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Learning Rule-Described and Non-Rule-Described Categories: A Comparison of Children and Adults

John Paul Minda and Amy S. Desroches
The University of Western Ontario

Barbara A. Church
University at Buffalo, State University of New York

Three experiments investigated the ability of 3-, 5-, and 8-year-old children as well as adults to learn sets of perceptual categories. Adults and children performed comparably on categories that could be learned by either a single-dimensional rule or by associative learning mechanisms. However, children showed poorer performance relative to adults in learning categories defined by a disjunctive rule and categories that were nonlinearly separable. Increasing the task demands for adults resulted in child-like performance on the disjunctive categories. Decreasing the task demands for children resulted in more adult-like performance on the disjunctive categories. The authors interpret these results within a multiple-systems approach to category learning and suggest that children have not fully developed the same explicit category learning system as adults.

Keywords: category learning, multiple systems, rules, children, adults

The ability to form and use categories is present in all humans. Psychologists have studied categorization in infants (Quinn, Palmer, & Slater, 1999; Younger & Cohen, 1985), children (Hayes, Foster, & Gadd, 2003; Sloutsky & Fisher, 2004), and adults (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Minda & Smith, 2001; Murphy, 2002). Most of this research has focused on the learning of both natural and artificial categories, with no studies to our knowledge comparing the abilities of children and adults to learn novel categories of artificial stimuli. This comparison is crucial because artificial category learning may tap into the building blocks of more complex, natural category learning. While much is known about how adults deal with these building blocks, comparatively little is known about how these abilities develop.

There are several reasons to suspect that children and adults will perform similarly in learning some kinds of categories but will exhibit specific differences in learning others. One reason is that children, relative to adults, have a reduced working memory capacity (e.g., Gathercole, 1999; Swanson, 1999). In cases where category learning relies on verbal working memory, children should not perform as well as adults. However, when learning a new category does not tax working memory (or the involvement is minimal), children and adults should perform similarly. A second reason is that compared with adults, children have a generally reduced capacity for executive functioning and rule selection (Bunge & Zelazo, 2006; Casey, Giedd, & Thomas, 2000; Frye, Zelazo, & Palfai, 1995; Zelazo, Frye, & Rapus, 1996). As with the previous example of working memory, this suggests that when category learning depends on rule selection, children should be impaired relative to adults. This impairment should not be present when the categories to be learned have little or no rule selection component.

The idea that working memory and executive functioning play a role in the learning of some categories but not in others is one of the central predictions of a multiple-systems theory of category learning called the Competition of Verbal and Implicit Systems (COVIS; Ashby et al., 1998; Ashby & Ell, 2001; Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). This theory suggests that at least two broadly-defined brain systems are fundamentally involved in category learning. The *explicit system* is assumed to learn rule-described categories. These are categories for which the optimal rule is relatively easy to describe verbally (Ashby & Ell, 2001). For example, consider a category set in which round objects belong to one group and angular objects belong to another group. These categories could be quickly mastered by the explicit system because a rule is easy to verbalize ("Category 1 items are round"). According to COVIS, the explicit system is mediated by the prefrontal cortex, and it requires sufficient cognitive resources (e.g., working memory and executive functioning) to search for, store, and apply a rule (Zeithamova & Maddox, 2006). Furthermore, this system is assumed to be the default approach for normally-functioning adults learning new categories (Ashby et al., 1998).

However, not all categories can be easily described by a verbal rule. COVIS also assumes that a *procedural system* learns non-rule-described categories. These are categories for which no easily verbalizable rule exists or for which two or more aspects of the stimulus must be integrated at a predecisional stage (Ashby & Ell, 2001). That is, the dimensions themselves may be perceptually

John Paul Minda and Amy S. Desroches, Department of Psychology, The University of Western Ontario; Barbara A. Church, Department of Psychology, The University at Buffalo, State University of New York.

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Correspondence concerning this article should be addressed to John Paul Minda, Department of Psychology, University of Western Ontario, Social Science Centre, London, Ontario, Canada N6A 5C2. E-mail: jpminda@uwo.ca

separable, but they might need to be combined or integrated in order to make a categorization decision. For example, consider a category in which most of the objects are small, most are round, most are reddish, and most are shiny. The objects in this category share an overall family resemblance with each other, but there is no single feature to act as the rule. The rule, "most are small, most are round, etc." is difficult, though not impossible, to verbalize. COVIS assumes that a category like this can be learned more accurately by the procedural system, without relying on a verbal rule.

The procedural system is thought to be mediated by subcortical structures in the tail of the caudate nucleus. It relies on a dopamine-mediated reward signal to learn categories and does not rely heavily on working memory and controlled attention. The process of learning in the procedural system is assumed to be a gradual process of associating the perceptual aspects of an object with the correct response. As a result, this system is well-suited to learn categories for which the boundary between the categories is linear and for which the stimuli within each resemble each other more than they resemble the members of another category (Ashby et al., 1998).

Both of these systems are assumed to operate in normally-functioning adults, and both can contribute to performance, even after learning has progressed. In general, COVIS assumes that the system with the more successful responding will eventually dominate performance. For instance, although the verbal system is considered the default system for adults, some categories may not be easily learned by a verbal rule. In this case, the procedural system would produce more accurate responses and would take over. Also, if rule-based categories are learned under conditions in which the learner is distracted and working memory is being used for another task, the procedural system would have to take over for the struggling explicit system. Finally, there may be situations in which both systems are expected to contribute to performance, such as when a rule is used to classify some items but perceptual process supplements that rule.

Because COVIS makes specific assumptions about the brain regions involved in the two types of category learning, there are clear predictions to be made about developmental effects. Recent work has suggested that the prefrontal cortex develops later than other areas (Bunge & Zelazo, 2006; Casey et al., 2000; Giedd, 2004). Furthermore, verbal working memory and executive functioning develop substantially during childhood and are related to these physical developments in the prefrontal cortex (Gathercole, 1999; Swanson, 1999). Since the prefrontal cortex is assumed to mediate the explicit system, COVIS predicts that children should be impaired relative to adults when learning categories that rely heavily on this explicit system, particularly when learning requires substantial working memory resources (e.g., categories for which the optimal rule is a complex verbal rule). On the other hand, the procedural system of COVIS is mediated by the tail of the caudate nucleus. This structure seems to be fully developed in children (Casey et al., 2004), and as a result, young children should be able to learn non-rule-defined categories as well as adults. Furthermore, because this system does not require working memory resources (Zeithamova & Maddox, 2006), the learning of non-rule-defined categories should not be impacted by developmental differences in working memory.

Motivation for the Current Research

The current research examined a specific prediction of COVIS, namely that younger children should have difficulty with rule switching and should be impaired on category learning tasks for which the optimal rule is a complex verbal rule (Ashby et al., 1998, p. 457). Furthermore, a key part of this prediction is that younger children should show greater difficulty when compared with older children. As such, we specifically examined category learning by using participants from several different age groups. We also targeted types of categories that placed differing demands on the explicit and procedural system.

Our starting point was the influential work of Shepard, Hovland, and Jenkins (1961). They created six types of categories from a set of eight stimulus objects. Each item was defined by three dimensions (size, color, and shape), and each category contained four objects. This collection of categorization sets is well-suited for children because of the modest number of items and the relative simplicity of the stimuli. Four of these category sets are shown in Figure 1, although Shepard et al. (1961) did not show the stimuli with faces.[1]

Under typical learning conditions, the relative ease with which adults learn these categories follows the pattern (least difficult to most difficult): I $<$ II $<$ III $=$ IV $=$ V $<$ VI (Shepard et al., 1961). Each category set presents specific information-processing demands. Although these category sets have not been specifically tested with COVIS, we argue that some of these information-processing demands are best met by the verbal rule learning processes of the explicit system, and other demands are best met by the nonverbal, stimulus, and response learning processes of the procedural system. COVIS assumes that both systems operate when learning each of these category sets (with varying degrees of success). However, the relative pattern with which these categories are learned by adults suggests how the default explicit system is engaged when learning each type.

Type I (referred to as SD for single dimension) is a single-dimensional set, and perfect performance can be attained by the formation of a straightforward verbal rule using a single proposition (e.g., *if* black *then* Category 1). As such, COVIS predicts easy learning of this category by the explicit system. The procedural system could also learn this category without a verbal rule by learning to associate a cue (black) with a response (Category 1), but learning would proceed more gradually. Furthermore, some degree of associative learning may also be involved in terms of associating the rule and response. However, the rapid learning that is typically observed is assumed to be evidence that these categories are learned by a verbal rule (Shepard et al., 1961; J. D. Smith, Minda, & Washburn, 2004; but also see Nosofsky, Gluck, Palmeri, McKinley, & Glauthier, 1994) .

The Type II (referred to as DR for disjunctive rule) set is best described by a disjunctive rule that puts black triangles and white

[1] The original Shepard et al. (1961) sets also included Type V, which was a nonlinearly separable set with extreme exceptions, and Type VI, which was an ill-defined category set with no easily verbalized rule that could be mastered only by learning the individual exemplars. We focused on the first four because Type VI is hard to learn under any circumstances and because the inclusion of Type III allowed for a nonlinearly separable category, thus making Type V less relevant.

