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Current theories of category learning posit separate verbal and nonverbal learning systems. Past research suggests that the verbal system relies on verbal working memory and executive functioning and learns rule-defined categories; the nonverbal system does not rely on verbal working memory and learns non-rule-defined categories (E. M. Waldron & F. G. Ashby, 2001; D. Zeithamova & W. T. Maddox, 2006). However, relatively little research has explored the importance of visual working memory or visual processing for either system. The authors investigated the role of working memory (Experiment 1a and 1b), visual processing (Experiment 2), and executive functioning for each system, using a concurrent task methodology. It was found that visual tasks with high executive functioning demands and verbal tasks with high or low executive demands disrupted rule-defined learning, whereas any visual task, regardless of executive functioning demand, disrupted non-rule-defined learning. Taken together, these results confirm the importance of verbal working memory and executive functioning for the verbal system and provide new evidence for the importance of visual processing for the nonverbal system. These results help to clarify understanding of the nonverbal system and have implications for multiple systems theories of category learning (F. G. Ashby, L. A. Alfonso-Reese, A. U. Turken, & E. M. Waldron, 1998).

Keywords: categorization, multiple systems, visual working memory, executive functioning

The act of categorization allows like objects to be grouped together so that they can later be treated as equivalent for some other purpose. For example, a gardener may group plants into the "needs frequent watering" category and may treat these plants equivalently by watering them regularly. Psychologists and philosophers alike have been interested in the processes that govern this type of categorization. Intuitively, it seems that categorization may involve both visual and verbal processes: Visual processes may be important for forming a perceptual representation of a category and its members, whereas verbal processes may be important for forming a compressed category representation that is easy to store, access, and communicate. That is, our gardener could learn to represent the category in terms of the visual features that are typically found in plants that need regular watering. The gardener could also store the important category features verbally (e.g., "Water plants that have thin leaves that lack a waxy coating"). In both cases, the gardener would water a new plant frequently if it shared features with other plants in the "needs frequent watering" category, but the decision process could vary according to whether a verbal or a visual category representation was used.

A substantial amount of research shows that verbal processes are indeed important during categorization, but comparatively little research has focused on the role of visually based cognitive processes, such as visual working memory and visual processing, during categorization. One of the goals of the present study is to investigate the role of these visual processes during category learning. Another goal is to specify how these various cognitive components (verbal resources, visual resources, and executive functions) fit together in an overall theory of category learning.

Multiple Systems in Category Learning

Recent categorization theories suggest that multiple brain/cognitive systems are involved in learning categories (Poldrack & Foerde, 2008; Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby & O'Brien, 2005). This type of multiple systems framework provides an ideal way to differentiate the role of verbal and visual processes during category learning. Although the majority of multiple systems theories propose a verbally based categorization system and some sort of nonverbal categorization system, relatively little research has investigated the differential role of verbal working memory, visual working memory, and executive functioning within these systems.

The Competition Between Verbal and Implicit Systems model (COVIS) is a multiple-systems theory which proposes that categories are learned using at least two systems: a verbal system and an implicit, nonverbal system (Ashby et al., 1998). For our purposes, we refer to these two systems as the *verbal system* and the *nonverbal system*. Although these two systems are in constant competition with each other, the verbal system is typically the default categorization system. The verbal system determines an item's category membership through the use of a verbalizable rule. For example, imagine a category set in which blue items go in one category and red items go in another category. This category set is

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called a rule-defined (RD) category and could be learned easily by the verbal system, because the rule "Category 1 items are blue" is easy to verbalize. To find the optimal rule, the verbal system may have to engage in hypothesis testing, which involves holding a rule candidate in memory, processing categorization feedback to determine whether the rule was correct, and remembering which rules have already been tested to optimally select the best rule candidate. To engage in hypothesis testing, the verbal system relies heavily on domain-specific verbal working memory resources (to hold a description of the candidate rule for active processing) and domain-general executive functioning (to facilitate selection among rules, to coordinate attentional resources, to inhibit responding to other features or rules, and to inhibit incorrect responses). With respect to its neural underpinnings, the verbal system involves conscious, controllable processes that are mediated by the prefrontal cortex (for rule generation and testing), the medial temporal lobe (to store the categorization rule), and the head of the caudate nucleus (for working memory and executive functioning; Ashby et al., 1998; Ashby & Valentin, 2005; Nomura et al., 2007; Nomura & Reber, 2008).

Rather than hypothesis-driven rule testing, the nonverbal system uses feedback to extract the properties that are common to a category, and it associates these extracted properties with a category label. Although the nonverbal system can learn RD categories (albeit in a non-rule-based way), it is optimally suited for learning categories that are not easily described by a verbal rule. For example, information integration (II) is one type of category that is learned well by the nonverbal system. Imagine a set of line stimuli that vary in terms of the length and orientation of each line. For II categories, multiple stimulus values, such as a line's length and orientation, must be integrated or combined before a categorization decision is made. Although II categories can sometimes be described verbally, such a description is difficult to apply, because stimulus dimensions are expressed in different units and are not readily comparable. In accordance, even if a verbal description is possible, it is unlikely to be used for classification. For example, "a line whose orientation is greater than its length goes in Category 1" might be an optimal rule for an II category, but this rule is not likely used for categorization because length and orientation are not directly comparable (Ashby et al., 1998). Because the nonverbal system is based on nonverbal processes, its functional attributes do not enter into verbal working memory. Rather, the system is assumed to rely on the visual processing of the stimuli and the correct association of cues to responses. The nonverbal system is mediated by the body and tail of the caudate nucleus, where dopamine-mediated learning takes place, and the nonverbal system learns incrementally as well as automatically and without conscious control (Ashby & Ennis, 2006). Once a to-be-categorized stimulus is viewed, the visual information is sent from the visual cortex to the caudate nucleus, where a motor program is chosen to carry out the categorization. When an item is categorized correctly, correct feedback acts as an unexpected reward and causes dopamine to be released, strengthening the association between the stimulus and the correct categorization response. When an item is categorized incorrectly, the release of dopamine is depressed and the association between the stimulus and categorization response is not strengthened (Ashby et al., 1998; Ashby, Ennis, & Spiering, 2007).

There is ample research, using a range of techniques, which has consistently provided support for the existence of separate category learning systems, such as those suggested by COVIS. Specifically, research has shown that verbal and nonverbal categories are learned in different ways, using different neuropsychological mechanisms. A number of fMRI studies have confirmed COVIS's prediction that the verbal and nonverbal systems rely on different regions of the brain (Ashby et al., 1998, 2007; Seger & Cincotta, 2002). In addition, patients with Huntington's disease and Parkinson's disease, who have a degeneration of the dopamine-mediated learning system that is important to the nonverbal system, have particular difficulty learning II categories (Ashby & Waldron, 1999; Ashby, Waldron, Lee, & Berkman, 2001; Filoteo, Maddox, & Davis, 2001). As well, the learning of II categories is impaired when no feedback is provided (Ashby, Maddox, & Bohil, 2002; Ashby, Queller, & Berretty, 1999), or when feedback is delayed (Maddox, Ashby, & Bohil, 2003; Maddox & Ing, 2005), because the presence and timing of the dopamine release is important for nonverbal learning. In contrast, hypothesis testing is impaired when verbal resources are occupied by a concurrent task (Minda, Desroches, & Church, 2008; Waldron & Ashby, 2001; Zeithamova & Maddox, 2006) or when feedback processing is restricted (Zeithamova & Maddox, 2007), resulting in impaired learning by the verbal system but intact learning by the nonverbal system. Therefore, there is converging evidence from a wide range of techniques suggesting that there are at least two category learning systems. Furthermore, this evidence supports COVIS's account of verbal and nonverbal systems that rely on separate neuropsychological learning mechanisms.

Procedural Learning and the Nonverbal System

Although the verbal system is well understood in terms of the resources it uses and the experimental manipulations that affect it (Ashby et al., 2007), comparatively less is known about the nature of the nonverbal system. It has been suggested that the nonverbal system learns via procedural learning mechanisms (Ashby et al., 1998), but this claim has become less clear with more recent research. For example, initial evidence for the procedural nature of the nonverbal system comes from a category learning study whose results mirrored those of a previous procedural learning study. For both the procedural memory system and the nonverbal categorization system, the ability to associate each stimulus with a consistent response location facilitated learning (Ashby, Ell, & Waldron, 2003; Willingham, Wells, Farrell, & Stemwedel, 2000). For the nonverbal category learning system, this involved learning a consistent response for each category (e.g., if Category A, push the left button). However, a recent study has shown that II categories can be learned when neither a consistent response location nor a consistent motor response is available (Spiering & Ashby, 2008). This evidence suggests that motor response is just one of many cues that the nonverbal system can learn to associate with a category.

In another study investigating the importance of response type (Maddox, Bohil, & Ing, 2004), participants indicated whether a stimulus was a member of Category A (or Category B) by pressing the "yes" or "no" button. Stimuli were not associated with a consistent response location, because each stimulus could have elicited a "yes" response or a "no" response, depending on the wording of the question. Again, II categorization was diminished, suggesting that consistent response location and/or motor response is important for the nonverbal system and implicating procedural learning as the driving mechanism of the nonverbal system. However, a more recent study showed that II categorization is only impaired when a difficult response type (i.e., yes/no) is coupled with an inconsistent response location, a finding that suggests that task difficulty, not just procedural interference, may be responsible for poor performance on II categories (Spiering & Ashby, 2008). Taken together, these studies suggest that the nonverbal system may not be solely reliant on procedural learning mechanisms. In accordance, our current study aims to investigate other learning mechanisms, such as visual processing and visual memory, that may be used by the nonverbal system in conjunction with procedural learning or when purely procedural learning is not effective.

Categorization, Working Memory, and Executive Functions

An important distinction between the verbal and nonverbal systems has been their relative reliance on conscious, controlled cognitive processes, such as working memory and executive functions. Recall that the verbal system engages in hypothesis testing to identify the optimal categorization rule. In comparison, because the nonverbal system does not rely on a verbal rule during categorization, it does not engage in hypothesis testing and therefore taxes cognitive resources to a lesser extent. In addition, the verbal system benefits from the ability to recode visual stimuli into verbal descriptions. These verbal descriptions may be used to convey information about the stimulus, act as a compact format for stimulus storage in working memory, and decrease vulnerability to visual interference. However, this utility comes at a cost, as the translation process takes time and cognitive resources. Therefore, decreasing available working memory and executive function resources should result in poor performance by the verbal system but leave nonverbal system performance intact.

Studying children's categorization confirms the importance of working memory and executive functioning in categorization, because these resources are not fully developed in children (Luciana & Nelson, 1998; Luna, 2001). Young children who were trained on a category set learned by the verbal system acquired the category less quickly and accurately than did older children. However, when trained on a category set learned by the nonverbal system, young children performed as accurately as older children and acquired the category at a similar rate (Kemler Nelson, 1984). Similarly, performance on a very simple verbal category increased with age in young children, but all children performed poorly on categories based on more complex verbal rules (Minda et al., 2008). However, even 3-year-old children performed similarly to adults on a family-resemblance category that could be learned via similarity and without a verbal rule. Taken together, these studies support the idea that verbal working memory and executive functions are important for the verbal system but seem to be less important for the nonverbal system.

An alternative way of approaching the relationship between working memory and categorization is by comparing individual differences in working memory and categorization ability. It is not surprising that people with low working memory capacity are slower at learning RD categories than people with high working memory capacity. More interesting, people with low working memory capacity are faster at learning II categories than people with high working memory capacity (DeCaro, Thomas, & Beilock, 2008). Not only do these results point to the importance of working memory for the verbal system, they also suggest that verbal working memory resources may actually be detrimental to the nonverbal system by prolonging hypothesis testing and slowing down the transition from the verbal to the nonverbal system.

