inhibit that dimension to their benefit. This pattern of performance is not entirely surprising since explicit learning is specifically theorized to be dependent upon executive functionality (Bunge, 2004; Bunge & Zelazo, 2006).

Conclusion

Over the course of two studies in school-aged 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 in middle childhood. The current study, which maps the performance of typically developing children, is an important first step to utilization of the COVIS model and paradigm to study important childhood outcomes, potentially including psychiatric disorders with basal ganglia involvement.

Acknowledgments

This work was supported in part by National Institutes of Mental Health Grant R01 MH084947 to Cynthia Huang-Pollock. We thank the children and families who made this work possible.

Bibliography

Akaike H. A new look at statistical-model identification. IEEE Transactions on Automatic Control, AC. 1974; 19:716–723.

Ashby, FG. Multivariate probability distributions. Erlbaum; Hillsdale: 1992.

Ashby FG, Alfonso-Reese LA, Turken AU, Waldron EM. A neuropsychological theory of multiple systems in category learning. Psychological Review. 1998; 105:442–481. [PubMed: 9697427]

Ashby FG, Ell SW. The neurobiology of human category learning. Trends in Cognitive Sciences. 2001; 5:204–210. [PubMed: 11323265]

Ashby FG, Maddox WT. Human category learning. Annual Review of Psychology. 2005; 56:149–178.

Ashby FG, Maddox WT. Human category learning 2.0. Annals of the New York Academy of Sciences. (in press).

Ashby FG, Waldron EM, Lee WW, Berkman A. Suboptimality in human categorization and identification. Journal of Experimental Psychology-General. 2001; 130:77–96. [PubMed: 11293461]

Batty M, Taylor MJ. Visual categorization during childhood: An ERP study. Psychophysiology. 2002; 39:482–490. [PubMed: 12212640]

Bunge SA. How we use rules to select actions: a review of evidence from cognitive neuroscience. Cogn Affect Behav Neurosci. 2004; 4:564–579. [PubMed: 15849898]

Bunge SA, Zelazo PD. A brain-based account of the development of rule use in childhood. Current Directions in Psychological Science. 2006; 15:118–121.

Casey BJ, Davidson MC, Hara Y, Thomas KM, Martinez A, Galvan A, et al. Early development of subcortical regions involved in non-cued attention switching. Developmental Science. 2004; 7:534–542. [PubMed: 15603286]

Cools R, Clark L, Owen AM, Robbins TW. Defining the neural mechanisms of probabilistic reversal learning using event-related functional magnetic resonance imaging. Journal of Neuroscience. 2002; 22:4563–4567. [PubMed: 12040063]

Ellis AE, Nelson CA. Category prototypicality judgments in adults and children: Behavioral and electrophysiological correlates. Developmental Neuropsychology. 1999; 15:193–211.

Fellows LK. The cognitive neuroscience of human decision making: a review and conceptual framework. Behav Cogn Neurosci Rev. 2004; 3:159–172. [PubMed: 15653813]

Filoteo JV, Lauritzen S, Maddox WT. Removing the Frontal Lobes: The Effects of Engaging Executive Functions on Perceptual Category Learning. Psychological Science. 2010; 21:415–423. [PubMed: 20424079]

Filoteo JV, Maddox WT, Salmon DP, Song DD. Information-integration category learning in patients with striatal dysfunction. Neuropsychology. 2005; 19:212–222. [PubMed: 15769205]

Filoteo JV, Maddox WT, Salmon DP, Song DD. Implicit category learning performance predicts rate of cognitive decline in nondemented patients with Parkinson’s disease. Neuropsychology. 2007; 21:183–192. [PubMed: 17402818]

French RM, Mareschal D, Mermillod M, Quinn PC. The role of bottom-up processing in perceptual categorization by 3-to 4-month-old infants: Simulations and data. Journal of Experimental Psychology-General. 2004; 133:382–397. [PubMed: 15355145]