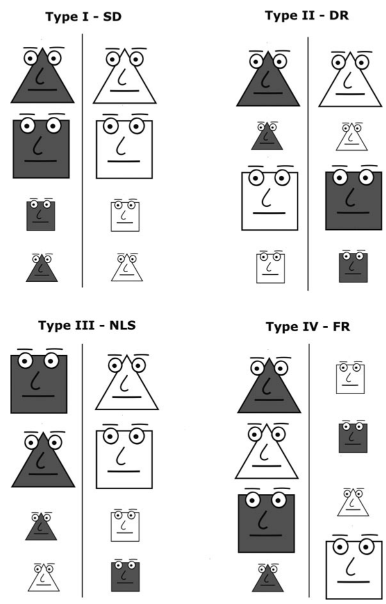

Figure 1. An example of the stimuli used in this experiment. Shapes on the left side of the line belonged to one category and shapes on the right side belonged to the other category. The actual stimuli were shown in blue or orange (rather than grey or white). SD = Type I (single dimension) from Shepard et al. (1961); DR = Type II (disjunctive rule) from Shepard et al. (1961); NLS = Type III (nonlinearly separable) from Shepard et al. (1961); FR = Type IV (family resemblance) from Shepard et al. (1961).

squares in the same category. COVIS predicts relatively easy learning of this category set by the explicit system, since the two-predicate rule is readily verbalized. The procedural system would not learn this category set easily because it would be undermined by the structure. Specifically, the structure of this category set is such that items in a category are as perceptually distant from each other (e.g., black triangles and white squares) as they are similar to members of the opposite category (e.g., white triangles and black squares). Furthermore, each of the relevant cues (e.g., color and shape) is non-predictive on its own, and each is equally associated with both categories. As a result, these categories are difficult or impossible for the procedural system to learn because it relies in part on high within-category perceptual similarity, it benefits from greater perceptual distance between categories, and it relies on a consistent mapping between cue and response (Zeithamova & Maddox, 2006). If the explicit system is not fully developed or not accessible, a learner should have difficulty with this type of category since he or she would then have to rely on the procedural system.

Type III (referred to as NLS) is a nonlinearly separable category set that is defined as having a rule and some exceptions. COVIS predicts accurate learning of the categories by the explicit system (finding the verbalizable rule and memorizing the exceptions). For example, one could learn "black objects and the small white triangle" as the rule for Category 1. These categories should place a heavier demand on the explicit system than do the SD and DR categories because the viable rule is potentially more complex than the rule for either the SD or DR categories (Feldman, 2000, 2003). This heavier demand and complexity is a result of the extra cognitive resources required to learn the exceptions and because attention to all three dimensions is needed in order to learn them. These categories require verbalizing multiple propositions to learn exclusively via the explicit system. This category set would be difficult for the procedural system to learn to perfection because of the nonlinear boundary and because there is no consistent association of cues and responses to correctly classify the exceptions. As with the DR set, if the explicit system is not fully developed or not fully accessible, the procedural system would take over, and the learner would have difficulty with this type of category.

Type IV (referred to as FR) is a family resemblance category set because all category members share the majority of their features with the other category members, but no one feature is perfectly diagnostic. Although this type of category might be describable by a complex rule with multiple propositions (possibly, "any two of the following three features" or "black objects and the large white triangle"), the rule is difficult to verbalize and learn. Unlike the NLS categories, which can also be learned by a rule and exception strategy, the FR categories allow for perfect performance by nonverbal, similarity-based mechanisms. Strengthening the association between the three cues (large size, black color, and triangle-shaped) with a response (Category 1) will result in the correct response for all the items in the category. As a consequence, COVIS predicts that the procedural system should dominate in the acquisition of these categories by learning the family resemblance structure, even in cases when the explicit system would otherwise be compromised (Waldron & Ashby, 2001).

The learning of these different category sets has been tested in a number of studies (Nosofsky & Palmeri, 1998; Shepard et al., 1961; J. D. Smith et al., 2004), all of which generally demonstrated that the SD and DR categories are learned more easily than the NLS and FR categories. Because SD and DR categories have an optimal verbal rule with one or two propositions, the explicit system, which is assumed to be the default in normal adults, learns these category sets quickly and easily. The other categories do not have an uncomplicated optimal verbal rule, and so the explicit system may take longer, as in the case of the NLS categories, or the procedural system may learn them, as in the case with the FR categories.

Research has examined the learning of these categories in a number of different experimental conditions, and the results are generally consistent with the predictions of COVIS. For example, one study trained rhesus monkeys to learn all six types of categories (J. D. Smith et al., 2004). Monkeys and humans showed a different rank-order difficulty for these categories: DR was the second easiest for humans but was the second most difficult for monkeys. J. D. Smith et al. (2004) suggested that humans defined the DR category set with a verbal rule that worked well to classify the stimuli. Since the DR categories cannot be learned by the association of cues to a response, it was not learned well by the monkeys. Human performance on these six categories suggested that they used either the explicit or procedural systems, depending on the category, whereas the monkeys' performance suggested the use of the procedural system only. Given that monkeys have a much smaller prefrontal cortex and no verbal abilities, this result is consistent with the claim that the explicit system (which relies on the prefrontal cortex) is involved in the learning of the DR categories in human adults.

Another study examined the characteristics of the stimuli (Nosofsky & Palmeri, 1996). Effective learning of DR categories involves the learner's ability to selectively attend to the two relevant dimensions and ignore the third irrelevant dimension. Research has shown that when the dimensions are perceptually integral instead of separable (e.g., hue, saturation, and brightness instead of shape, color, and size), participants have a significantly harder time learning this category structure, with performance on DR categorization being the second most difficult to learn (Nosofsky & Palmeri, 1996). This finding again highlights the claim that when the explicit system can be recruited to extract and use a disjunctive rule, learning the DR categories is relatively easy. However, when such access is not available, either due to cognitive limitations (as in the case of nonhuman primates) or stimulus demands (when the dimensions are not easily separable), learning these categories is more difficult because it is occurring via the procedural system.

Finally, other research supports the claim that certain cognitive factors can influence the ability of adults to learn other kinds of rule-described and non-rule-described category sets. For example, Waldron and Ashby (2001) found that participants who were asked to perform a numerical Stroop task (which relies heavily on working memory) were impaired relative to control participants when learning a rule-described category (similar to the SD categories). They found no impairment for learning a non-rule-described category (similar to the FR category). Zeithamova and Maddox (2006) used a similar working memory manipulation and found that it affected the learning of rule-described categories (with a disjunctive rule like the DR categories, but with continuous rather than binary features). Again, the same working memory manipulation did not affect the learning of non-rule-described categories, providing further support for multiple systems under the framework of COVIS.

Overview of the Current Experiments

We conducted three experiments designed to examine the effects of cognitive development and working memory on category learning. The primary predictions are summarized in Table 1. In Experiment 1, children of three age groups (3-, 5-, and 8-year-olds) as well adults were asked to learn several sets of categories of varying complexity. We used four of the six categories of Shepard et al. (1961). The SD, DR, and NLS were all rule-described categories, since they could be learned most accurately by a verbal rule (or a rule plus exception for NLS) and the explicit system. However, since the rules vary in complexity and the number of propositions needed, the relative ease for acquiring such rules should differ for each of these structures. In contrast, the FR set was non-rule-described because it could be learned well without a verbal rule via the procedural system. Experiment 1 minimized the methodological differences between the child and adult versions of the task in order to focus on the age-related differences in category learning.

In Experiment 2, three groups of adults were asked to learn the same four category sets. One group of adults learned in a standard condition, a second group learned while performing a verbal concurrent task (a coarticulation task), and a third group learned while performing a nonverbal concurrent task. We hypothesized that the verbal concurrent task group would be impaired relative to the other groups on the DR and the NLS categories because these categories require the learning of multiproposition rules for perfect performance. We assumed that the verbal concurrent task would disrupt the working memory component of the explicit system, thus making learning difficult (Baddeley, Lewis, & Vallar, 1984). We did not predict a decrease in performance for the concurrent task participants learning the SD categories because the rule was simple and requires minimal working memory resources. Finally, we predicted no decrease in performance for the FR categories because the concurrent task should not interfere with the procedural system.

In Experiment 3, we investigated the ability of 5-year-olds and adults to learn a subset of the same categories used in Experiments 1 and 2, the DR set and the FR set. These participants received a pretraining condition that allowed them to name all the features and view the full set of exemplars. We reasoned that this would reduce the overall processing and working memory demands of the task and as a result should increase performance by children learning the DR categories.