A decrease in working memory and executive resources is induced when participants perform a concurrent task during category learning. In a series of studies (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006), participants learned either an RD or a non-rule-defined category set (II categories or family resemblance categories). Half of participants did so while also performing a verbal task that used working memory and executive resources; the others had no concurrent task. The concurrent verbal task impaired performance on all types of RD categories to a greater extent than it impaired performance on non-rule-defined categories. Still, it is possible that the correct type of concurrent task may interfere with the nonverbal system. For example, the effect of a concurrent visual task on category learning is unknown.

The Visual Nature of the Nonverbal System

Although the research discussed above has specified the role of verbal processing and procedural learning in category acquisition, most multiple systems theories do not directly address the visual processes that are used during categorization by either system. Studying the categorization abilities of animals gives us an idea of the level of categorization proficiency that can be reached without the use of any verbal resources. For example, rhesus monkeys are able to abstract a prototype after seeing a number of category exemplars (Smith, Redford, & Haas, 2008). Perhaps more surprisingly, dogs (Range, Aust, Steurer, & Huber, 2008) and pigeons (Herrenstein & Loveland, 1964) are able to learn complex categories (i.e., human) without the use of any verbal resources. Not only can these animals correctly categorize old exemplars, they can also generalize the categories to novel stimuli. Even more impressive, when a category member (i.e., human) is superimposed on a previously trained noncategory member (i.e., mountains), animals can identify the category member and inhibit the noncategory response to make the correct category-member-present response (Range et al., 2008). The categorization abilities of animals that lack language illustrate the significance of visual categorization.

Research on human categorization has largely ignored the role of visual resources in categorization. For example, claims about the working memory requirements of the categorization systems have largely been based on the effects of concurrent tasks that can be solved verbally (i.e., verbal information or visual information that can easily be translated into a verbal code). In fact, these tasks have often been chosen specifically for their tendency to use brain regions specific to the verbal system (Waldron & Ashby, 2001). Therefore, it is not surprising that the nonverbal system is unimpaired by these concurrent tasks. Intuitively, it is reasonable to expect that a visual concurrent task could interfere with the nonverbal system to a greater extent than the verbal system.

In addition, neurobiological evidence suggests that the tail of the caudate, which mediates the nonverbal system, is involved in visual processes that may be important to category learning. The tail of the caudate receives projections from the extrastriate visual cortex (Ashby et al., 1998), and these projections are unique because they allow for the compression of a large amount of visual information into a relatively small number of caudate cells (Wilson, 1995), a process that is akin to categorization. As well, rats with lesions to the tail of the caudate nucleus are impaired at visual discrimination learning, a skill that is particularly important to categorization (Packard & McGaugh, 1992). The visual underpinnings of the tail of the caudate may predispose the nonverbal system to be especially reliant on visual processes.

The nonverbal system learns to associate the visual representation of an object with its category label. The caudate receives projections from extrastriate visual areas and learns to associate patterns of activation in the extrastriate with the correct category label through dopamine-mediated learning (Ashby & Ennis, 2006). Essentially, the caudate learns to associate a category label with clusters of visual cortical cells that respond to perceptually similar stimuli (Maddox, Filoteo, & Lauritzen, 2007). Therefore, the nonverbal system learns best when visual similarity within a category is high. Discontinuous categories that have multiple clusters of stimuli within a single category are not learned well by the nonverbal system because within category similarity is low (Maddox et al., 2007). The nonverbal system struggles to associate multiple dissimilar clusters of visual cortical cells with a single category label, likely because additional caudate cells are needed to represent these extra stimulus clusters. In contrast, during RD categorization, each stimulus is categorized by applying the categorization rule. It is not necessary to store stimuli that follow the categorization rule in long-term memory. Instead, each time an item is to be categorized, the rule is applied and a categorization decision is made (Davis, Love, & Maddox, 2009). Because the verbal system uniformly applies the categorization rule, within-category similarity is relatively unimportant, and discontinuous categories are learned as well as continuous categories.

In addition, when novel stimuli are categorized, the similarity of the novel stimulus to previously learned stimuli affects nonverbal categorization accuracy but not verbal categorization accuracy (Maddox et al., 2007). For II categorization, low perceptual similarity to trained stimuli generates a weak response from the caudate, resulting in poor categorization performance. For RD categorization, low perceptual similarity is inconsequential for rule application, and categorization performance remains high. Therefore, whereas RD categorization relies on verbal resources and executive functioning to correctly search for and apply a categorization rule, II categorization relies on perceptual similarity and visual resources to activate the correct category label.

Based on neurobiology and reliance on similarity, the nonverbal system seems to be more dependent on visual processes than the verbal system.[1] However, these claims have never been tested directly. One aim of the current set of studies is to directly test the importance of visual cognitive resources by measuring categorization performance by each system when visual cognitive resources are made unavailable through the use of a visual concurrent task.

To the best of our knowledge, no visuospatial task has been used concurrently with categorization to investigate whether visuospatial resources are used during category learning. Zeithamova and Maddox (2007) used a visuospatial task, but it was implemented following the categorization decision (i.e., sequentially), rather than during the trial (i.e., concurrently). That is, immediately after receiving feedback on their categorization, subjects completed either a visuospatial working memory task, a verbal working memory task, or no task. It was reasoned that because the nonverbal system does not process feedback verbally (Maddox, Bohil, & Ing, 2004), it may instead do so using visuospatial resources. In this case, the sequential visuospatial task could impair the nonverbal system by using up the cognitive resources that it uses for feedback processing. In actuality, Zeithamova and Maddox's results revealed that the sequential visuospatial working memory task did not interfere with information integration learning. Although initially somewhat surprising, these results illustrate that the nonverbal system processes feedback automatically, without the use of visuospatial working memory. However, Zeithamova and Maddox's study did not address how the nonverbal system initially encodes categories or with what resources this information is processed. Using a concurrent visuospatial task, rather than one that is sequential, may help address these issues.

The Current Studies

The goal of the present studies was to examine the nature of the cognitive resources used during RD and II category learning. Specifically, we examined separately the role of verbal and visual processing as well as the role of executive functioning during category learning by using a concurrent task paradigm. The roles of verbal working memory, visual processing, and executive functioning were isolated using concurrent tasks that targeted each cognitive process. Experiments 1a and 1b investigated the role of verbal and visual working memory during RD and II category learning. Experiment 2 focused more closely on the contributions of visual processing on category learning by the nonverbal system. To anticipate, our results suggest that RD categories are learned via the coordination of executive functioning resources and verbal processes, whereas II categories are learned via the use of visual processing resources and feedback with minimal contributions from working memory or executive functions.

In all experiments, participants either learned a rule-defined category or an information integration category. For each type of category, participants learned to place pictures of crystal balls into Category A or Category B. Figure 1A illustrates a RD category where the vertical line separating Category A and Category B, known as the decision bound, represents the strategy that maximizes categorization accuracy (Ashby & Gott, 1988). Points falling to the left of the decision bound are members of Category A and points falling to the right of the decision bound are members of Category B. Therefore, this category is described by the rule "Crystal balls with few lines go in Category A, crystal balls with many lines go in Category B." Figure 1B illustrates the II category used in the current study. The decision bound in Figure 1B can be expressed as "If the lines in the crystal ball have a greater orientation than frequency, the ball goes in Category A; otherwise, it goes in Category B." However, this is not a practical categoriza-

[1] We are only suggesting that visual categorization by the nonverbal system depends on visual processes. Categorization in other modalities likely relies on other types of perceptual memory.

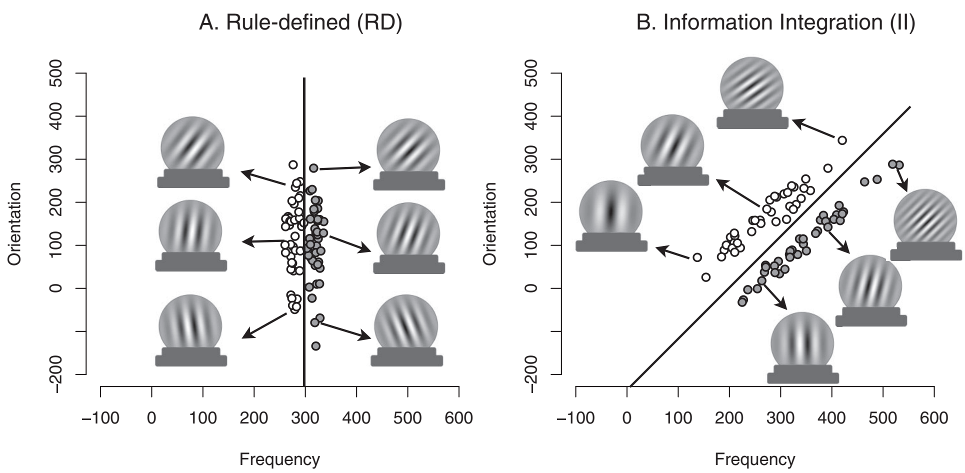

Figure 1. A. Category structure for a rule-defined category. Each light circle represents a stimulus from Category A, and each dark circle represents a stimulus from Category B. B. Category structure for an information integration category.

tion rule because frequency and orientation are not directly comparable; instead, this category is thought to be learned nonverbally.

Experiment 1a

In Experiment 1a, participants learned to categorize either an RD or an II category set. Some participants learned to categorize while performing a concurrent verbal working memory task, some learned to categorize while performing a concurrent visuospatial working memory task, and some learned to categorize without a concurrent task.

A numerical Stroop task was used for the concurrent verbal task. Participants were shown two digits, varying in value and size, at the beginning of each categorization trial and were asked to recall this information at the end of the trial (Waldron & Ashby, 2001). Therefore, participants were required to hold the value and size of each digit in verbal working memory and use executive functioning to inhibit responses based on a single dimension. In the visual concurrent task condition, a visuospatial analog of the Sternberg (1966) memory scanning task was used. In this task, participants were shown a dot pattern at the beginning of each categorization trial and were asked to recall information about the location of the dots at the end of the trial. Therefore, participants were required to hold the pattern of dots in visuospatial working memory for the duration of the categorization trial. In accordance with previous research (Minda et al., 2008; Waldron & Ashby, 2001; Zeithamova & Maddox, 2006, 2007), it was expected that the verbal working memory task would tax verbal resources and executive processing and interfere with RD learning by the verbal system. In addition, because the visuospatial working memory task also taxed executive processing (by requiring the allocation of resources and necessitating the temporary inhibition of a response to the visual task), it was also expected to interfere with RD learning, but perhaps to a lesser extent than the verbal working memory task.

Also in accordance with previous research (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006), the verbal working memory task was not expected to have as much of an effect on II learning, which is thought to be learned without using verbal working memory and executive functioning. Finally, because visual processes seem to be especially important for the nonverbal system, it was expected that the visuospatial working memory task would interfere with II learning.

Method

Participants. Participants included 148 adults (72 men, 76 women) from the University of Western Ontario, London, Ontario, Canada, with a mean age of 18.92 years (SD = 0.99) who participated in the study for course credit. Each participant learned either an RD or an II category set, and each type of category was learned either with no concurrent task, a concurrent verbal task, or a concurrent visuospatial task. The data from three participants was discarded from analysis because more than 25% of their categorization reaction times occurred within 500 ms of stimulus onset.[2] The remaining participants took part in one of six conditions, described in detail in the next section.

Materials. Participants learned to classify sine wave gratings (a visual pattern) that varied in spatial frequency and spatial orientation. For the RD category, a total of 80 stimuli were generated (Ashby & Gott, 1988; Zeithamova & Maddox, 2006), with 40 stimuli in Category A and 40 stimuli in Category B. The distribution of each category was specified by a mean and variance for frequency and orientation and covariance between frequency and orientation, which were the same as those used by Zeithamova and Maddox (2006). Category A stimuli were generated by randomly sampling 40 values from a multivariate normal distribution described by Category A's parameters, and Category B stimuli were generated by randomly sampling 40 values from a multivar-

[2] In Experiments 1a and 1b, the participants discarded on the basis of response time also exhibited poor categorization performance. In Experiment 1a, the average performance of discarded participants was .53, whereas the average performance of the remaining participants was .72. In Experiment 1b, the averages were .52 and .70, respectively. In both cases, a t test revealed that the performance of the discarded participants was significantly worse than that of the remaining participants.

iate normal distribution described by Category B's parameters (see Table 1). Stimuli for the II category set were generated in the same way, except that different parameter values (i.e., different distributions) were used. The resulting category structures for RD and II category sets are illustrated in Figures 1A and 1B.