Gabrieli JDE, Brewer JB, Desmond JE, Glover GH. Separate neural bases of two fundamental memory processes in the human medial temporal lobe. Science. 1997; 276:264–266. [PubMed: 9092477]

Ghods-Sharifi S, Haluk DM, Floresco SB. Differential effects of inactivation of the orbitofrontal cortex on strategy set-shifting and reversal learning. Neurobiology of Learning and Memory. 2008; 89:567–573. [PubMed: 18054257]

Haber SN, Kim KS, Mailly P, Calzavara R. Reward-related cortical inputs define a large striatal region in primates that interface with associative cortical connections, providing a substrate for incentive-based learning. Journal of Neuroscience. 2006; 26:8368–8376. [PubMed: 16899732]

Herbranson WT, Fremouw T, Shimp CP. Categorizing a moving target in terms of its speed, direction, or both. Journal of the Experimental Analysis of Behavior. 2002; 78:249–270. [PubMed: 12507003]

Herbranson WT, Shimp CP. “Artificial grammar learning” in pigeons: A preliminary analysis. Learning & Behavior. 2003; 31:98–106. [PubMed: 18450072]

Huang-Pollock C, Carr TH, Nigg JT. Development of selective attention: Perceptual load influences early versus late attentional selection in children and adults. Developmental Psychology. 2002; 38:363–375. [PubMed: 12005380]

Keri S. The cognitive neuroscience of category learning. Brain Research Reviews. 2003; 43:85–109. [PubMed: 14499464]

Knowlton BJ, Squire LR, Gluck MA. Probabilistic classification learning in amnesia. Learning & Memory. 1994; 1:106–120. [PubMed: 10467589]

Maddox WT, Ashby FG. Dissociating explicit and procedural-learning based systems of perceptual category learning. Behavioural Processes. 2004; 66:309–332. [PubMed: 15157979]

Maddox WT, Ashby FG, Ing AD, Pickering AD. Disrupting feedback processing interferes with rule-based but not information-integration category learning. Memory & Cognition. 2004; 32:582–591.

Maddox WT, Filoteo JV, Hejl KD, Ing AD. Category number impacts rule-based but not information-integration category learning: Further evidence for dissociable category-learning systems. Journal of Experimental Psychology-Learning Memory and Cognition. 2004; 30:227–245.

Maddox WT, Glass BD, Wolosin SM, Savarie ZR, Bowen C, Matthews MD, et al. The Effects of Sleep Deprivation on Information-Integration Categorization Performance. Sleep. 2009; 32:1439–1448. [PubMed: 19928383]

Maddox WT, Pacheco J, Reeves M, Zhu B, Schnyer DM. Rule-based and information-integration category learning in normal aging. Neuropsychologia. 2010; 48:2998–3008. [PubMed: 20547171]

Mareschal D, Quinn PC. Categorization in infancy. Trends in Cognitive Sciences. 2001; 5:443–450. [PubMed: 11707383]

Minda JP, Desroches AS, Church BA. Learning Rule-Described and Non-Rule-Described Categories: A Comparison of Children and Adults. Journal of Experimental Psychology-Learning Memory and Cognition. 2008; 34:1518–1533.

Monchi O, Petrides M, Petre V, Worsley K, Dagher A. Wisconsin card sorting revisited: Distinct neural circuits participating in different stages of the task identified by event-related functional magnetic resonance imaging. Journal of Neuroscience. 2001; 21:7733–7741. [PubMed: 11567063]

Nomura EM, Maddox WT, Filoteo JV, Ing AD, Gitelman DR, Parrish TB, et al. Neural correlates of rule-based and information-integration visual category learning. Cerebral Cortex. 2007; 17:37–43. [PubMed: 16436685]

Quinn PC, Westerlund A, Nelson CA. Neural markers of categorization in 6-month-old infants. Psychological Science. 2006; 17:59–66. [PubMed: 16371145]

Reber, A. Implicit learning and tacit knowledge: An essay on the cognitive unconscious. Oxford University Press; New York: 1992.