Experiment 1

In Experiment 1, we examined the ability of children and adults to learn a subset (Types I, II, III, and IV; referred to as the SD, DR, NLS, and FR sets) of the Shepard et al. (1961) categories. To our knowledge, this experiment is the first to compare participants of various age groups on this fundamental set of categorization tasks. We predicted that older children and adults would perform comparably well on the SD categories because the rule was a single stimulus dimension. COVIS assumes that the explicit system would learn these categories (see Table 1). Although the areas that

Table 1
Primary Predictions of COVIS for Experiments 1–3

	Category type			
Experiment	SD	DR	NLS	FR
Experiment 1	Children = adults	Children < adults	Children < adults	Children = adults
Experiment 2	NT = VT = NVT	VT < NT = NVT	VT < NT = NVT	NT = VT = NVT
Experiment 3		Children = adults		Children = adults

Note. COVIS = Competition of Verbal and Implicit Systems; NT = no concurrent task; VT = verbal concurrent task; NVT = nonverbal concurrent task; SD = Type I (single dimension) from Shepard et al. (1961); DR = Type II (disjunctive rule) from Shepard et al. (1961); NLS = Type III (nonlinearly separable) from Shepard et al. (1961); FR = Type IV (family resemblance) from Shepard et al. (1961).

mediate the explicit system are not fully developed in the children (Bunge & Zelazo, 2006; Casey et al., 2004; Giedd, 2004), this single-dimensional rule is fairly easy to find and verbalize with a single proposition. Learning these categories should not place heavy demands on the explicit system of the children or adults. Therefore, we also predicted a developmental trend such that only the youngest children would show obviously poor performance, with performance on these categories predicted to increase with age.

We also predicted that all of the children would be impaired relative to adults on the DR and NLS category sets because these categories require more complex verbal rules with more than a single proposition to be learned accurately. COVIS assumes that these category sets should be learned by the explicit system. Therefore, we expected there to be marked differences between the children and adults because the brain areas that mediate the explicit system and working memory are not fully developed in children. As such, the adults have full access to the explicit system whereas children do not. Again, we predicted a developmental trend and expected performance on these categories to be the worst among the youngest children, better among the oldest children, and best in adults.

Finally, we predicted that children and adults would perform comparably on the FR category set, because there was no easy optimal verbal rule for these categories but a good family resemblance structure. The procedural system, which is mediated by areas that are equally developed in both the children and adults, should learn these categories in all age groups.

Method

Participants. Our participants included 28 three-year-old children, 24 five-year-old children, and 25 eight-year-old children from Buffalo, NY. These participants were recruited through local schools and child care centers. Our participants also included 24 adults from the University of Western Ontario who participated for course credit. Four 3-year-olds and one 8-year-old were dropped from the analysis because they failed to complete the training phase. Each age group was left with data from 24 participants available for analysis. The details for participants are found in Table 2.

Materials. Participants were trained on one of the four category sets shown in Figure 1 (based on random assignment). Faces were added to the more commonly used simple shapes in order to make the stimuli more child-friendly. Adding eyes can also change the way children construe objects by reducing a "shape bias" in which very young children will attend to shape only (Jones, Smith, & Landau, 1991). Each object was defined by three dimensions: size (small or large), color (orange or blue), and shape (square or triangle). Each category set was made up of eight objects with four objects belonging to each category.

The SD set was a single-dimensional category with one of the three features acting as the single-dimensional rule. The DR set was a disjunctive rule category set with two of the three features relevant for the disjunctive rule. The NLS set was a nonlinearly separable category set with a rule and exception structure with one feature acting as the rule and the other features defining the exception. The FR set was a linearly separable, family resemblance category set in which each category member shared the majority of its features with the other category members and all the features were relevant. All category sets were counterbalanced across participants such that some participants were presented with an SD set for which size was the relevant dimension, others were presented with a set for which color was the relevant dimension, and so on.

Procedure. Children were tested individually and were seated at the computer along with an experimenter. Children were first told that they would be playing a game in which they would see pictures of different creatures on the screen. They were told that some of these creatures lived in the mountains and some lived in the forest. Their job was to help these creatures find their "homes" by pointing to the correct place on the screen. Younger children were rewarded for participation with stickers regardless of their performance. Eight-year-olds were also offered stickers, though none wanted them. Participants were asked to indicate to the experimenter if they did not wish to continue with the game, though the experimenters tried to be as encouraging as possible to keep the children interested.

On each trial, the stimulus appeared in the center of the screen, and the two category icons (mountains or trees) were shown to the left and the right of the stimulus. When the child pointed to a location on the screen, the experimenter made the selection with a mouse, and the stimulus moved to where the child had pointed. The stimulus was animated to show a smile for 2 s as feedback for a correct choice. For an incorrect classification, the stimulus frowned for 1 s and then moved to the correct location and smiled for 2 s as feedback. Parents who wished to observe their child during the experiment were seated behind their child and were asked not to talk during the experiment so that they would not inadvertently provide cues to the child. Experimenters were seated next to the child in order to manipulate the mouse for the children, but they wore sunglasses so that the child could not determine where the experimenter's gaze fell on the computer screen.

Stimuli were presented in six random blocks of the eight stimuli for a total of 48 consecutive trials. When the procedure was over, the nature of the experiment was explained to the children and their parents/caretakers.

Table 2
Participant Characteristics for Experiment 1

Age group	*N*	Age (years)	Male	Female	Dropped
Three-year-old	28	3.45	15	13	3 male, 1 female
Five-year-old	24	5.63	12	12	0
Eight-year-old	25	8.46	13	12	1 male
Adult	24	20.12	12	12	0

Adults were tested with the same software and the same basic procedure. The primary differences were that adults were not rewarded with stickers, the instructions were given in age appropriate language, and adults made categorization decisions by selecting one of the two locations with the mouse.

Results

Learning curve. For each participant, we calculated the proportion correct for each block of eight trials. The resulting learning curves for each age group and each category are shown in Figure 2. Three observations can be made from this figure. First, for the SD categories, it is clear that only the 3-year-olds had difficulty learning categories defined by a single dimension: Their performance as a group actually declined with practice. Second, only the adults displayed any mastery of the DR categories. Finally, all four groups of participants displayed remarkably similar learning curves for the FR categories.

Best block analysis. In order to formally analyze the differences between the age groups, we found the best block of performance for each participant. We used the best block of the six in our analyses because the number of blocks was so low that using an overall performance measure included a fair amount of early learning noise. The final block was also not ideal, because it included some cases in which younger children started to lose interest in the task, as reported by the experimenter.[2]

The proportion correct for the best block for each participant group (adult, age 8, age 5, and age 3) and each category (SD, DR, NLS, and FR) is shown in Figure 3. The main results of interest

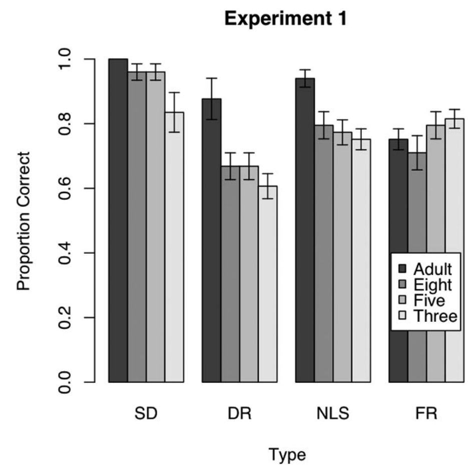

Figure 3. Performance in Experiment 1 on the best block for each category set and age group (in years). SD = Type I (single dimension) from Shepard et al. (1961); DR = Type II (disjunctive rule) from Shepard et al. (1961); NLS = Type III (nonlinearly separable) from Shepard et al. (1961); FR = Type IV (family resemblance) from Shepard et al. (1961). Bars depict standard error.

were the differences between groups on the various category sets. An analysis of variance (ANOVA) with age and category found a main effect for age, $F(3, 80) = 9.09$, $MSE = 0.01$; and a main effect for category, $F(3, 80) = 24.53$, $MSE = 0.01$. All analyses assume $p < .05$ unless otherwise stated. These main effects were expected, as we assumed adults would perform best overall and that the SD categories would be the easiest to master overall. However, we also found a significant interaction between age and category, $F(9, 80) = 2.93$, $MSE = 0.01$.

We explored this interaction by conducting four separate ANOVAs for each category set including age as the single factor. We found a significant effect of age for the SD categories, $F(3, 20) = 4.07$, $MSE = 0.01$. Post hoc tests indicated that 3-year-old performance ($M = .83$) differed significantly from the performance of adults ($M = 1.00$), but not from the performance of 8-year-olds ($M = .96$) or 5-year-olds ($M = .96$). No other effects were significant. We found a significant main effect of age for the DR categories, $F(3, 20) = 6.19$, $MSE = 0.01$. Post hoc tests indicated that adult performance ($M = .88$) differed significantly from the performance of 8-year-olds ($M = .67$), 5-year-olds ($M = .67$), and 3-year-olds ($M = .61$). No other effects were significant. We found a significant main effect of age for the NLS categories,

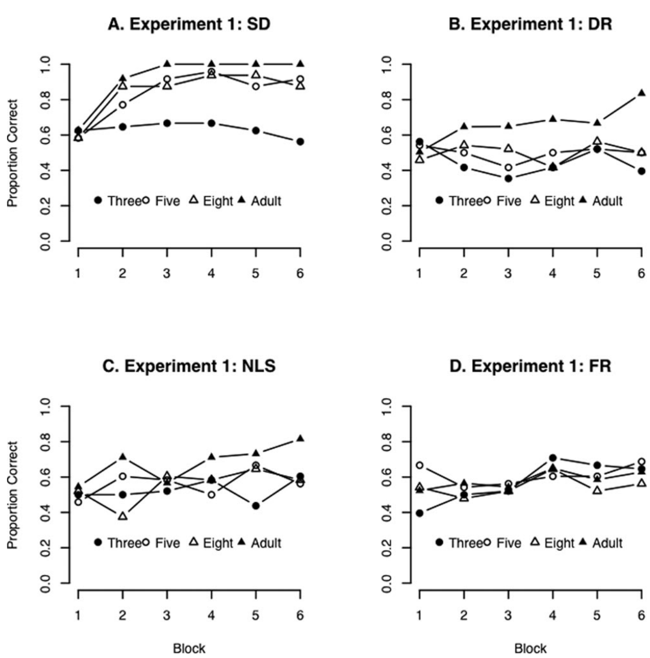

Figure 2. Average performance (across participants) in Experiment 1 for each category set and each age group (in years). SD = Type I (single dimension) from Shepard et al. (1961); DR = Type II (disjunctive rule) from Shepard et al. (1961); NLS = Type III (nonlinearly separable) from Shepard et al. (1961); FR = Type IV (family resemblance) from Shepard et al. (1961).