We then used the PsychoPy package (Pierce, 2007) and the Python computer language to generate a sine wave grating corresponding to each coordinate sampled from the distributions above. For both II and RD categories, sine wave grating frequency was calculated as $f = .25 + (x_f/50)$ cycles per gradient and orientation was calculated as $o = 0.36x_0$ degrees. Each stimulus was 230×230 pixels on a 1440×900 screen. We added two solid lines to the bottom of each stimulus, so that the entire stimulus resembled a crystal ball, which would then be classified as belonging to a certain wizard (category). The order of the 80 stimuli was randomly generated on each block for each participant.

Procedure. Half of participants in each condition learned the RD category set, and half of participants learned the II category set. On each trial, participants in the control conditions (RD-C and II-C) completed the categorization task only, and participants in the verbal and visuospatial conditions (RD-V, II-V, RD-VS, and II-VS) saw a memory stimulus, performed the categorization task, and then recalled some aspect of the memory stimulus. Figure 2 illustrates the trial sequence for each condition, including the exact timing of the events in each trial. All participants completed four blocks of 80 trials.

Participants in the control condition (C) performed a categorization task that consisted of assigning the crystal ball stimulus to the correct wizard category, as indicated by the two wizards on the screen. The stimulus remained on the screen throughout the entire trial. On each trial, the participant indicated which wizard owned the crystal ball by pushing the "blue" key for the blue wizard and the "green" key for the green wizard.[3] The word "correct" was displayed in orange for a correct categorization, and the word "incorrect" was displayed in black, followed by an intertrial interval.

Participants in the verbal condition (V) completed a verbal working memory task concurrent with the categorization task. The method used to generate stimuli for the concurrent verbal task was similar to that used by Waldron and Ashby (2001). At the beginning of each trial, two digits were flashed to the left and the right of the categorization stimulus, followed by a black rectangular mask. The digits varied in numerical value (between two and eight) and in physical size (90 pixels or 180 pixels). The value and size of the digits were assigned so that on 85% of trials, the numerically largest digit was physically smallest. On the remaining 15% of trials, the numerically largest digit was also physically largest. Participants were to remember the size and value of each digit throughout the trial. Next, in the categorization stage of the task, participants categorized a wizard's crystal ball and received feedback as described in the control condition. In the final stage of the trial, the question "Which number had the largest size?" appeared on the screen for half of the trials, and "Which number had the largest value?" appeared on the screen for the other half of trials. Participants indicated on which side of the screen the number with the largest size/value appeared by pressing the "left" or "right" key. For example, if a large 5 appeared on the left side of the screen and a small 7 appeared on the right side of the screen, followed by the question "Which number had the largest size?" the correct response was "left." Feedback on the verbal task was given by presenting the word "correct" in orange or the word "incorrect" in black, followed by an intertrial interval. After the tenth trial, the word "value" or "size" was used to prompt the participant's response for the verbal task, instead of the entire question, "Which number had the greatest value (size)?" We wanted to ensure that participants remembered the response type that was expected at each stage of the trial, so we embedded instructions within the first 10 trials. However, the presentation of extra verbal information may interfere with working memory and category processing so the prompting questions were removed once participants were familiarized with the experiment procedures. For similar reasons, feedback was no longer given for the concurrent task after the tenth trial, although feedback remained for the categorization task.

Participants in the visuospatial condition (VS) completed a dot pattern task concurrently with the categorization task. On each trial, a new dot pattern was generated using a method that was similar to the one used by Zeithamova and Maddox (2007). At the beginning of each trial, we defined a 9×9 grid in the center of the screen and placed nine dots on the grid so that one grey dot (50 pixels in diameter) appeared in every row and every column. Then a memory set was created by highlighting four of the nine dots with a red circle (30 pixels in diameter), followed by a mask where all nine dots turned red. In the categorization stage of the task, participants categorized a wizard's crystal ball and received feedback as described in the control condition. In the final stage of the trial, the original pattern of nine dots reappeared, and a memory probe was created by turning one of the nine dots red. On half of trials, the memory probe dot was one that was also turned red in the initial memory set. At the same time, the question "Was this dot originally red?" appeared on the screen, and participants pressed the "old" button if the dot was one of the four red dots in the memory set or pressed the "new" button it was not. Feedback on the dot pattern task was given by presenting the word "correct" in orange or the word "incorrect" in black, followed by an intertrial interval. As with the verbal condition above, the question "Was this dot originally red?" was no longer presented after 10 trials, and feedback was no longer given for the concurrent task.

Table 1
Distribution Parameters for Rule Defined and Information Integration Category Sets

Category structure	μ_f	μ_o	$\sigma2_f$	$\sigma2_o$	$\mathrm{cov}_{f,\,o}$
Rule defined					
Category A	280	125	75	9,000	0
Category B	320	125	75	9,000	0
Information integration					
Category A	268	157	4,538	4,538	4,351
Category B	332	93	4,538	4,538	4,351

[3] In all experiments, the "1" and "0" keys on a standard USB keyboard were labeled "blue" and "green." The "Q" and "O" keys were labeled either "left" and "right," "new" and "old," or "no" and "yes," depending on the wording of the concurrent task question.

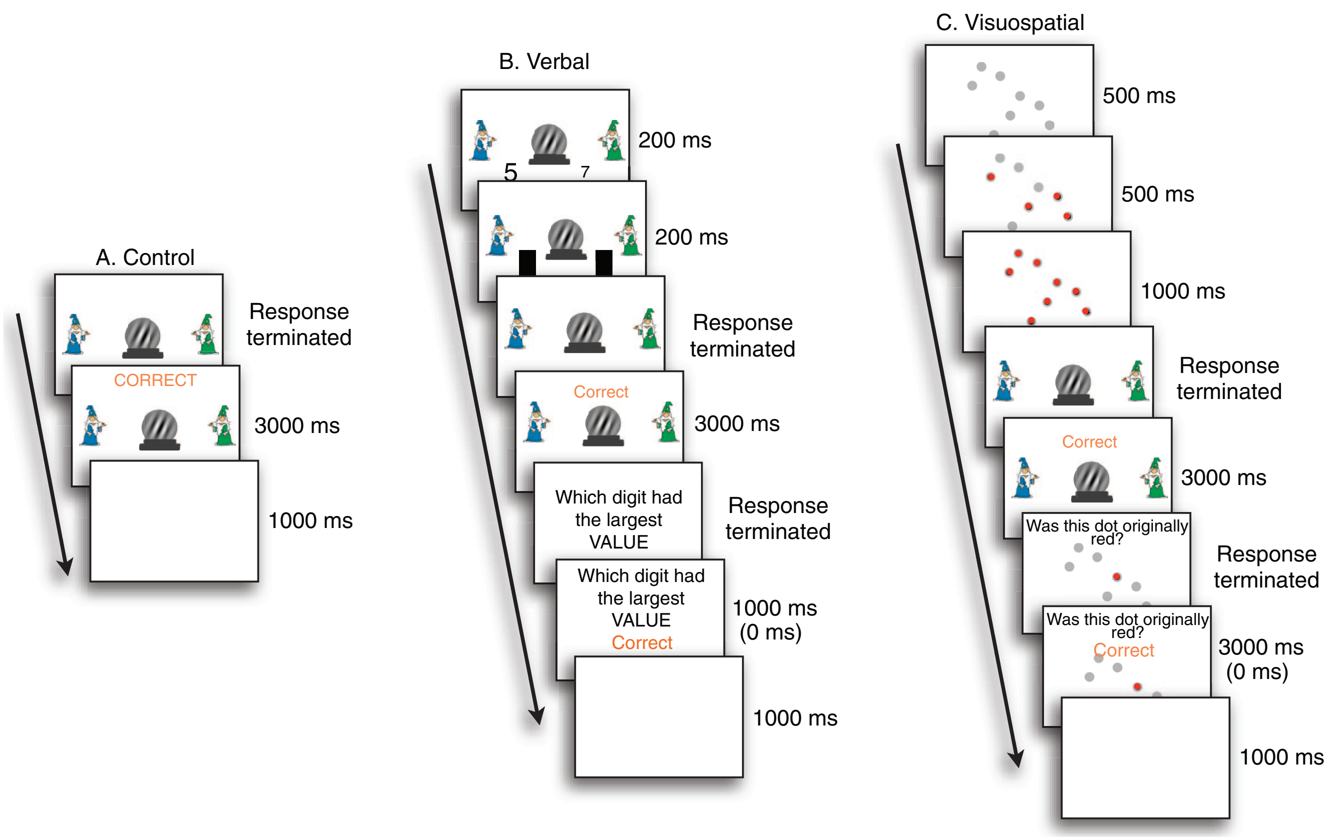

Figure 2. Task designs for the first 10 trials of Experiment 1a. A. Control condition. B. Verbal condition. C. Visuospatial condition. Timing for trials 11–320 is given in parentheses.

It was important that participants attended to the concurrent tasks in the verbal and visuospatial conditions to ensure a decrease in resources available for the subsequent categorization task. Participants were instructed to do as well as possible on the concurrent task and to use leftover resources for the categorization task. Every 10th trial, performance on the concurrent task was checked, and the participant was warned to improve performance if it had dropped below 80%.

Results

Concurrent task performance. Average performance on the verbal concurrent task was .90 (SD = 0.09) for RD learners and .87 (SD = 0.11) for II learners, and performance on the visuospatial task was .87 (SD = 0.10) and .84 (SD = 0.10) for RD and II learners, respectively. A 2 (Set) × 2 (Concurrent Task) analysis of variance (ANOVA) illustrated that verbal and visuospatial concurrent task performance did not differ, $F(1, 99) = 2.15$, $p = .15$, concurrent task performance did not differ depending on category set, $F(1, 99) = 1.57$, $p = .21$, and there was no interaction between concurrent task type and category set, $F(1, 99) = 0.04$, $p = .84$. These results suggest that the verbal and visuospatial concurrent tasks roughly taxed cognitive resources to the same extent, although different sets of resources were taxed.

Of the participants who completed a concurrent task during categorization, 20 (approximately 19%) were excluded from analysis because they failed to achieve 80% correct on the concurrent task. Twelve participants (seven II-VS, five RD-VS) failed to reach 80% correct on the visuospatial task, and eight (six II-V, two RD-V) failed to reach 80% correct on the verbal task.[4] The number of remaining subjects in each condition is given in Table 2.

Categorization performance: Individual data. To illustrate the range of performances that our participants showed, we first examined the individual learning data. Figure 3 illustrates individual learning curves for participants in each condition. First considering the RD category set, performance in the RD-C condition was uniformly quite high, suggesting consistent rule learning across participants. In contrast, performance in the RD-V condition was composed of a group of participants who appear to have learned the categorization rule quickly, a group of participants who showed delayed rule learning, and a group who showed no learning across the entire experiment. It is interesting that performance in the RD-VS condition mirrored that of the RD-V condition, suggesting that taxing verbal and visual working memory stores resulted in similar RD category learning deficits. Whereas all participants in the RD-C condition learned the category, 32%

[4] There was no effect of set or condition on the number of participants who failed to reach criterion in each condition, $\chi^2(1) = 0.08$, $p = .77$.

Table 2
Participant Ns, Means, and Standard Deviations for Overall Categorization Performance in Experiment 1a

Condition	*N*	*M*	*SD*
Rule defined			
Control	22	.82	.12
Verbal	22	.72	.19
Visuospatial	19	.72	.17
Information integration			
Control	20	.71	.08
Verbal	21	.69	.10
Visuospatial	21	.65	.09

failed to learn in the RD-V condition and 26% failed to learn in the RD-VS condition.[5]

Performance on the II categories was less clear. In the II-C condition, participants' categorization performance clustered relatively tightly around 70% correct. A similar pattern emerged in the II-V condition, showing that taxing verbal working memory and executive functions did not impair II performance. Of particular interest, performance in the II-VS condition was shifted slightly lower than the other II conditions and individual performance appeared to be more variable. These results suggest that II performance was impaired by a concurrent visual task but not by a concurrent verbal task. In the next section, comparing mean performance across conditions provides a more formal examination of the above trends.