Schacter DL, Wagner AD. Medial temporal lobe activations in fMRI and PET studies of episodic encoding and retrieval. Hippocampus. 1999; 9:7–24. [PubMed: 10088896]

Schnyer DM, Maddox WT, Ell S, Davis S, Pacheco C, Verfaellie M. Prefrontal contributions to rule-based and information-integration category learning. Neuropsychologia. 2009; 47:2995–3006. [PubMed: 19643119]

Seger CA. How do the basal ganglia contribute to categorization? Their roles in generalization, response selection, and learning via feedback. Neuroscience and Biobehavioral Reviews. 2008; 32:265–278. [PubMed: 17919725]

Seger CA, Cincotta CM. The roles of the caudate nucleus in human classification learning. Journal of Neuroscience. 2005; 25:2941–2951. [PubMed: 15772354]

Shaffer D, Fisher P, Lucas CP, Dulcan MK, Schwab-Stone ME. NIMH Diagnostic Interview Schedule for Children Version IV (NIMH DISC-IV): Description, differences from previous versions, and reliability of some common diagnoses. Journal of the American Academy of Child and Adolescent Psychiatry. 2000; 39:28–38. [PubMed: 10638065]

Smith JD, Beran MJ, Crossley MJ, Bloomer J, Ashby FG. Implicit and Explicit Category Learning by Macaques (Macaca mulatta) and Humans (Homo sapiens). Journal of Experimental Psychology-Animal Behavior Processes. 2010; 36:54–65. [PubMed: 20141317]

Smith JD, Minda JP, Washburn DA. Category learning in rhesus monkeys: A study of the Shepard, Hovland, and Jenkins (1961) tasks. Journal of Experimental Psychology-General. 2004; 133:398–414. [PubMed: 15355146]

Takahashi YK, Roesch MR, Stainaker TA, Haney RZ, Caiu DJ, Taylor AR, et al. The Orbitofrontal Cortex and Ventral Tegmental Area Are Necessary for Learning from Unexpected Outcomes. Neuron. 2009; 62:269–280. [PubMed: 19409271]

Waldron EM, Ashby FG. The effects of concurrent task interference on category learning: Evidence for multiple category learning systems. Psychonomic Bulletin & Review. 2001; 8:168–176. [PubMed: 11340863]

Wechsler, D. Wechsler Intelligence Scale for Children. 4th Ed (WISC-IV) Technical and Interpretive Manual. Harcourt Brace; San Antonio: 2003.

Wickens, TD. Models for behavior: Stochastic processes in psychology. W.H. Freeman; San Francisco: 1982.

Zeithamova D, Maddox WT. On the generality of working memory task effects on rule-based, but not in formation-integration category learning. Journal of Cognitive Neuroscience. 2005:107–107.

Zeithamova D, Maddox WT. Dual-task interference in perceptual category learning. Memory & Cognition. 2006; 34:387–398.

Zeithamova D, Maddox WT. The role of visuospatial and verbal working, memory in perceptual category learning. Memory & Cognition. 2007; 35:1380–1398.