[2] Using the best block raises two concerns: first, that we would not obtain the same pattern of results when using a more general dependent variable; and second, that our results were skewed by our selecting a high performance that had occurred early on and by chance. We tried to address both of these concerns. We conducted a parallel set of analyses to all those reported in the text but substituted average performance across all blocks as the dependent variable. These analyses found the same pattern (weaker, but still significant) of results as reported in the text. To address the second concern, we conducted an ANOVA with age and type on when the best block occurred and found no significant effects or interactions. Best blocks were 4.45 for the adults, 4.38 for the 8-year-olds, 3.00 for the 5-year-olds, and 3.45 for the 3-year-olds.

$F(3, 20) = 5.78$, $MSE = 0.01$. Post hoc tests indicated that adult performance ($M = .94$) differed from the performance of 8-year-olds ($M = .80$), 5-year-olds ($M = .77$), and 3-year-olds ($M = .75$). No other effects were significant. We failed to find a main effect of age for the FR categories, $F(3, 20) = 1.35$, $MSE = .01$, *ns*. That is, all four groups performed equivalently (*M*s = .75, .71, .80, and .81 for adults through 3-year-olds).

Strategy analysis. In addition to overall learning curves and the best performance of each participant, we were also interested in whether participants had employed a single-dimensional rule strategy in learning any of the categories. This is a crucial piece of information, because in many cases, what may appear to be moderate performance on the FR and NLS categories might be a result of participants learning an imperfect single-dimensional rule (e.g., attention to a single dimension in the FR case would result in 75% correct, which is what many participants showed). If participants were simply using an imperfect, single-dimensional rule when learning the FR categories, it could undermine the conclusion that they were using the procedural system to learn the categories.

For each participant, we found the response (Category A or B) on each stimulus. We then calculated for each block the correlation between the value of each dimension (e.g., square or triangle) and the response. If a participant responded to a single dimension, then the correlation between stimulus and response would be 1.0 regardless of which category that participant was learning. This analysis would indicate if a participant had adopted a single-dimensional rule, even if the rule was suboptimal.

After calculating the correlations, we counted how many participants showed at least two blocks (including nonconsecutive blocks) of perfect rule-response correlations. As Table 3 shows, we typically observed single dimension responding only in the SD categories. Only 1 of the 24 participants showed a single-dimensional performance–dimension correlation for the DR categories, and only 1 of the 24 participants showed a single-dimensional performance–dimension correlation for the NLS categories. No participants responded to single dimensions for the FR categories, suggesting that performance was due to participants learning the family resemblance structure and not to the application of an imperfect single-dimensional rule.[3]

Developmental trends. Finally, we examined our data for evidence of a developmental trend for learning categories that were predicted to most depend on the explicit system. That is, we predicted performance on the SD, DR, and NLS categories to improve with a child's age. This trend is expected, given the maturation in prefrontal cortical areas between ages 3 and 8 (Bunge & Zelazo, 2006; Casey et al., 2000; Giedd, 2004). We calculated the correlation between age (in months) and the best block performance for each category type. We found a significant positive correlation for the SD categories, $r(16) = .48$, suggesting that performances on the SD categories and age were related and confirming our prediction that performance in simple rules improves with age along with the development of the prefrontal cortex. We also found a nonsignificant positive correlation for the DR categories, $r(16) = .40$, $p = .09$, suggesting that performance on the DR categories may have also improved with age. There was essentially no correlation between age and performance for the NLS categories, $r(16) = .11$, *ns,* and our prediction was not supported. We also found no correlation between age and performance on the FR categories, $r(16) = -.16$, *ns,* suggesting that age and performance were not related and confirming our (null) prediction in this case. Overall, these correlations are in line with the neuropsychologically motivated predictions of COVIS, and they prompt further research into the relationship between maturation and performance.

Table 3
Number of Participants Using Single-Dimensional Rules in Experiment 1

Age group	SD	DR	NLS	FR
Three-year-old	2	0	0	0
Five-year-old	4	0	0	0
Eight-year-old	4	1	1	0
Adult	6	0	0	0

Note. Total possible number of participants in each cell is 6. SD = Type I (single dimension) from Shepard et al. (1961); DR = Type II (disjunctive rule) from Shepard et al. (1961); NLS = Type III (nonlinearly separable) from Shepard et al. (1961); FR = Type IV (family resemblance) from Shepard et al. (1961).

Discussion

Experiment 1 compared the ability of children and adults to learn rule-described and non-rule-described categories. Adults and children differed on the DR categories, which required the formation of a disjunctive rule, and on the NLS categories, which required the formation of a rule and exception strategy. Adults performed relatively well on these categories, whereas children performed very poorly. Children and adults displayed similar levels of performance on the SD categories that were rule-described, but for which the rule was simple, easy to describe, and directly related to perception (e.g., orange = forest). Children and adults also displayed similar levels of performance on the FR categories, which was the one category set for which associative learning mechanisms allow for accurate learning. Subsequent analyses of individual responses indicated that performance on the DR, NLS, and FR categories was not due to participants choosing an imperfect single-dimensional rule. In summary, children generally lagged behind adults when learning categories that depended on complicated verbal rules but not when learning categories that required a simple rule, or when the categories did not depend on verbal rules.

Consider these results in the context of the multiple-systems theory (Ashby et al., 1998; Ashby & Ell, 2001). COVIS predicts that the explicit system should be able to learn DR categories by testing various rules and eventually applying a verbal description

[3] This analysis does not rule out the possibility that participants may have learned the FR categories by application of a multidimensional rule. However, given the low dimensionality of the FR categories, a multidimensional rule might be difficult to distinguish from family resemblance responding. We favor the conclusion that the FR categories are learned via the procedural system because of converging evidence of earlier research with this category set (Waldron & Ashby, 2001), the lack of any observable differences between children and adults on the FR category set, and the general neuropsychological similarities between children and adults in the areas that mediate the implicit/procedural system.

of the correct disjunctive rule. Adults default to this explicit system under most learning conditions (Ashby et al., 1998), and so the learning of the DR categories occurs relatively quickly. In the current experiment, the procedural system would be most effective in learning the FR categories. The family resemblance structure is difficult to verbalize because of the number of propositions in the verbal rules but is less difficult to learn procedurally because of the straightforward relationship between features and responses. Children, unlike adults, have more difficulty relying on the explicit system because the prefrontal cortex has not sufficiently developed to allow for its full operation (Bunge & Zelazo, 2006; Casey et al., 2004; Giedd, 2004). Without the efficient use of the explicit system, the child struggles to learn the DR and NLS categories via the procedural system. This would explain the marked differences we observed among our participants in learning these categories. This would also explain the equivalent performance between children and adults on FR categories.

The explicit system relies on working memory to test and store hypotheses and rules. As such, the category learning differences between children and adults are consistent with other observed differences in working memory ability between children and adults (Gathercole, 1999; Swanson, 1999). Working memory plays a large role in the explicit system and is required to learn categories for which the optimal rule is verbalizable (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). Adult participants (but children less so) rely on verbal working memory to help learn the categories with the explicit systems whenever possible. Other research has shown that younger children are more sensitive to the relational complexity of hypothesis-testing tasks (Andrews & Halford, 2002; Bunge & Zelazo, 2006; Zelazo et al., 1996), which is also consistent with our claims here.

Experiment 2

In order to test the hypothesis that the explicit system and verbal working memory play a crucial role in learning rule-defined categories but not non-rule-defined categories, we conducted a second experiment in which three groups of adults learned the four category sets used in Experiment 1. Previous research using a Stroop-like task and different category sets found results consistent with the prediction that working memory plays a role in learning rule-described but not non-rule-described category sets (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). In the present experiment, some participants learned categories while performing a verbal concurrent task, others while performing a nonverbal concurrent task, and others in a control condition with no concurrent task. We predicted that participants who performed the verbal task would be impaired relative to the other groups in learning categories that required a complex verbal rule (such as the DR and NLS categories). We also predicted that participants who performed the nonverbal concurrent task would not be impaired relative to the control group on any of the categories, since the nonverbal task would not interfere with the use of working memory by the explicit system.

Method

Participants. Our participants included 72 adults from the University of Western Ontario who received a research credit for being in our experiment.

Materials. Participants were trained with stimuli that were similar to those used in Experiment 1 and shown in Figure 1. This included the four types of categories. However, the stimuli did not have faces on them.