Categorization performance: Averaged data. The individual data presented in Figure 3 were averaged together by subject to examine the effects of block and condition. The resulting learning curves for each condition are shown in Figure 4. Our hypotheses addressed the effect of concurrent task type on each category set, so we carried out ANOVAs to examine the effect of condition on RD category learning and on II category learning.

For the RD category set, a 3 (Condition) × 4 (Block) mixed ANOVA revealed an effect of block, $F(3, 180) = 41.94$, $p < .001$. This effect was expected and simply indicates category learning throughout the experiment. More interesting, a main effect was found for condition, $F(2, 60) = 4.34$, $p = .017$, and no interaction was found between block and condition, $F(6, 180) = 0.81$, $p = .56$. To further investigate the effect of condition, we conducted planned comparisons to compare overall performance in the control condition with each of the concurrent task conditions. Table 2 illustrates overall performance, collapsed across blocks, for each condition. Performance in RD-C was significantly better than RD-V, $F(1, 61) = 6.48$, $p = .013$, and RD-VS, $F(1, 61) = 6.47$, $p = .014$. These analyses corroborate the trends demonstrated in the individual learning curves.

The analogous analyses were carried out for the II category set. A 3 (Condition) × 4 (Block) mixed ANOVA again found the expected effect of block, $F(3, 177) = 10.10$, $p < .001$. There was also a significant Block × Condition interaction, $F(6, 177) = 2.42$, $p = .028$. Examination of Figure 4B reveals that in the first block of learning both concurrent tasks affected II performance, but for the remainder of learning, only the visuospatial task caused impairments. Recall that participants were instructed to perform well on the concurrent task and use their remaining cognitive resources for the categorization task. Therefore, the low II-V performance early in learning is likely a result of favoring the concurrent task while learning to do the two tasks simultaneously.

There was also a significant effect of condition, $F(2, 59) = 3.55$, $p = .035$. It was explored further by carrying out planned comparisons that compared overall performance in II-C to II-V and II-VS (see Table 2). Overall, the verbal task did not affect II performance relative to the control, $F(1, 60) = 0.32$, $p = .57$, but the visual task did, $F(1, 60) = 6.59$, $p = .013$. In contrast with RD category learning, which was impaired by both concurrent tasks, II category learning only showed evidence of impairment as a result of the concurrent visuospatial task.[6]

Discussion

In Experiment 1a, we found that RD learning was impaired by the addition of both a verbal and a visual concurrent task, suggesting that the verbal system uses some combination of verbal and executive functioning resources throughout learning. II learning was only impaired by the visual task, suggesting that visual resources are important for learning by the nonverbal system. However, there are alternate explanations of our data that need to be addressed.

First, although the numerical Stroop task did have a verbal component (e.g., storing and rehearsing the information "big five, little seven"), it also taxed executive functions (inhibiting a simple response based on magnitude). It is difficult to disentangle the decrements in RD performance caused by the verbal component of the Stroop task from those caused by the executive function component. The use of a verbal task with less of an executive function component could help to clarify their relative contributions.

Second, it is possible that participants may have been solving the numerical Stroop task with a visual strategy rather than a verbal strategy. In that case, the observed RD-V impairment could suggest that both the verbal and nonverbal system rely on visual processing resources. We do not think the Stroop task was solved visually, as this should also cause low II-V performance, and most participants reported solving the task verbally. However, the use of a more standard verbal task that is unlikely to be solved visually would resolve this issue.

Third, the verbal and visuospatial tasks were not entirely comparable. They differed in timing and whether the categorization

[5] Only those participants who learned the RD category set were classified as learners or nonlearners, because in all three experiments, there was a clear delineation between learners and nonlearners by the final block for the RD category but not for the II category. For all experiments, the cluster of learners fell above 70%, and the cluster of nonlearners fell below 70%, so nonlearners were those who failed to perform above 70% correct on the final block of categorization.

[6] One may be inclined to argue that the II task is generally more susceptible to interference because it is a more difficult task, indicated by lower overall performance. If this was the case, then II should be impaired by all types of concurrent tasks. Because we only found interference from visual tasks, this suggests that the overlap in cognitive resources used for the visual task and for learning the II category, not task difficulty, accounts for decrements in II performance.

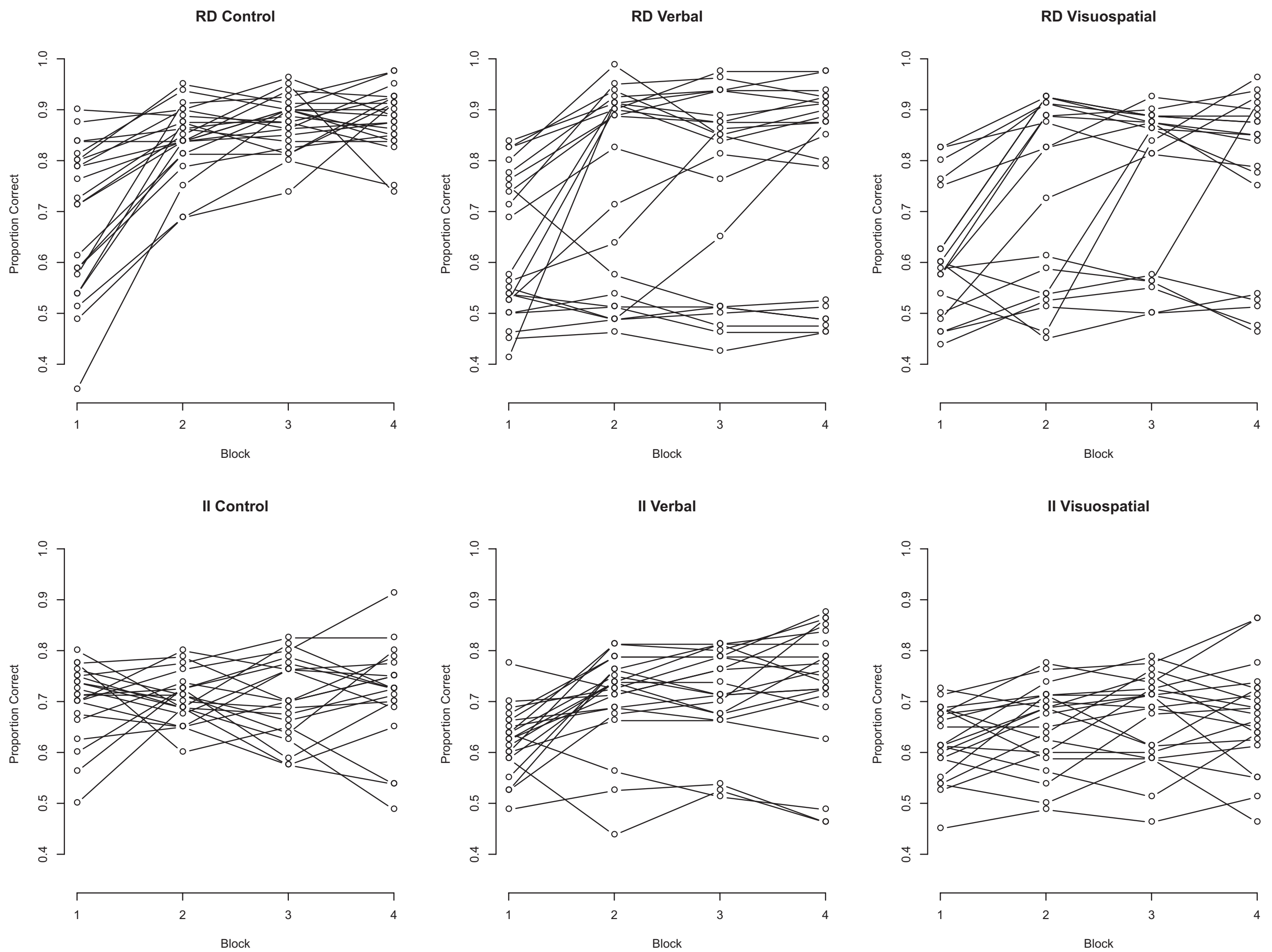

Figure 3. Individual learning curves, by condition, for Experiment 1a. Each curve represents a single participant's performance. RD = rule defined; II = information integration.

stimulus was on the screen during the concurrent task. Although we do not think these small differences affect our conclusions, more comparable verbal and visuospatial tasks would confirm our conclusions. We carried out Experiment 1b to replicate the findings of 1a using an alternate verbal task to address the above concerns.

Experiment 1b

Just like Experiment 1a, Experiment 1b tested the effect of verbal and visual concurrent tasks on II and RD learning. Experiment 1b used the same visual task as 1a but used a different verbal task that was more analogous to the visual task and that was less taxing for executive functions than the one used in our first experiment. The Sternberg memory scanning task (Maddox, Ashby, Ing, & Pickering, 2004; Sternberg, 1966; Zeithamova & Maddox, 2007) was chosen for the verbal concurrent task. At the beginning of each trial, participants saw a series of four digits, which they stored in memory throughout the categorization decision and categorization feedback. At the end of each trial, participants were shown a single digit and indicated whether it was one of the four digits they saw at the beginning of the trial. This task taxed verbal memory, as did the Stroop task in Experiment 1a, but put less strain on executive functions, because the answer to the memory question was simpler to compute for the memory scanning task than for the Stroop task.

It was expected that the memory-scanning task would interfere with RD learning but perhaps to a lesser extent than in Experiment 1a, because the memory scanning task was less taxing for executive functions. In accordance with Experiment 1a, the memory scanning task was not expected to affect II learning. Because the visual working memory task was the same as the one used in Experiment 1a, the task was still expected to decrease performance on both the RD and the II category sets.

Method

Participants. Participants included 151 adults (76 men, 75 women) from the University of Western Ontario with a mean age of 19.85 years (*SD* = 3.54) who participated in the study for

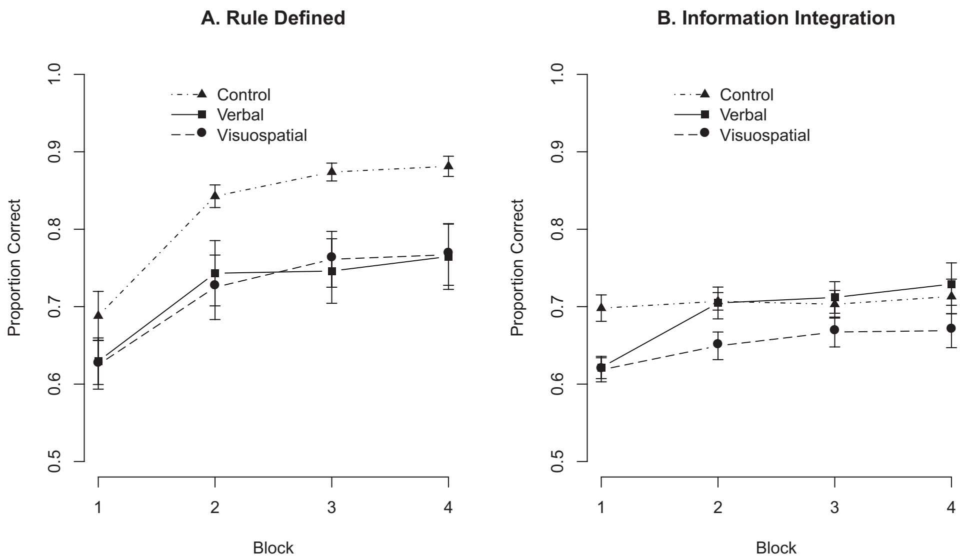

Figure 4. Average proportion correct by condition and category type for Experiment 1a. Error bars denote standard error of the mean.

course credit or for payment of \$10.[7] Ten participants were excluded because more than 25% of their categorization reaction times were faster than 500 ms from stimulus onset. Another two participants were excluded from analyses because they were inattentive to the task. The remaining participants took part in one of six conditions, described below.