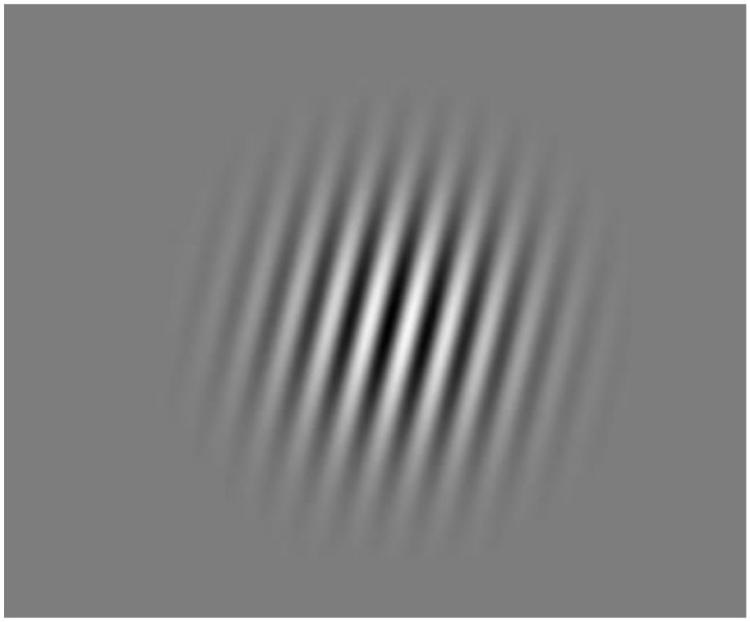

Figure 1.
Example Gabor patch.

NIH-PA Author Manuscript
NIH-PA Author Manuscript

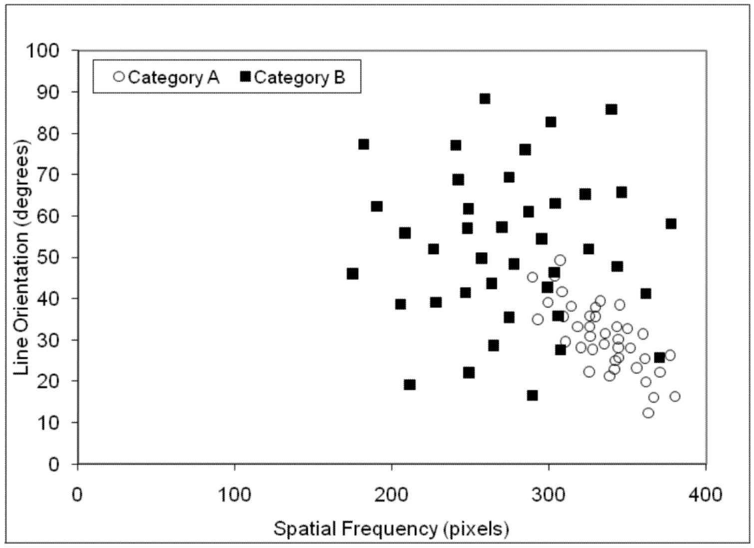

Figure 2.
Scatter-plot of stimuli used in Study 1. The optimal decision rule involves information-integration and a quadratic decision bound.

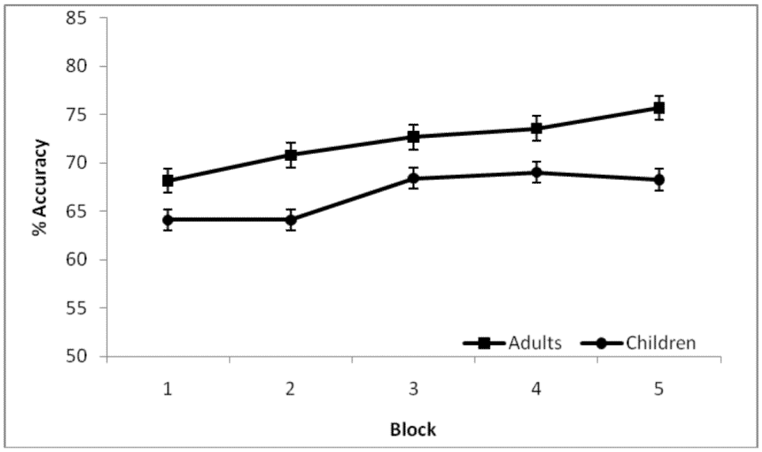

Figure 3.
Performance over time for Study 1.

NIH-PA Author Manuscript
NIH-PA Author Manuscript

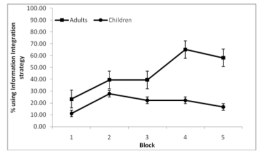

Figure 4.
Model based performance over blocks of trials for children and adults Study 1.