Procedure. Participants were assigned to one of the three concurrent task conditions and were assigned to learn one of the four category sets. In the no-concurrent-task condition, participants saw a stimulus on the screen and were instructed to press the *1* or the *2* key to indicate Category 1 or Category 2, respectively. After responding, participants were given feedback indicating a correct or an incorrect response: The word *CORRECT* appeared for 800 ms, or the word *INCORRECT* appeared for 1,200 ms. The stimulus remained on the screen while feedback was given, and then another trial began. Training continued for 20 blocks of the 8 stimuli (160 trials). Stimuli were presented in a random order within each block, and these blocks were presented in an unbroken fashion.

The verbal concurrent task condition was similar to the no-task condition except that as participants were learning to classify the stimuli, they performed a coarticulation task (Baddeley et al., 1984). In this task, random letters appeared at the rate of one per second in the center of the screen, right below the stimulus. Participants were instructed to read these letters aloud as they were viewing the stimuli and making responses. We reasoned that the demands placed on the phonological loop of working memory by this task should interfere with the processing of verbal rules and therefore impact the learning of the DR and the NLS categories.

The nonverbal concurrent task condition was similar to the no-task condition except that as participants were learning to classify the stimuli, an asterisk flashed at the rate of one per second (with 20 ms variation faster or slower), and participants were instructed to tap their fingers each time they saw the asterisk. We reasoned that the verbal working memory requirements of this task were sufficiently low to allow participants to still learn the DR and NLS categories via the explicit system. Since this nonverbal task did not have a spatial component and required only a single motor response, we did not expect it to interfere with the procedural system.

Results

Learning curve. As in Experiment 1, we calculated the proportion correct for each participant for each block of trials. The resulting learning curves for each experimental group and each category type are shown in Figure 4. As can be seen in the figure, learning was similar across the groups for the SD and NLS categories, but the verbal concurrent task group was impaired in learning the DR categories, and the nonverbal concurrent task group seemed to show a small advantage in learning the FR categories.

Average performance analysis. We calculated the average proportion correct for each participant across all trials, and the resulting average proportion correct scores are shown in Figure 5. As expected, all participants performed best on the SD categories and worst on the NLS and FR categories. More importantly, participants in the nonverbal concurrent task condition did not appear to differ from participants in the no-task condition. However, participants in the verbal concurrent task condition appeared to be impaired relative to the other groups at learning the DR categories.

An ANOVA with task (no task, nonverbal concurrent task, verbal concurrent task) and category (SD, DR, NLS, FR) found a main effect for task, $F(2, 60) = 6.29$, $MSE = 0.01$; and a main effect for category, $F(3, 60) = 36.39$, $MSE = 0.10$. All analyses assume $p < .05$ unless otherwise stated. We failed to find a significant interaction between task and category, $F(6, 60) = 1.40$, $MSE = 0.01$, *ns*. However, as Figure 5 shows, this interaction was not expected, since performance was equivalent for many of the task-by-category groups. Our real interest was in the differences on the DR categories between the concurrent task conditions.[4]

As in Experiment 1, we conducted four separate ANOVAs for each category set including task as the single factor. We found only a nonsignificant effect of task for the SD categories, $F(2, 15) = 3.67$, $MSE = 0.001$, $p = .050$. Post hoc tests indicated that performance by the verbal concurrent task group ($M = .92$) was slightly lower than performance by the no-task group ($M = .96$) but not lower than performance by the nonverbal concurrent task group ($M = .94$), but performance was very high for all three groups. No other effects were significant. As expected, we found a significant effect of task for the DR categories, $F(2, 15) = 7.63$ $MSE = 0.01$. Post hoc tests indicated that performance by the verbal concurrent task group ($M = .61$) was lower than performance by the no-task group ($M = .82$) and the nonverbal concurrent task group ($M = .79$). No other effects were significant. We found no main effect of task for the NLS categories, $F(2, 15) = 0.28$; $MSE = 0.01$; *Ms* = .68, .69, and .65 for the no-task, nonverbal concurrent task, and the verbal concurrent task groups, respectively. We also found no main effect of the FR categories, $F(2, 15) = 2.08$; $MSE = 0.01$; *Ms* = .65, .67, and .54 for the no-task, nonverbal concurrent task, and the verbal concurrent task groups, respectively.

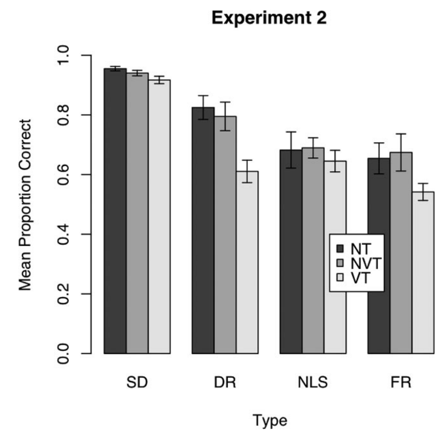

Figure 5. Average performance (across all blocks) in Experiment 2 for each category set and concurrent task group. NT = no task; NVT = nonverbal task; VT = verbal task. SD = Type I (single dimension) from Shepard et al. (1961); DR = Type II (disjunctive rule) from Shepard et al. (1961); NLS = Type III (nonlinearly separable) from Shepard et al. (1961); FR = Type IV (family resemblance) from Shepard et al. (1961). Bars depict standard error.

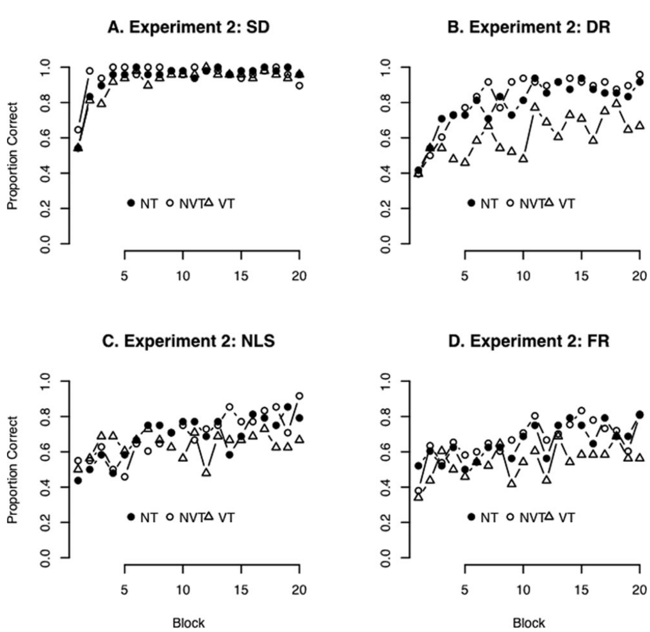

Figure 4. Average performance (across participants) in Experiment 2 for each category set and each age group. NT = no concurrent task; NVT = nonverbal concurrent task; VT = verbal concurrent task. SD = Type I (single dimension) from Shepard et al. (1961); DR = Type II (disjunctive rule) from Shepard et al. (1961); NLS = Type III (nonlinearly separable) from Shepard et al. (1961); FR = Type IV (family resemblance) from Shepard et al. (1961).

Finally, we carried out an analysis on the average block for the NT and NVT participants, in order to ensure that we replicated the standard rank-order effect (SR > DR > NLS = FR) for these categories (J. D. Smith et al., 2004; Shepard et al., 1961). We did not include the performance of the VT group in this analysis, since the experimental manipulation affected their performance. We conducted an ANOVA on average performance by using category type as the single factor and found a significant main effect, $F(3, 43) = 18.06$, $MSE = 0.011$. Post hoc tests found that performance on SD categories was significantly higher than performance on the DR, NLS, and FR categories. Performance on DR categories was significantly higher than performance on NLS or FR categories, and performance on NLS categories and FR categories did not differ from each other.

Strategy analysis. We again performed a strategy analysis as in Experiment 1 in order to investigate any instance of rule-based performance in any of the categories. For each participant we found the response (Category A or B) for each stimulus. We then calculated for each block the correlation between the value of each dimension (e.g., square or triangle) and the response. We counted how many participants showed at least two blocks (including

[4] In order to parallel Experiment 1, we also conducted an analysis on the best block for Blocks 1–6, and the same patterns as the primary analyses on average performance were found. An ANOVA found a significant effect of Type, $F(3, 59) = 21.77$, $MSE = .011$; and a nonsignificant interaction of condition and type, $F(6, 59) = 1.99$, $MSE = .011$, $p = .08$. Our post hoc tests pointed to the same conclusions as the main analyses on average performance (verbal concurrent task was impaired relative to the other groups for the DR categories), though the results failed to reach significance in this case.

nonconsecutive blocks) of perfect rule-response correlations. As shown in Table 4, we typically observed single dimension responding only in the SD categories. Only 3 of the 18 participants showed a single-dimensional performance–dimension correlation for the NLS categories. No participants responded to a single dimension for the DR or the FR categories.

Discussion

The key finding in Experiment 2 is that participants in the verbal concurrent task group were impaired relative to both the nonverbal concurrent task and the no-task groups on the DR categories but not on the NLS or FR categories. There was a nonsignificant main effect for the SD categories, but performance in this set was still high for all three groups. In short, it appears that the verbal concurrent task only seriously interrupted the learning of DR categories. The nonverbal concurrent task did not appear to disrupt performance at all. This suggests that learning the DR categories well depends on having access to verbal working memory, whereas learning other categories does not depend on this as strongly.