Materials. Categorization stimuli were the same as those used in Experiment 1a, except for one change. Orientation was now calculated using the formula $o = x_o \times (\pi/20)$ to translate sampled x_o values into degrees.

Procedure. Participants were split into the control (C), verbal (V) and visuospatial (VS) conditions. Figure 5 illustrates the events and timing of each condition. As in Experiment 1a, half of participants learned the RD category set and half learned the II set, and all participants completed four blocks of 80 trials.

The C and VS conditions were exactly the same as those used in Experiment 1a. Participants in the V condition carried out the Sternberg memory scanning task concurrently with categorization. Each trial began with four dashes in the center of the screen. Next, four digits between 1 and 9 were randomly selected without replacement and were displayed briefly on the screen, followed by a mask. Participants were to remember the value of the digits throughout the trial. Next, participants categorized the crystal ball and received feedback, as in the C condition. Finally, a single digit was shown on the screen along with the question "Was this digit originally shown?" Half of the time the digit was one of the four initial digits. Participants responded by pushing the "yes" or the "no" key.

Consistent with Experiment 1a, the concurrent task question ("Was this digit originally shown?" or "Was this dot originally red?") was only presented for the first 10 trials, and feedback on the concurrent task was only given for the first 10 trials. Also in line with the first experiment, participants were instructed to do as well as possible on the concurrent task.

Results

Concurrent task performance. Average concurrent task performance was .94 ($SD = 0.05$) and .92 ($SD = 0.09$) in the RD-V and II-V conditions, respectively, and .87 (SDs = 0.09 and 0.08, respectively) in both the RD-VS and II-VS conditions. A 2 (Set) $\times$ 2 (Concurrent Task) ANOVA showed that performance on the verbal task was significantly higher than performance on the visual task, $F(1, 92) = 14.57$, $p < .001$, suggesting that the verbal task was easier than the visual task. It is important to note, however, that there was no effect of category set, $F(1, 92) = 0.48$, $p = .49$, and no interaction between concurrent task type and category set, $F(1, 92) = 0.06$, $p = .80$. This shows that any differential effect of concurrent task for each category type is not simply due to concurrent task performance. Three participants in the RD-VS condition, five in II-VS, and one in II-V were excluded from further analyses because they failed to achieve 80% correct on the concurrent task. The number of remaining subjects in each condition in given in Table 3.

Categorization performance: Individual data. Figure 6 shows that, similar to Experiment 1a, performance in the RD-C condition was uniformly high. As well, the majority of subjects who learned the RD set with a concurrent task (RD-V, RD-VS) learned the category well; however, a subset of participants failed to learn anything. This was true whether the concurrent task was verbal or visual in nature, as everyone in the RD-C condition learned, but 27% of participants in the RD-V and 32% of participants in the RD-VS condition failed to learn.

For the II category set, performance in the II-C and II-V conditions looked similar. Most participants performed moderately well, and very few participants failed to learn at all. In the II-VS

[7] Categorization performance did not differ between participants who received course credit and those who were paid in any experiment.

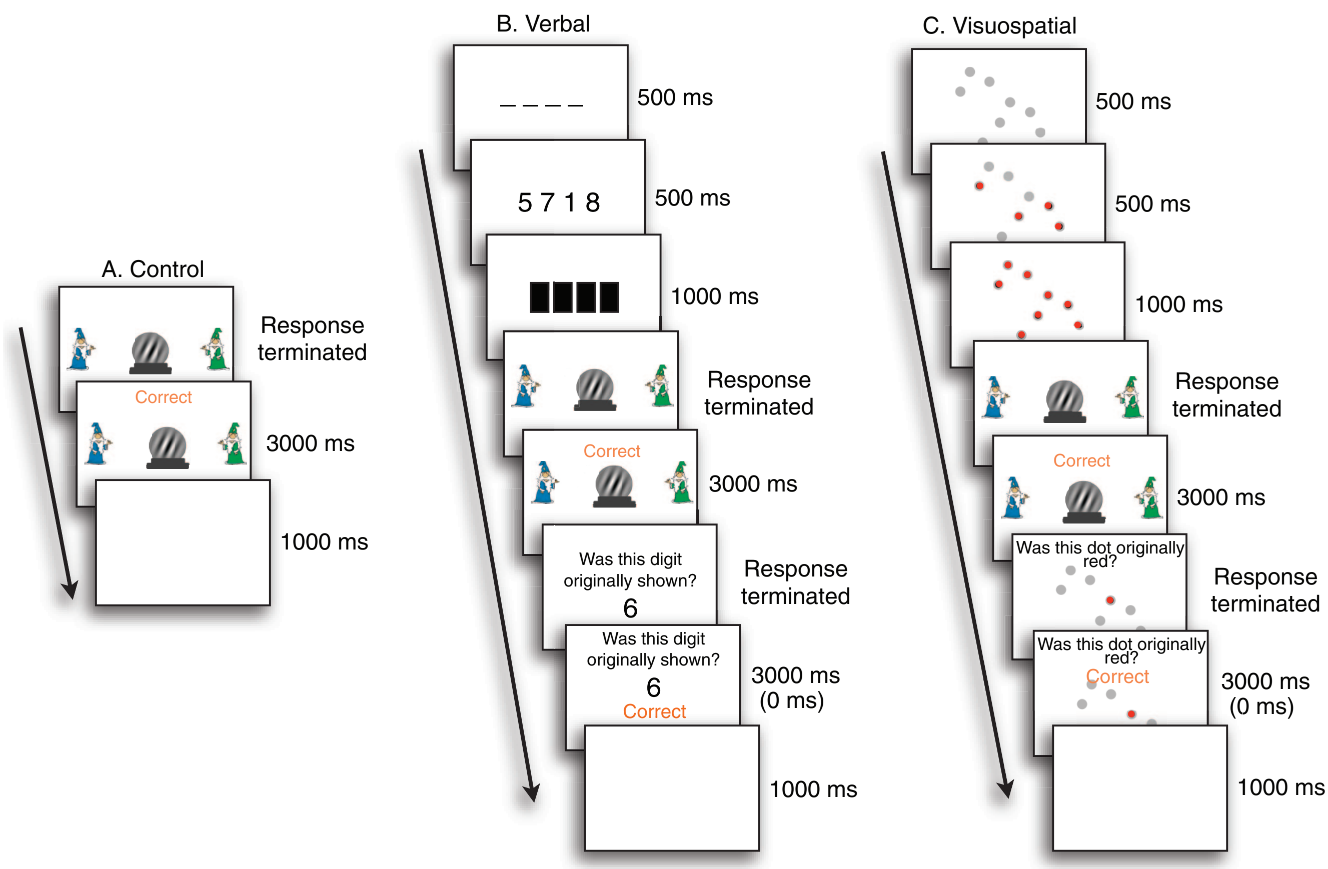

Figure 5. Task designs for the first 10 trials of Experiment 1b. A. Control condition. B. Verbal condition. C. Visuospatial condition. Timing for trials 11–320 is given in parentheses.

condition, the distribution was shifted down so that many participants failed to learn throughout the experiment. This pattern suggests that only the visual concurrent task decreased II learning, similar to what was found in Experiment 1a.

Categorization performance: Averaged data. As in the first experiment, averaged learning curves were computed for each condition and are displayed in Figure 7. A 3 (Condition) $\times$ 4 (Block) mixed ANOVA was carried out for the RD category set, and there was a significant effect of block, $F(3, 186) = 66.18$, $p <$ .001. Unlike in Experiment 1a, there was no effect of condition, $F(2, 62) = 1.85$, $p = .17$. However, there was an interaction between block and condition, $F(6, 186) = 3.68$, $p = .002$. Inspection of Figure 7a reveals that the effect of condition emerges over time. Initially, there was no difference between conditions, but in later blocks, participants in the RD-C condition outperformed participants in the RD-V and RD-VS conditions. When a one-way ANOVA with a pooled error term was used to examine the simple main effect of condition at each block, this trend was confirmed. There was no effect of condition at the first block, $F(2, 84) = 0.09$, $p = .91$, the effect of condition was nearing significance for the second, $F(2, 84) = 2.11$, $p = .13$, and third blocks, $F(2, 84) = 2.35$, $p = .10$, and reached significance at the fourth block, $F(2, 84) = 3.94$, $p = .02$. That is, by the end of learning, performance in the RD-V and RD-VS conditions was worse than RD-C.

Similarly, a 3 (Condition) $\times$ 4 (Block) mixed ANOVA was carried out for the II category set. Again, a significant effect of block was found, $F(3, 186) = 28.86$, $p < .001$. Although the interaction between block and condition was not significant, $F(6, 186) = 0.78$, $p = .58$, there was a marginally significant effect of condition, $F(2, 62) = 3.10$, $p = .052$. To further investigate this marginal effect, performance was collapsed across blocks (see Table 3), and planned comparisons were carried out to compare performance in the control condition to each of the concurrent task conditions. II-C and II-V performance did not differ, $F(1, 63) = 0.003$, $p = .95$, but II-VS performance was significantly worse than II-C, $F(1, 63) = 4.70$,

Table 3
Participant Ns, Means, and Standard Deviations for Overall Categorization Performance in Experiment 1b

Condition	*N*	*M*	*SD*
Rule defined			
Control	21	.79	.13
Verbal	22	.72	.18
Visuospatial	22	.72	.18
Information integration			
Control	22	.67	.10
Verbal	22	.66	.11
Visuospatial	21	.61	.10

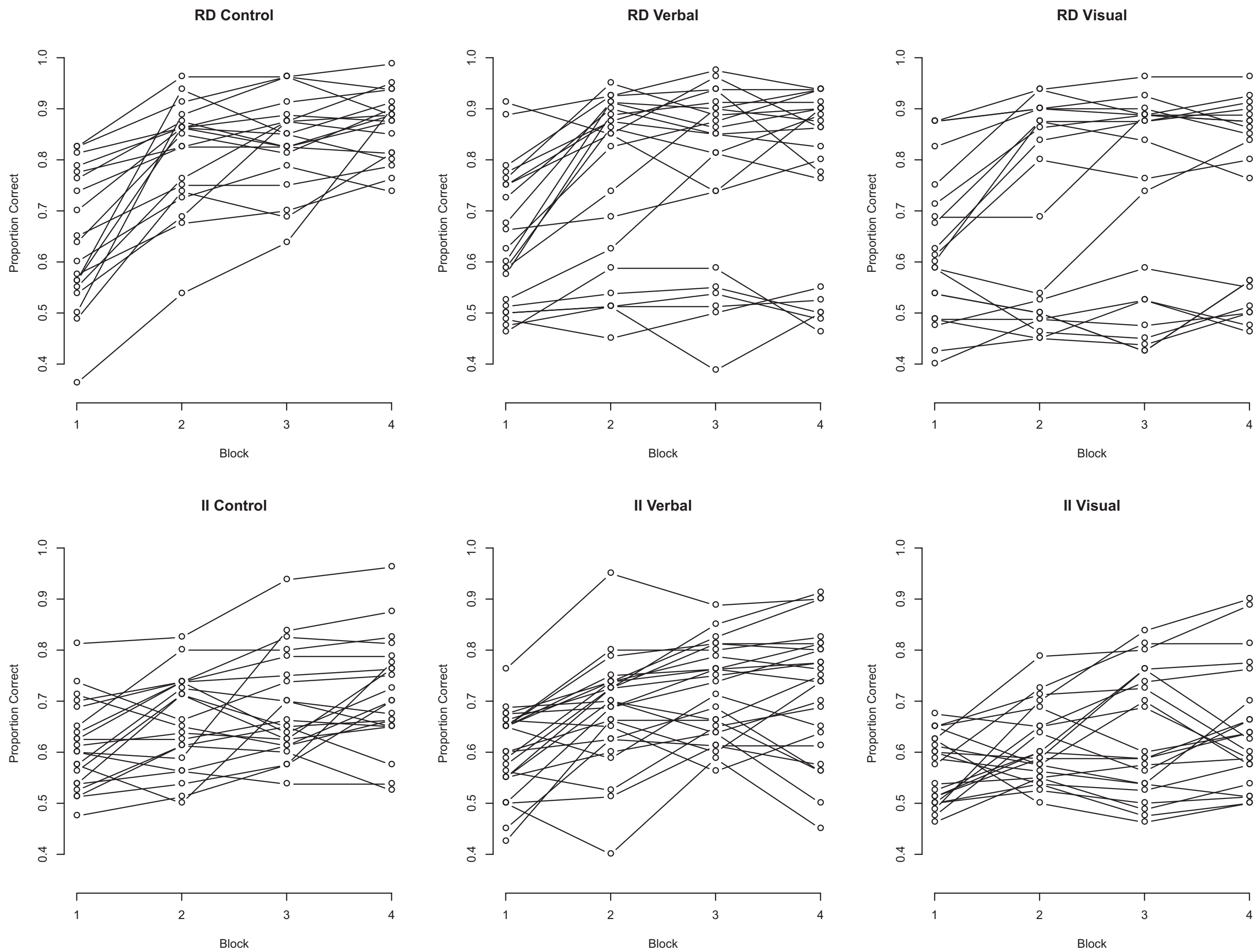

Figure 6. Individual learning curves, by condition, for Experiment 1b. Each curve represents a single participant's performance. RD = rule defined; II = information integration.

p = .03. Therefore, as in the first experiment, only the visual task impaired II performance.