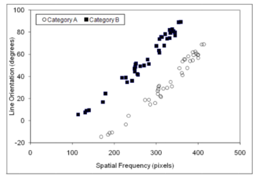

Figure 5.
Scatterplot of stimuli used in Study 2. The optimal decision rule involves information-integration and a linear decision bound.

NIH-PA Author Manuscript
NIH-PA Author Manuscript

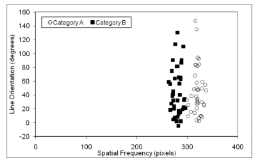

Figure 6.

Scatterplot of stimuli used in Study 2. The optimal decision strategy involves a uni-dimensional rule.

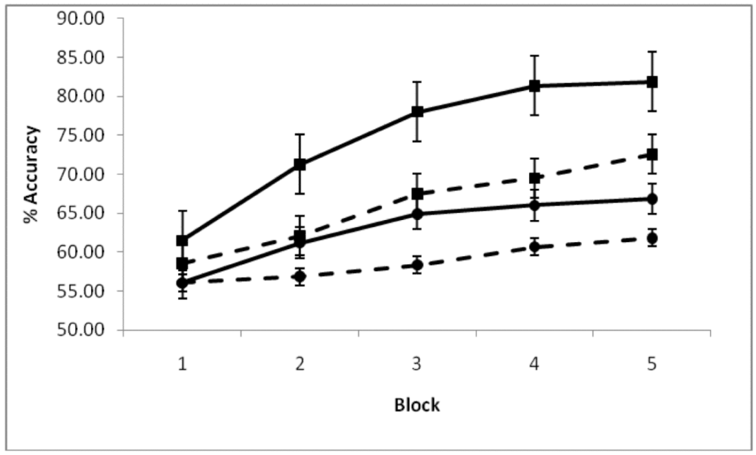

Figure 7.
Accuracy over blocks of trials for linear information integration and rule based tasks. Solid line = rule based, Dashed line = Information Integration. Squares = Adults, Circles = Children.

NIH-PA Author Manuscript

NIH-PA Author Manuscript

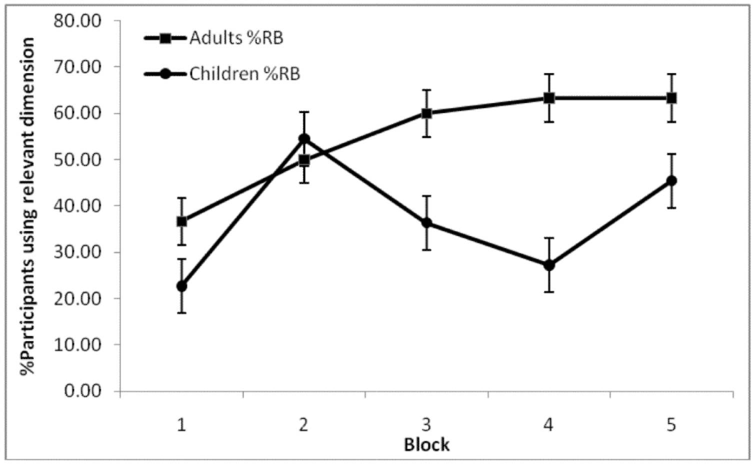

Figure 8.
Percentage of participants using relevant dimension on rule based task.

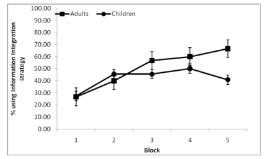

Figure 9.

Study 2. Percentage of children and adults using information integration approach on linear information integration task over blocks of trials.

Table 1

Description of groups.

	M:F	Age (yrs)	Est FSIQ	GPA	% Acc		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					LI	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: Quad: Quadratic Information Integration task, II: Linear Information Integration Categorization task; RB = Rule-Based task.