These results are consistent with other findings in the literature that demonstrate a role for verbal working memory in the learning of rule-described categories but not in the learning of non-rule-described categories (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). Although we have described the NLS set as one that could engage the explicit system (because of the rule and exception strategy), we did not observe the expected effect of the verbal concurrent task. One possibility is that the three-predicate NLS rule takes longer to acquire than does the two-predicate DR rule, since even the no-task group performed poorly. This is consistent with other research using these category sets (J. D. Smith et al., 2004; Shepard et al., 1961). This additional difficulty might obscure any effect of the verbal concurrent task on average performance. However, Figure 4 shows performance on the NLS categories by the verbal concurrent task group dropping relative to the other groups as the experiment ends. It is also possible that some participants have learned the category set via an imperfect similarity-based strategy (perhaps by the procedural system) or even by both systems. Our data do not allow for a clear distinction among these alternatives, but the learning of NLS categories remains an interesting area for future research.

The results of Experiment 2 also suggest that a parsimonious explanation for the failure of the children to learn the DR categories in Experiment 1 is that children have less verbal working memory ability. However, working memory ability is not entirely absent in children, and it is not clear from the results of Experiments 1 or 2 whether children (at any of the ages) can learn rule-defined categories like the DR category set under some circumstances. We suspect that (at least by age 5) they can make use of the explicit system and learn these kinds of categories if given the appropriate task support so that working memory is less burdened. In the same way that increasing the task demands in Experiment 2 resulted in "child-like" performance by some adults, we predicted that decreasing the task demands might result in "adult-like" performance by some of the children. To investigate this possibility, we conducted a third study that attempted to reduce the task demands for 5-year-old children learning the DR and the FR categories.

Table 4
Number of Participants Using Single-Dimensional Rules in Experiment 2

Task	SD	DR	NLS	FR
No task	6	0	0	0
Verbal task	6	0	1	0
Nonverbal task	6	0	2	0

Note. Total possible number of participants in each cell is 6. SD = Type I (single dimension) from Shepard et al. (1961); DR = Type II (disjunctive rule) from Shepard et al. (1961); NLS = Type III (nonlinearly separable) from Shepard et al. (1961); FR = Type IV (family resemblance) from Shepard et al. (1961).

Experiment 3

In a third experiment, we investigated a possible reason why the children in Experiment 1 performed so poorly on the DR categories. Taken together, the findings of Experiments 1 and 2 not only provide support for the multiple-systems account of category learning but also highlight the critical role of working memory for the explicit system. Working memory capacity and efficiency develops throughout childhood (Gathercole, 1999; Swanson, 1999), which also seems to coincide with the development of prefrontal cortex (Casey et al., 2000), a region of the brain implicated in many cognitive processes. Since learning DR categories relies heavily on working memory and attentional capacity, children's difficulties with DR category learning could be due to working memory capacity limitations interfering with the operation of the verbally-based explicit system (Ashby et al., 1998).

Experiment 3 was designed to determine whether changing the task demands would enable young children to extract and use DR rules and to perform at adult-like levels on this task. Since traditional category learning tasks utilize working memory and attentional resources in a number of different ways (e.g., being able to focus on all the relevant dimensions, determining that each exemplar is a consistent member of a given category, remembering where each exemplar belonged, and ultimately formulating and holding onto the propositions of the underlying rules for the category), we attempted to limit some of these demands by increasing the transparency of the category learning task. Prior to categorization, participants in Experiment 3 were asked to name each of the exemplars. This manipulation placed attentional focus on all three of the relevant dimensions (size, shape, and color). In addition, when completing this naming activity, children were shown the exemplars in their category grouping and were told that each was going to be one "family" of creatures. While there was no explicit mention of the rule or the relationships between the exemplars, this manipulation made children aware that they would later have to group the items consistently into families. By altering the instructions we gave to the children, and by familiarizing them with the exemplars, we attempted to reduce the overall processing load of the category learning task.

Although we reduced the task demands for the category learning task in general, we predicted that the improvement would be selective. Since working memory plays a critical role only in the learning of rule-described categories (via the explicit system), we expected that the improvement would be seen only in the acquisition of the DR categories and not the FR categories. If the procedural system is engaged in the learning of the FR categories, then a reduction of task demands should not result in much improvement of performance (Waldron & Ashby, 2001).

Method

Participants. Since all groups of children showed comparable difficulties learning the DR categories in Experiment 1, only one group of children, 5-year-olds, was selected for testing in the present experiment. A total of 24 five-year-old children were recruited from a preschool and a daycare center in London, Ontario, Canada. In order to facilitate a comparison of child–adult performance, we also included 20 adults who were undergraduate students at the University of Western Ontario. Four children were dropped from the analyses because they failed to complete the task, so the final analyses included 20 children. Details about the participants are found in Table 5.

Materials. Participants were trained on either the DR or the FR category sets used in Experiment 1. The exemplars used were identical to those used in Experiment 1, varying on three dimensions (color, shape, and size), with faces to appeal to the children. Each set was composed of eight items. Again, as in Experiment 1, the category sets were counterbalanced across participants, so that the irrelevant dimension in the DR set differed across participants.

Procedure. Children were tested individually in a quiet room at their school/daycare. Each child was randomly assigned to one of the two category types. As in Experiment 1, children were told that they would be playing a game in which they would see pictures of different creatures. They were also told that some creatures lived in the mountains and some creatures lived in the forest, and that their job was to help the creatures find their way home by pointing to the correct place on the screen.

The key distinction in Experiment 3 was that prior to the category learning task, children were familiarized with each of the exemplars and the category structure before the category training. Children were shown each of the two groupings of creatures, one grouping at a time, and were then asked to name each of the exemplars. For the first grouping, they were told (for example), "This is the forest family. This one is the big orange triangle (pointing). Can you name the other members of the forest family?" As the experimenter pointed, the child was then required to name the other category members in the same way and was corrected if he or she failed to name all of the features of any given exemplar (e.g., calling the next one a blue square instead of the large blue square). The child was then shown the next category grouping and was told (for example), "This is the mountain family. This one is the big blue triangle (pointing). Can you name the other members of the mountain family?" The child was again asked to name each member and corrected as necessary. The child was then shown both groupings simultaneously, with each group on the side of the screen where their "home" was located, and was told, "This is the forest family, and this is the mountain family. Would you like to play our game now?" This final display, which showed both groups on the screen, was shown only as long as it took the experimenter to read the above statement and the child to respond, about 3 to 5 s.

The training task was identical to Experiment 1. Children were asked to point to either the mountains or trees, and feedback was delivered via animation. Stimuli were presented in 6 random blocks of 8 stimuli for a total of 48 consecutive trials. On completion of the experiment, children at the daycare center were given stickers for their participation, and children at the preschool were given a smiley face drawn on their feedback sheets (a procedure consistent with the preschool's research participant program).

Adults were tested with the same software and basic procedure. The task instructions and the familiarization instructions were presented visually on the computer screen instead of verbally, and the language used was age appropriate. Adults received a partial course credit for their participation.

Table 5
Participant Characteristics for Experiment 3

Age group	N	Age (years)	Male	Female	Dropped
Five-year-old	24	5.37	14	10	4 male
Adult	20	18.5	10	10	0

Results

Learning curve. As with Experiments 1 and 2, we calculated for each participant the proportion correct for each block of trials. The resulting learning curves for each age group and each category type are shown in Figure 6. As can be seen in the figure, although the children perform well, the adults appeared to outperform the 5-year-old children on learning both categories. This would seem to suggest that the pretraining task may have had little effect in children's performance, but the key prediction is whether or not adults and children would perform equivalently on the DR categories in the best block analysis.

Best block analysis. As with Experiments 1 and 2, the proportion correct for each block of trials for each participant was calculated, and as in Experiment 1, we again carried out an analysis on the best block. The average proportion correct for the best block for each participant group on each category is shown in Figure 7. By using an ANOVA with age (adult and 5-year-old) and category (DR and FR), we found a significant main effect of age $F(1, 37) = 8.82$, $MSE = .10$; and of category $F(1, 37) = 5.23$, $MSE = .01$. We failed to find a significant interaction between age and category, $F(1, 37) = 2.32$, $MSE = 0.10$, *ns*, however, this result was not surprising given that the experiment was designed to determine if children could show adult-like performance on the DR categories in particular. Post hoc tests revealed that adults and children did not perform significantly differently from each other on DR category learning (M for adults = .94, M for children = .87) but did perform differently from each other on FR categories (M for adults = .91, M for children = .76). Furthermore, children performed significantly better on DR categories ($M = .87$) than on FR categories ($M = .76$).[5] This pattern (DR > FR) is the usual

[5] As with Experiment 1, we also conducted a parallel analysis with average block that found the same pattern and smaller, though still significant, results. We also conducted the analysis on when the best block occurred. An ANOVA with age and category type on when the best block occurred found no significant effects or interactions. Best blocks were 4.7 for 5-year-olds learning DR, 3.5 for adults learning DR, 3.3 for 5-year-olds learning FR, and 3.8 for adults learning FR.

order of difficulty for adults (J. D. Smith et al., 2004), and this is the same pattern found in our adults in Experiment 2.