Discussion

Experiment 1b investigated the role of verbal and visual resources in category learning by the verbal and nonverbal systems. As in Experiment 1a, RD performance was impaired equally by the verbal and visual concurrent task. This is noteworthy because the current verbal task likely used less executive functioning than the verbal task in Experiment 1a, which suggests that the verbal working memory component of the task harmed the verbal system's performance. Also corroborating Experiment 1a, II performance was only reduced by the visual concurrent task.

Taken together, the first two experiments replicated previous research (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006) and conformed to our expectations that verbal working memory and executive functioning used in the verbal concurrent task would diminish performance by the verbal system, which also uses verbal working memory and executive functioning. In addition, the individual learning curves suggested that the locus of the effect seemed to be a reduction or delay in the rule acquisition of some, but not all, participants.

More interesting, the visual working memory task also impaired RD learning in both experiments. This visual task uses little, if any, verbal resources, but it does tax executive functioning. Specifically, executive functioning could be used to bind color and location information and to actively rehearse to the visual information through the categorization trial. This finding, perhaps to a greater extent than any previous results, points to the importance of executive functioning for the verbal system. Even when very few working memory resources are shared between the categorization task and concurrent task, the overlap in executive functioning resources was so detrimental that RD categorization was impaired to the same extent as when both working memory and executive functioning overlapped. At this point, we cannot rule out visual interference as the locus of the RD-VS impairment, but Experiment 2 is designed to test this possibility.

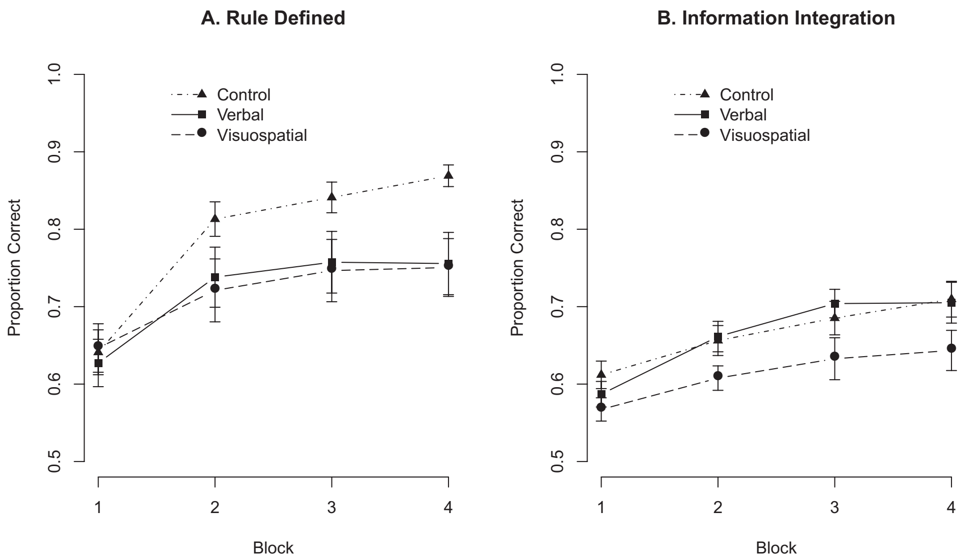

Figure 7. Average proportion correct by condition and category type for Experiment 1b. Error bars denote standard error of the mean.

Second, II category learning was impaired by the visual working memory task but not by the verbal working memory task in both experiments. Because the verbal task did not impair II learning, it suggests that neither executive functioning nor verbal working memory play a very big role in learning categories for which there is no verbalizable rule. That is, verbal working memory is not important for learning II categories because no verbal rule can produce optimal categorization performance. Similarly, executive functioning is not important for learning this II set because there is no need for hypothesis testing procedures. Instead, II categories are probably learned via a nonverbal, similarity-based system.

Because the visuospatial task did impair II learning, these results indicate the importance of visual processing resources for the nonverbal learning system. Specifically, some cognitive process unique to the visual working memory task must also be important for the nonverbal category learning system. The effect of the visuospatial task on II categories is important in that we have demonstrated an effect of interference on the learning of II categories by a task with specific processing requirements. Because the effect of visuospatial tasks previously had not been tested concurrently with category learning, we feel that our results, which do suggest a special reliance of visual processing in learning II categories, shed some much needed light on how the nonverbal system encodes and processes category information and extends existing theories.

Leaving Experiment 1a and 1b, we were faced with a general “concurrent task” effect in which verbal and visual concurrent tasks reduced performance for participants learning the rule defined categories. This general effect suggests a key role for executive functions in learning categories that require not only verbal encoding of stimulus features but also hypothesis testing and inhibition. We were also faced with a more specific “visual processing” effect in which only the visuospatial task disrupted learning in the II categories. The specific effect suggests that learning II categories may rely very little on working memory and executive functions. In Experiment 2, we sought to clarify both of these effects.

Experiment 2

One potential weakness of Experiment 1a and 1b is that our manipulations may have failed to isolate working memory (i.e., visuospatial rehearsal) from more general visual processing in the concurrent visuospatial task. That is, II performance may have been impaired by the visuospatial task because the task taxed the visual working memory system or because the task impaired *general* visual processing abilities. This is an important distinction, because visuospatial working memory suggests a conscious process, but we do not assume that the visual processes at work in the nonverbal category learning system are necessarily open to conscious inspection. If visual processing, rather than visual working memory, is important to nonverbal categorization, then doing a simple visual processing task during categorization should impair II learning. In addition, although we suspect that executive functioning is responsible for the breakdown in performance by participants learning the RD categories, we could not rule out the possibility that the visuospatial task affected RD learning simply because it disrupted visual processing *in general*. The aim of Experiment 2 was to replicate some of the key findings, to disambiguate these alternative explanations of Experiments 1a and 1b, and to provide a strong source of evidence for the cognitive processes involved in learning RD and II categories.

In Experiment 2, a modified version of the visual working memory task from Experiment 1a and 1b was used. In Experiment 2, we embedded the visuospatial task within the categorization task, rather than embedding the categorization task within the visuospatial task, as in Experiment 1. That is, in our previous experiments, participants were required to hold the visuospatial stimulus in memory while carrying out the categorization task, whereas in Experiment 2, participants were required to hold the categorization stimulus in memory while carrying out the visuospatial task. The visuospatial task in Experiment 1a and 1b was a difficult working memory task, because visuospatial information was held in memory throughout categorization. On the other hand, the visuospatial task in Experiment 2 was less taxing for visual working memory, because the visuospatial stimulus was held in memory for a very short period of time, although it still did use some visual working memory. We also included a condition that featured a visual task with no memory component at all, to investigate the effects of pure visual interference on learning II categories. This task was more akin to a visual interference task, because processing the visuospatial stimulus interfered with visual processing resources, but not verbal memory resources, that may have been necessary for the nonverbal system.

As in our previous experiments, participants either learned an RD or an II category set. Some participants learned to categorize with a visual memory task inserted between stimulus viewing and categorization response (visual memory condition), some learned with a visual interference task inserted between stimulus viewing and categorization response (visual processing condition), and some learned with no concurrent task (i.e., an unfilled delay) between stimulus viewing and categorization response (control condition).[8]

Method

Participants. Participants included 160 adults (55 men, 105 women) from the University of Western Ontario, with a mean age of 20.52 years ($SD = 5.73$) who participated in the study for course credit or for payment of $10. Two of these participants were excluded from analyses because they were inattentive to the task. The remaining participants took part in one of six conditions, described below.

Materials. Categorization stimuli were the same as those used in Experiment 1b.

Procedure. Participants were split into the control condition (C), visual memory condition (VM) and a visual processing condition (VP). Figure 8 illustrates the trial sequence for each condition, including the exact timing of the events in each trial. All participants completed four blocks of 80 trials.

Participants in the C condition completed a categorization task similar to the one completed in the C condition in Experiments 1a and 1b, except that there was a delay between the stimulus presentation and categorization response. At the beginning of each trial, a crystal ball and a blue wizard and a green wizard appeared on the screen. Then the screen turned blank for 4,000 ms (the amount of time taken to complete the visual task in the VP and VM conditions, excluding response times of approximately 300 ms). Next, the wizards and the question "Does the crystal ball go with the blue wizard or the green wizard?" reappeared on the screen until the participant indicated which wizard owned the crystal ball by pressing the appropriate key. Categorization feedback was given, followed by an intertrial interval. Note that, unlike in Experiments 1a and 1b, the question "Does the crystal ball go with the blue wizard or the green wizard?" was printed at the bottom of the screen for part of each trial, and the categorization stimulus was not visible during categorization feedback. These changes were necessary because of the delay between the stimulus and response.

Each trial in the VM condition was similar to trials in the C condition, except that the blank screen was filled by a visuospatial task. After the crystal ball disappeared from the screen, a fixation point appeared in the middle of the screen, indicating the beginning of the dot pattern task. Next, nine grey dots appeared on the screen and the memory set turned red, followed by a series of four quickly presented masks. Each mask was a 9×9 grid of grey dots, half of which had a red center. Following the masks, the memory probe appeared on the screen along with the question "Was this dot originally red?" Participants made a response using the appropriate button and received feedback. Next, the wizards and categorization question reappeared on the screen, the participant categorized the previously seen crystal ball, and feedback was given.

Finally each trial in the VP condition was similar to trials in the VM condition. This condition presented participants with the same visual information but without the memory component. When the probe dot was displayed, participants were simply asked "Is this dot red?" and they made a response using the appropriate button and received feedback. Next, the wizards and categorization question reappeared on the screen, the participant categorized the previously seen crystal ball, and feedback was given.

Similar to Experiments 1a and 1b, after the 10th trial, the question "Does the crystal ball go with the blue wizard or the green wizard?" was no longer presented. In the VM and VP conditions, the fixation point was no longer shown, the question "Was this dot originally red?" or "Is this dot red?" was no longer presented, and concurrent task feedback was no longer given. Therefore, the total time taken to complete the dot pattern task was reduced from approximately 4,000 ms to approximately 2,000 ms. The blank screen delay in the C condition was shortened from 4,000 ms to 2,000 ms to reflect the tasks in the VM and VP conditions.

As before, participants in the VM and VP conditions were instructed to do as well as possible on the concurrent task, using any left over cognitive resources for the categorization task. Participants were warned when concurrent task performance dropped below 80%.

Results

Concurrent task performance. Performance on the visual memory task was .98 ($SD = 0.04$) for RD-VM and .97 ($SD = 0.06$) for the II-VM condition. Performance on the visual processing task was 1.00 ($SD = 0.00$) in both the RD-VP and II-VP conditions. A 2 (Set) $\times$ 2 (Concurrent Task) ANOVA revealed that performance on the visual processing task was significantly higher than performance on the visual memory task, $F(1, 103) = 13.16$, $p < .001$. These results suggest that the visual processing task was easier than the visual memory task. Note, however, that performance on both tasks was consistently very high and that errors on the visual processing task were almost nonexistent. More important, concurrent task performance was equal for RD and II category sets, $F(1, 103) = 0.16$, $p = .69$, and there was no interaction between concurrent task type and category set, $F(1, 103) = 0.18$, $p = .68$. One participant in the RD-VM condition and one participant in the II-VM condition were excluded from further

[8] We also ran a condition with no delay between stimulus viewing and categorization response. Performance in this condition was similar to performance in the control condition for the RD and II category set.

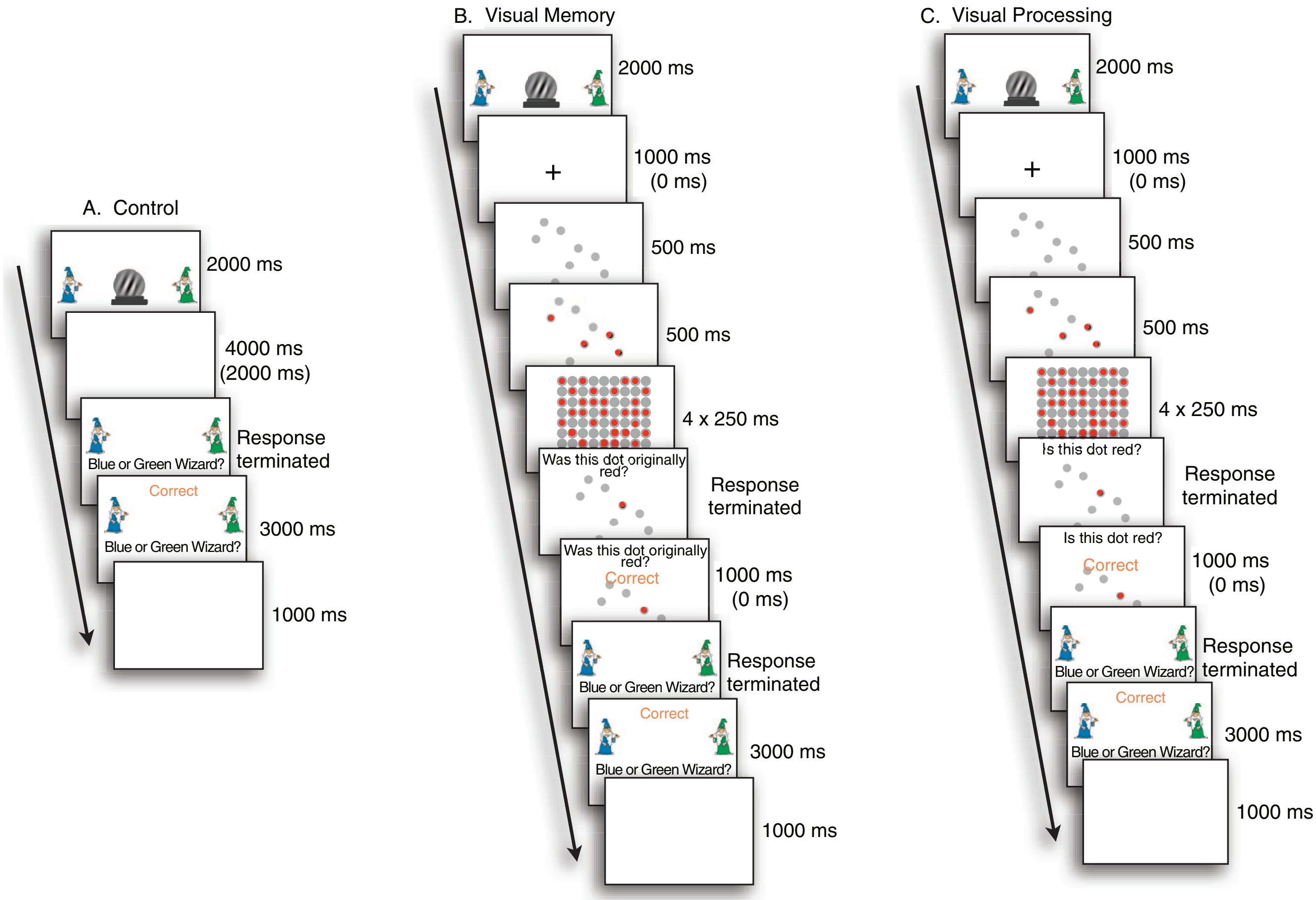

Figure 8. Task design for the first 10 trials of Experiment 2. A. Control condition. B. Visual memory condition. C. Visual processing condition. Timing for trials 11–320 is given in parentheses.

analyses because they failed to achieve 80% correct on the concurrent task.

Categorization performance: Individual data. As with the previous experiments, we first examined the individual learning data. Figure 9 illustrates individual learning curves for participants in each condition and shows a range of performance. First, considering the RD category set, performance in the control condition was high, and although most participants seemed to learn the rule, some (36%) did not. The same pattern was observed in the VM and VP conditions (40% and 35%, respectively), and in general, these conditions all looked nearly identical.

Performance on the II categories was variable, and there was little evidence of two groups of responders, as in the RD conditions. In the II-C condition, participants' categorization performance clustered around 70% correct. Performance in the II-VM and II-VP conditions was shifted slightly lower than the control condition, suggesting a possible effect of the secondary task. We next compared the average learning curves across conditions to provide a better examination of the above trends.

Categorization performance: Averaged data. Learning curves, presented in Figure 10, were calculated for each condition, and two separate ANOVAs were carried out to investigate the effect of condition across blocks for the II and RD category sets. For the RD category set, a 3 (Condition) × 4 (Block) mixed ANOVA found the expected main effect of block, $F(3, 228) = 43.31$, $p < .001$. It is important to note that the ANOVA did not reveal an effect of condition, $F(2, 76) = 0.12$, $p = .88$, or an interaction between block and condition, $F(6, 228) = 0.94$, $p = .46$. The nonsignificant effect of condition and lack of interaction between block and condition show that the visual aspect of the VP and VM tasks did not interfere with RD learning.

For the II category set, a 3 (Condition) × 4 (Block) mixed ANOVA also found an effect of block, $F(3, 222) = 10.44$, $p < .001$, indicating learning throughout the experiment. More interestingly, there was a main effect of condition, $F(2, 74) = 3.64$, $p = .031$. There was no interaction between block and condition, suggesting that differences between conditions were consistent across learning, $F(6, 222) = 0.45$, $p = .84$. We investigated the effects of the secondary task on learning the II categories further by averaging performance across all blocks (shown in Table 4) and conducting planned comparisons contrasting performance in each of the concurrent task conditions with the C condition. We found that performance in both the VM and VP conditions was lower than performance in the C condition, $F(1, 100) = 4.28$ and 4.97, $ps < .05$. In summary, analyses between blocks and averaged across all blocks showed that II category learning was impaired by

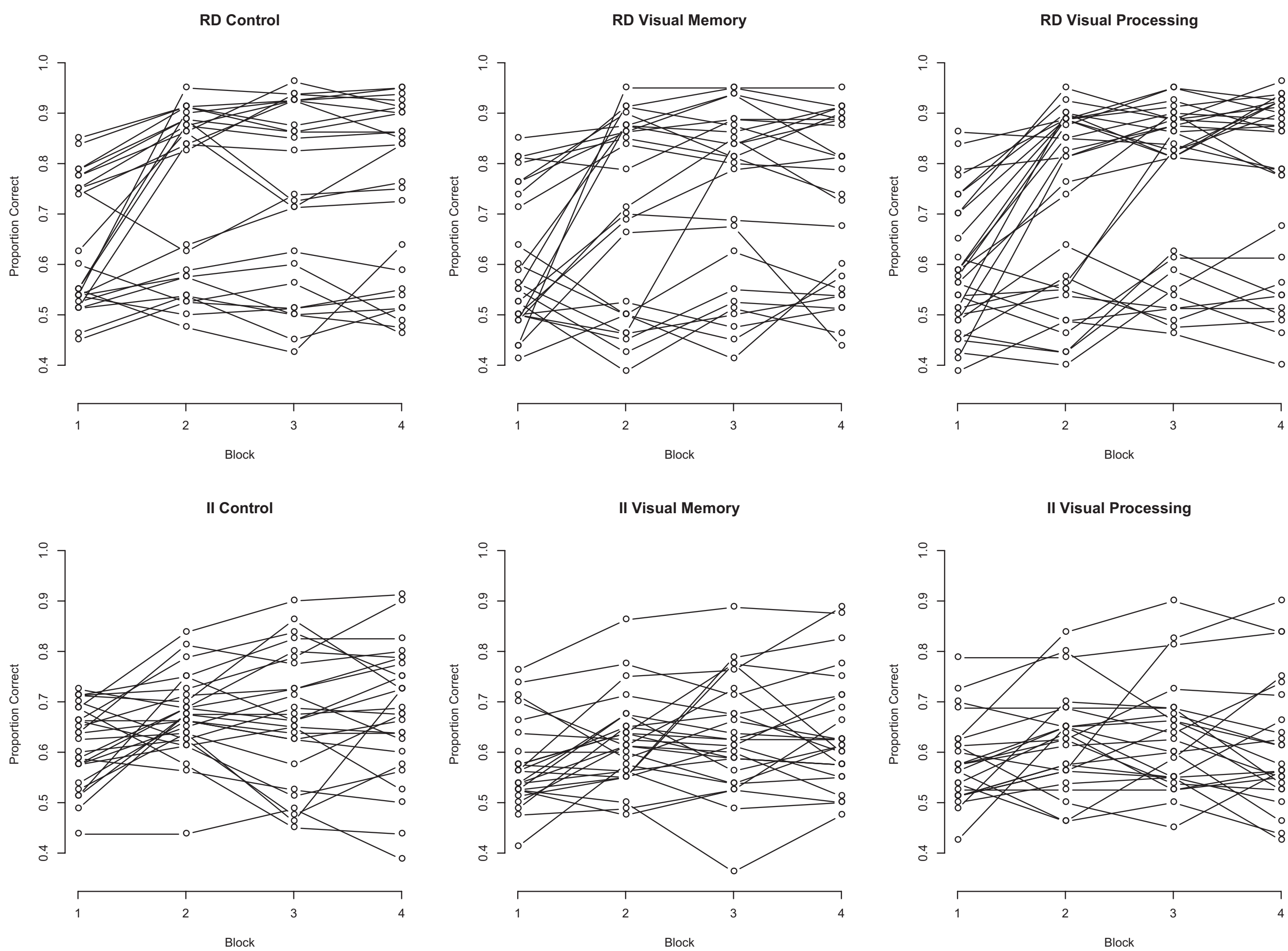

Figure 9. Individual learning curves, by condition, for Experiment 2. RD = rule defined; II = information integration.

both secondary visual tasks (VM and VP), whereas RD category learning was unaffected by these tasks.

Discussion

Experiment 2 investigated the role of visual processing in category learning by the verbal and nonverbal systems. As expected, the visual processing and visual memory tasks did not affect the learning of RD categories. Although RD category learning was impaired by the visual working memory task from Experiment 1a and 1b, this task likely taxed executive functioning. The visual memory task and especially the visual processing task from Experiment 2, on the other hand, did not tax executive or verbal resources and, as a result, did not impair RD category learning. This finding confirms the importance of executive resources to the verbal system, because similar visual tasks, which differed in executive requirements, showed different patterns of interference to the verbal system. These studies are some of the first to manipulate explicitly executive resource task demands to illustrate the importance of executive resources for the verbal system.