We further explored these results by comparing the results of Experiment 3 with the appropriate comparisons from Experiment 1, since the primary methodological difference between the groups was the inclusion of the pretraining task.[6] We conducted an ANOVA with age (adult and 5-year-old), experiment (Experiment 1 and Experiment 3) and category (DR and FR) as between-subjects factors. We found a significant main effect of age, $F(1, 57) = 12.05$, $MSE = .01$; and a main effect of experiment, $F(1, 57) = 13.87$, $MSE = .01$. We also found a significant three-way interaction, $F(1, 57) = 10.02$, $MSE = .01$. No other effects were significant. Post hoc tests indicated that for the DR categories, performance by the 5-year-olds in Experiment 1 ($M = .67$) was worse than performance by the 5-year-olds in Experiment 3 ($M = .89$). The same was true for adults in Experiment 1 ($M = .88$) and Experiment 3 ($M = .94$). Post hoc tests showed that for the FR categories, performance by the 5-year-olds in Experiment 3 ($M = .76$) was lower than performance by the adults in Experiment 3 ($M = .91$) and also that adults in Experiment 3 performed better than adults in Experiment 1 ($M = .75$). No other effects were significant.

Strategy analysis. We again performed a strategy analysis as in Experiment 1 in order to investigate any instance of rule-based performance in any of the categories. For each participant, we found the response (Category A or B) for each stimulus. We then calculated for each block the correlation between the value of each dimension (e.g., square or triangle) and the response. We simply counted how many participants showed at least two blocks (including nonconsecutive blocks) of perfect rule-response correlations. As Table 6 shows, we did not observe any incidence of single-dimensional responding.

Discussion

In Experiment 3, we explored children's ability to learn rule-based categories. Specifically, we investigated the extent to which limitations of working memory and attention may be responsible for the difficulties that young children have with disjunctive rules in traditional category learning tasks. While the children in Experiment 1 performed significantly worse than did adults on DR category learning, in Experiment 3, children and adults showed similar abilities in using disjunctive rules. Furthermore, while in Experiment 1 children had difficulties learning DR categories compared with other category types, in Experiment 3 children performed significantly better on DR than on FR categorization. Finally, the pretraining session did not seem to help children learn the FR categories, since they performed no better in Experiment 3 than in Experiment 1. We suspect that the additional familiarization with the stimuli aided the child's ability to accurately represent the features, thus reducing the working memory load for the children, and allowed their explicit learning system to operate fully and in a way that was comparable with adults.

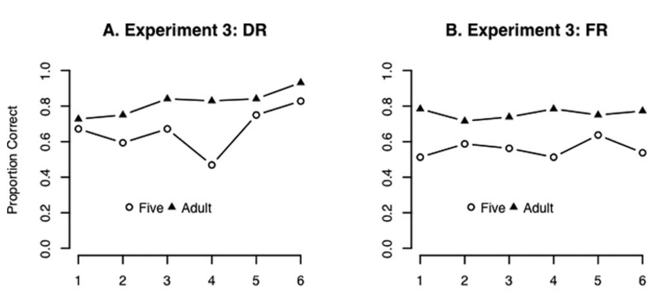

Figure 6. Average performance (across participants) in Experiment 3 for each category set and each age group (in years). DR = Type II (disjunctive rule) from Shepard et al. (1961); FR = Type IV (family resemblance) from Shepard et al. (1961).

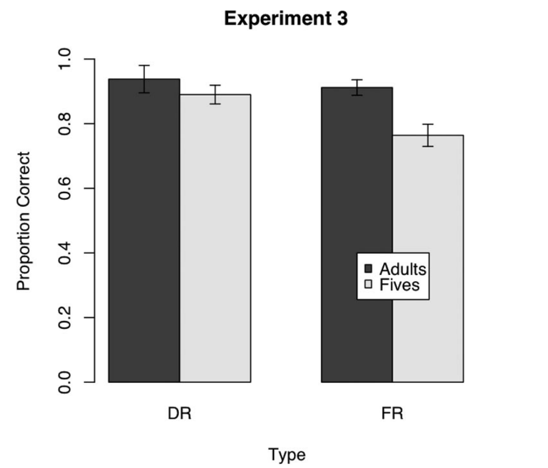

Figure 7. Performance in Experiment 3 on the best block for each category set and age group (in years). DR = Type II (disjunctive rule) from Shepard et al. (1961); FR = Type IV (family resemblance) from Shepard et al. (1961).

Adults, but not children, seemed to improve as a function of the pretraining task on performance of FR categories in the between-experiment comparison analysis. We had predicted that the pretraining would not help in the learning of FR categories, because the FR categories could be learned via the procedural system. There are several possibilities for this result. First, the pretraining session may have helped the adults by reinforcing the association between the features and the category labels (though not the actual motor response, since that was not part of the pretraining task). Second, the pretraining session might also have enabled adults to employ their explicit system to acquire the categories before the procedural system was able to create the cue and response connections. COVIS allows for this kind of simultaneous system learning. Finally, adults may have been able to rely on specific memories for some of the FR category members. We do not have the data to arrive at a clear conclusion, and these possibilities warrant additional work with the learning of FR categories and with the nature of the pretraining task.

Overall, the results of this experiment showed that preschool-aged children have the ability to extract and use disjunctive rules

[6] The children in Experiment 1 were recruited from preschools and daycare centers in Buffalo, NY, and the children in Experiment 3 were recruited from preschools and daycare centers in London, Ontario, Canada. We see no reason why this difference between our samples would lead to any differences in DR category learning.

Table 6
Number of Participants Using Single-Dimensional Rules in Experiment 3

Age group	DR	FR
Five-year-old	0	0
Adult	0	0

Note. Total possible number of participants in each cell is 10. DR = Type II (disjunctive rule) from Shepard et al. (1961); FR = Type IV (family resemblance) from Shepard et al. (1961).

when learning categories. These results, together with the findings of Experiments 1 and 2, illustrate that children's ability to learn disjunctive rules may be constrained by the extent to which the explicit category learning system (i.e., the prefrontal cortex and verbal working memory) is being recruited for other aspects of processing in these tasks, such as keeping the response alternatives in mind and processing the features of each stimulus.

As we and others (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006) have observed, working memory plays an integral role in learning rule-defined categories. The findings of this experiment provide further support for the multiple-systems account of category learning. As Ashby et al. (1998) predicted, on a traditional category learning task, children showed impaired performance when learning complex rule-defined categories but not when learning non-rule-defined categories. It has been assumed that the explicit category learning system relied on working memory for rule learning; the results of Experiments 2 and 3 provide evidence for this assumption.

The findings of Experiment 3 suggest that traditional category learning tasks place demands on working memory and by extension place demands on the explicit system, making it difficult for children to learn complex verbal rules. Our findings are consistent with the literature on the development of rule use and executive control, suggesting that young children have difficulty learning complex rules (Frye et al., 1995). Also consistent with our findings and interpretations, studies have implicated the late development of the prefrontal cortex in difficulties with learning and using specific types of complex rules (Bunge & Zelazo, 2006).

General Discussion

In three experiments, we explored category learning in children of several age groups and adults with various task constraints imposed. In general, children and adults learned the same categories somewhat differently. In Experiment 1, children learned the DR and NLS categories poorly relative to adults, but they learned the SD and FR categories about the same as adults. In Experiment 2, a verbal concurrent task impaired adult's abilities to learn DR categories but did not interfere with learning the other types of categories. Conversely, a nonverbal concurrent task had no effect on performance. Finally, in Experiment 3, children benefited from a reduction in task demands when learning the DR categories but not when learning the FR categories. While Experiment 1 provided the first developmental evidence for multiple category learning systems, Experiments 2 and 3 clarified the role that working memory plays in the development of category learning.

Multiple Systems in Category Learning

Our results suggest some very basic conclusions about how novel categories might be learned. Across the three experiments and the four category sets we tested, we have identified several cases in which a category set is likely to tap into a category learning process that depends on verbal rules and executive processing (e.g., SD, DR, and NLS categories). We also have cases in which a given category set is likely to tap into a nonverbal category learning system (e.g., FR categories). As such, our data can be interpreted within the multiple-systems COVIS theory of category learning (Ashby et al., 1998; Ashby & Ell, 2001; Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). COVIS predicts that the learning of rule-based categories by the explicit system should be disrupted in certain circumstances. Specifically, this theory predicts that an underdeveloped prefrontal cortex and/or a reduction in working memory ability should disrupt the learning of these rule-defined categories. This prediction was confirmed here. The prefrontal cortex and working memory are still developing in children (Bunge & Zelazo, 2006; Casey et al., 2000), and as a result, children performed poorly relative to adults on the DR and the NLS tasks. The adults in the verbal concurrent task condition in Experiment 2 also had a reduced working memory capacity because they were performing the verbal concurrent task, and as predicted, their ability to learn DR categories also suffered.

COVIS also predicts that the procedural system will operate to learn non-rule-defined categories such as the FR categories. The area that mediates the procedural system—the tail of the caudate nucleus—appears to be fully developed in children (Casey et al., 2004). This prediction was confirmed in that children in Experiment 1 performed much like adults in learning the FR categories. COVIS also predicts that since verbal working memory does not play a substantial role in the learning of non-rule-defined categories, any reduction in working memory should not affect the learning of these categories. This prediction was also confirmed because the adults in Experiment 2 who learned while performing the verbal concurrent task learned about the same as control participants on the FR set.

Consider these results in the context of the research by J. D. Smith et al. (2004). They found that humans (adults) learned DR categories relatively easily but that monkeys did not. Monkeys have no ability to learn verbal rules and relied on basic associative learning mechanisms (i.e., the procedural system). This predicts that DR categories will be difficult because of the number of between-category overlaps among the exemplars. In the present research, children behaved like monkeys in that they too found DR categories difficult to learn. The older children could have used language to learn some of these categories, but they did not. This is a key distinction between the present work and the research of J. D. Smith et al. (2004). Whereas Smith et al. claimed that language ability in general might allow for DR category learning (even speculating that language-trained chimpanzees might be able to acquire these categories), we suggest that DR category learning also depends on the development of the prefrontal cortex and adult-like verbal working memory for the explicit category learning system to fully operate. The monkeys do not have the required verbal working memory ability or the prefrontal capacity required to learn DR categories in the same way as adults. The results of the current set of experiments suggest that language-trained chimpanzees might still have difficulty on DR categories because they would still not possess the same degree of verbal working memory ability.

Relationship With the Holistic/Analytic Distinction

Our research can be considered in the context of earlier research regarding the holistic/analytic distinction (Brooks, 1978; Kemler Nelson, 1984; J. D. Smith & Kemler, 1984; J. D. Smith & Shapiro, 1989). This research linked children's performance on category learning tasks with a holistic process that encourages stimuli to be learned as whole exemplars and discourages rule-based performance. This process is not exactly like the procedural system of COVIS but shares with it the reliance on similarity. In the present results, this hypothesis accounts for the equivalence between adults and children on the FR categories and the relatively poor performance by children on the DR categories. A holistic category learning process would predict the FR categories should be relatively easy to acquire on the basis of overall similarity between category members. The DR categories would be problematic for a holistic learning process, since within-category similarity was low. Kemler Nelson (1984) also claimed that adults were more likely to show analytic processing, which favors (verbal) rule learning. This finding is consistent with adults' good performances on the DR categories, since the DR rule is easily verbalizable. The crucial issue is whether or not there are reasons to assume that children, unlike adults, should often default to the implicit system and holistic processing, rather than the more verbally-based explicit system. The multiple-systems theory, the observed differences between children and adults in terms of working memory ability, and the current data offer a compelling explanation for why children do not default to the analytic style like adults do. It is more difficult for them to use the analytic style because they do not have a fully developed prefrontal cortex and lack the necessary working memory capacity for the explicit system to operate effectively.

Single Versus Multiple Systems

The multiple-systems account of category learning has traditionally been contrasted with a single-system account of category learning (Nosofsky & Johansen, 2002; Zaki & Nosofsky, 2001). A common version of a single-system theory is exemplar theory (formalized as the Generalized Context Model), which assumes that people learn categories by storing exemplar traces and make classifications on the basis of similarity to the stored exemplar traces (Nosofsky, 1987, 1988; Nosofsky, 1991). Accordingly, we wondered how exemplar theory would explain our data.

With respect to learning the categories used here, the exemplar model can predict the basic ordering effect observed in most studies with human adults. That is, SD is learned the most quickly, followed by DR and finally the FR categories (Kruschke, 1992; Nosofsky et al., 1994). The reason lies with the number of dimensions needed to solve the task and the degree of exemplar similarity within and between categories. For the DR categories, the exemplar model learns that only two dimensions are relevant, which reduces the amount of information to be learned. As a result, the model accounts for rapid DR learning. However, in its basic form, an exemplar model has no way to account for poor learning of DR by young children.

However, an exemplar-similarity model can make additional assumptions in order to predict poor learning of the DR categories. If one makes the assumption that the dimensions of the task are perceived as *integral* (e.g., hue, saturation, and brightness) as opposed to *separable* (e.g., size, color, and shape), the exemplar model can adjust the exponential in the distance equation, and the result is that DR learning is affected more than learning on the other category structures. In fact, Nosofsky and Palmeri (1996) found that when participants learned the Shepard et al. (1961) Type I–VI categories with integral-dimension stimuli, learning on Type II (DR) was affected more than the learning of the other category types. So in order to explain the results of Experiment 1, in which children were impaired relative to adults on DR and NLS, the model must assume that the children were processing the dimensions as integral ones. This assumption is consistent with earlier work suggesting that children tend to perceive objects as integral wholes (Offenbach, 1990; J. D. Smith & Shapiro, 1989; L. B. Smith, 1989). However, an exemplar model does not make an a priori assumption about whether or not children or adults should perceive the stimulus dimensions as integral or separable, and it has no explanation for why an individual's ability to treat dimensions as integral versus separable should be impacted by working memory demands. On the other hand, COVIS makes clear a priori predictions about both developmental and working memory load differences because of the role it assigns to prefrontal cortical areas for the use of the explicit system. In fact, it may be this neurological evidence that helps to explain the earlier analytic/holistic results. Furthermore, the exemplar model does not offer an explanation for why learning should suffer on NLS categories for the children but not for the adults. Also, it is not clear why the verbal concurrent task of Experiment 2 would lead the adults to perceive the stimuli as integral-dimension stimuli. A more reasonable explanation is that rule use and hypothesis testing—the explicit system—was interrupted by the verbal concurrent task. In short, we argue that the multiple-systems approach to category learning is the best explanation for the results we observed across the three experiments. Nevertheless, the integral/separable dimension notion is an intriguing explanation for our data, and we are continuing to examine this hypothesis.

Although our data cannot be accounted for by an exemplar model, there are other existing single-system models in the literature that can account for our data. One possibility is the SUSTAIN model, which is a clustering model of category learning (Love, Medin, & Gureckis, 2004). This model does not make the assumption that categories are learned via different brain systems. Instead, it assumes that categories can be learned as clusters of similar stimuli. A single cluster can represent one or many exemplars. As such, SUSTAIN has the ability to represent categories as a single prototype, several prototypes, or as single exemplars. Furthermore, SUSTAIN has a mechanism for supervised learning (e.g., explicit, feedback-driven classification) and unsupervised learning. Clustering solutions for a given category set can differ as a result of the learning algorithm used. This model has been applied to developmental data as well as data from participants learning the Shepard et al. (1961) stimuli (Gureckis & Love, 2004; Love, 2002).

For example, Gureckis and Love (2004) applied SUSTAIN to existing infant categorization data and suggested that differences between infants and adults can be characterized by the limitations of the infant's memory and perceptual processes. More recently, SUSTAIN has been applied to a broad range of developmental and patient data (Love & Gureckis, 2007). In SUSTAIN, reduced memory capacity is modeled by reducing the number of clusters that the model forms (e.g., less memory = fewer possible clusters). In general, the mechanisms for forming new clusters are thought to be mediated in part by the prefrontal cortex as well as the hippocampus (Love & Gureckis, 2007). This suggests how the model might be applied to our current data. In the case of the DR categories, a reduced number of clusters would result in impaired learning (similar to the impaired learning observed in the young children in Experiment 1). However, reduced numbers of clusters would not be expected to have as much effect on the FR categories, since the optimal strategy (by SUSTAIN) is to create two prototype clusters.

In addition, there is related evidence that abstracting or learning the DR rule might depend on having explicit classification learning instructions (Love, 2002). In fact, when learning the Shepard et al. (1961) stimuli in an unsupervised learning condition, DR categories are learned very poorly but FR categories are not affected relative to supervised learning conditions. This suggests that classification encourages explicit rule formation, whereas unsupervised learning encourages the learning of family resemblances. This also suggests that a manipulation that does not encourage the formation of explicit rules will result in slower learning of DR categories.

We view the account provided by SUSTAIN to be a viable model for the data presented here because it emphasizes memory differences as a key component to the developmental trajectory. We prefer the COVIS account because of the neuropsychologically motivated predictions regarding prefrontal cortex and explicit category learning. It clearly predicts that the ongoing development of the prefrontal cortex in younger children is linked to their impairment in learning the DR categories. These predictions follow from COVIS and were confirmed in our data. In the end, however, COVIS and SUSTAIN may be complementary accounts, rather than alternative accounts.

Conclusions

The view that multiple brain systems mediate the acquisition of new categories has broad support in the literature (Ashby & Maddox, 2005). This support comes from a multifaceted set of data. In the last 10 years, evidence for this approach has come from studies of various cognitive variables (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006), from patient data (Ashby et al., 1998), from imaging data (Nomura et al., 2007), from comparative work (J. D. Smith et al., 2004), and now from developmental findings. Although our data are clear and encouraging, we used relatively simple and well-tested sets of categories. We are currently working to replicate and extend our results by using the continuous dimension stimuli that are typically used by COVIS researchers (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). Although we feel that the current data describe well the differences between children and adults, they do not yet describe the nature of the trajectory from child-like learning to adult-like learning. We believe that continued work with children and category learning, in concert with an informed neuropsychological account of category learning, will lead to a greater understanding of category learning and categorization across the lifespan.

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