It is important to note that II category learning was impaired by the addition of a visual processing task, indicating that a visual processing task on its own, without the addition of visual working memory demands, can impair learning by the nonverbal system. Of course, this means that any visual working memory task that involves visual processing, such as the one used in Experiment 2, also disrupts the nonverbal system. In other words, there is very little, if any, role for verbal resources or executive functioning in category learning via the nonverbal system. This underscores the existence of a visually based, procedural learning system that can learn categories in the absence of any rule. Our data also help to clarify the workings of the nonverbal system. This system can be a procedural system to be sure but can also rely heavily on visual resources to learn to classify visually similar stimuli into the same category. It may be more accurate to think of the nonverbal system as an associative system that can associate stimuli with responses and that this may involve visual information, sensory-motor information, as well as information from other modalities.

When considering the results of Experiment 2 in isolation, one possible cause of the poor II-VM and II-VP performance is that

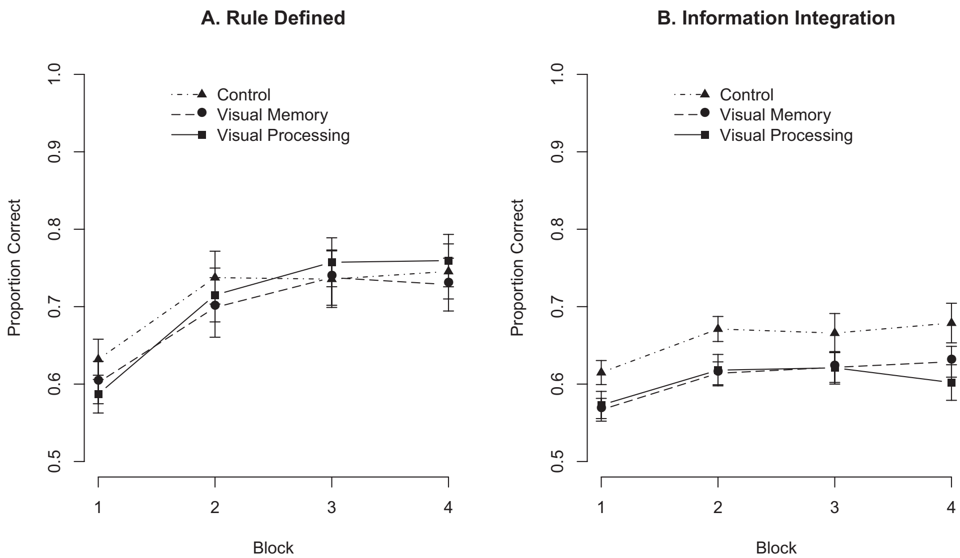

Figure 10. Average proportion correct by condition and category type for Experiment 2. Error bars denote standard error of the mean.

responding in the middle of the trial disrupts the stimulus-response-feedback loop and hinders dopamine-mediated learning. However, in Experiments 1a and 1b, no response was made during the II-VS conditions, but performance was still disrupted. One key feature that is common to all conditions in which II performance was disrupted is the visual nature of the concurrent task. Therefore, the poor performance in II-VP and II-VM in Experiment 2 is likely due to the visual nature of the concurrent task, not to making a response during the categorization trial.

General Discussion

Previous research has made clear the importance of verbal working memory for rule-based categories but not for family resemblance and information integration categories (DeCaro et al., 2008; Minda et al., 2008; Zeithamova & Maddox, 2006, 2007). We were interested in further exploring the cognitive resources used during categorization by investigating the role of visual processes and executive functioning in the learning of rule-defined and non-rule-defined categories. In Experiments 1a and 1b, a visual working memory task interfered with the learning of the verbal system, likely because the category learning task and the working memory task both taxed executive functioning. The visual working memory task also interfered with the nonverbal system. Because the nonverbal system places minimal demands on executive functioning, this interference reveals the importance of visual cognitive resources for the nonverbal system. In Experiment 2, we confirmed that poor performance by the verbal system was a result of interference with executive resources and that poor performance by the nonverbal system was a result of interference with visual processing resources through the use of a visual processing task, rather than a visual working memory task. Neither the visual processing task nor the visual memory task taxed executive functioning very much, and they did not disrupt verbal category learning. This result, in conjunction with the results of Experiments 1a and 1b, confirms that the verbal system does not rely heavily on visual processing and also confirms the importance of executive functioning to the verbal system. However the visual processing task still disrupted nonverbal category learning, showing that visual processing of stimuli is more important for the nonverbal than the verbal system.

It is possible that the poor performance displayed by the verbal system, when combined with the Stroop task in Experiment 1a and the memory-scanning task in Experiment 1b, was because these tasks could be solved visually and the verbal system relied on visual resources for category learning. This does not seem to be the case because the purely visual tasks (visual processing and visual memory) in Experiment 2 did not interfere with the verbal system. Therefore, it is more likely that participants were solving these tasks in a verbal manner, and it was the verbal and executive function components of the Stroop and memory scanning tasks that caused the verbal system's learning difficulty.

Table 4
Participant Ns, Means, and Standard Deviations for Overall Categorization Performance in Experiment 2

Condition	*N*	*M*	*SD*
Rule defined			
Control	25	.71	.17
Visual processing	29	.70	.10
Visual memory	25	.69	.18
Information integration			
Control	26	.66	.11
Visual processing	25	.60	.10
Visual memory	26	.61	.09

Implications for Multiple Systems Theories

Our data provide support for multiple systems theories like COVIS and add to the field's knowledge about the verbal and nonverbal systems. Our results replicated previous findings that verbal working memory is important for learning RD categories (DeCaro et al., 2008; Zeithamova & Maddox, 2006, 2007) and provided further evidence for the importance of executive functioning in the verbal category learning system. For the RD category in Figure 1, note that orientation is irrelevant to category membership but has large variation, making it perceptually salient. Frequency, which is relevant to category membership, has little variation and is less perceptually salient. When participants learn this category, they likely rely on their verbal system and use verbal resources to generate and test potential categorization rules. Participants also rely on executive functions to ignore or inhibit the more salient but irrelevant dimension (orientation) and focus instead on frequency information, which is predictive of category membership.

Our results confirm our prediction that executive functioning does not play a crucial role for the nonverbal system and in the learning of II categories. A verbal task that taxed executive resources did not interfere with II category learning. Important for our verbal/nonverbal theory and for COVIS, we found that visual processing was more important for the nonverbal system than for the verbal system. A visual working memory task and a visual processing task both interfered with learning by the nonverbal system. The visual processing task had minimal visual working memory demands but still affected nonverbal categorization, suggesting that the nonverbal system does not rely on visual working memory resources but does rely on the availability of visual processing resources. The verbal system, on the other hand, is able to recode visual stimuli into verbal code, which is easily stored throughout the categorization process. Perhaps the nonverbal system does not engage in verbal recoding but instead stores visual stimulus representations throughout categorization, therefore relying on visual processing to a greater extent than the verbal system.

According to our results, the nature of the concurrent task matters less for the verbal system than for the nonverbal system. That is, the verbal system's use of general executive functioning resources makes it susceptible to interference by many types of concurrent tasks. The nonverbal system relies on specific visual processing resources that are only used in a subset of concurrent tasks. Therefore, the nonverbal system should be generally resilient to the effects of concurrent tasks, except in the case that the concurrent task is particularly visually based. In other words, the learning of RD categories relies on executive functions and perhaps also on verbal working memory. Existing theories and models of category learning must specify more explicitly how these processes work together to learn categories.

The Development of the Nonverbal System

Our data suggest that visual processing resources alone, rather than visual working memory resources, could be important for the nonverbal system. Studying nonverbal category learning in children may help to confirm this prediction. Specifically, visual working memory is not fully developed in children (Klingberg, Forssberg, & Westerberg, 2002), but children's basic visual processes are fully developed (Martin et al., 1999).

Existing research suggests that children's nonverbal categorization performance is equal to that of adults (Minda et al., 2008). However, to date, children have only been tested on relatively easy nonverbal categories (i.e., simple family resemblance categories), that are not particularly taxing to visual resources. Testing children on more difficult nonverbal categories, like the information-integration category used in the current research, could provide a clearer picture of the role of visual working memory and/or processing in nonverbal categorization. If visual working memory is used by the nonverbal system, then children should perform worse than adults on difficult nonverbal categories, because children have reduced visual working memory capacities. On the other hand, if visual processing is important for the nonverbal system, then children may perform as well as adults on difficult nonverbal categories, because children have fully developed visual processing abilities.

A similar pattern of nonverbal categorization performance may also be expected from nonhuman primates. It has already been shown that nonhuman primates can learn random dot polygons (Smith et al., 2008). Whether animals can learn more complex II categories that perhaps rely on visual cognitive processes for more than abstracting a visual category prototype has not yet been tested. Future research should focus on identifying the specific visual processes that are important for the nonverbal system and the role that these processes play in category learning.

Delay Between Stimulus and Response

Because the nonverbal system does not appear to use visual working memory, perhaps instead stimuli representations are stored in visual perceptual memory. Visual perceptual memory involves the storage of visual sensory information and is considered to be distinct from visual working memory (Magnussen & Greenlee, 1999). The visual perceptual memory system maintains visual representations in an easily accessible form for approximately 3 s, before they are transferred into a more permanent memory trace (Magnussen & Greenlee, 1999). If, in fact, the nonverbal system uses the perceptual memory system, then increasing the stimulus–response delay beyond 3 s may dramatically interfere with nonverbal categorization. A finding of this sort would give us some sense of the type of visual processing resources that are important for the nonverbal system.

Stimulus Presence During Feedback

In Experiments 1a and 1b, the categorization stimulus was on the screen during feedback, but in Experiment 2 it was not. This is an important difference that resulted in overall worse performance in Experiment 2 than in 1a and 1b, especially for the verbal system. In fact, performance in the control condition of Experiment 2 was roughly equivalent to the concurrent task conditions in Experiment 1b, but this was only the case for the RD category.[9] Recent research has shown that the verbal system is affected by the quality of feedback to a greater extent than the nonverbal system (Maddox, Love, Glass, & Filoteo, 2008). Therefore, it is not surprising that the verbal system's performance is diminished when the stimulus is not present during feedback. Perhaps the verbal system encodes the categorization decision but not a representation of the

[9] A direct comparison between Experiments 1b and 2 is most suitable, because these experiments use the same stimulus set.

stimulus, so feedback is less useful when the stimulus is not on the screen, because the feedback cannot be related back to the stimulus representation. The nonverbal system, on the other hand, may encode the categorization stimulus visually, so even when the stimulus is not present during feedback, the feedback can be integrated with the stimulus representation. This would be in line with our findings that interfering with the nonverbal system's access to visual resources causes decrements in performance.

Limitations

The current studies were designed to determine the importance of visual processing for the verbal and nonverbal systems, but they do not directly address why visual processing is so important for the nonverbal system. Now that we have verified that visual processing plays a special role for the nonverbal system, future work should aim to further specify this role. As suggested above, visual processing may be particularly important for maintenance of the stimulus representation throughout the trial. However, visual processing may also be important for initial stimulus encoding, or to make a visual comparison of the stimulus to the category representation during the decision process.

In addition, the current research does not speak directly to the interaction between the verbal and nonverbal systems. According to COVIS, the two systems are in constant competition with one another, but this relationship has yet to be further specified. For example, a certain amount of visual processing is common to both systems. We do not know whether the verbal and nonverbal systems compete for these common visual resources, or whether the competition comes at a later stage in the categorization decision. Future research could investigate the allocation of shared cognitive resources throughout the course of each categorization decision and across category learning epochs.

Conclusions

Recent research seems to indicate that the nonverbal system, which was initially thought to rely heavily on procedural learning mechanisms, is able to learn new categories under conditions that do not favor procedural learning (Spiering & Ashby, 2008). We proposed that the nonverbal system is more dependent on visual processing resources than has previously been recognized. We found that a concurrent visual processing task impaired the nonverbal system but not the verbal system, suggesting that the nonverbal system uses visual cognitive resources to a greater extent than does the verbal system. We also found that a visual working memory task that taxed executive functions impaired the verbal system, but a visual processing task that did not tax executive functions did not impair the verbal system. These results confirm that the verbal system is particularly reliant on executive functioning. Taken together, our results provide support for some aspects of COVIS and clarify our understanding of the nonverbal system.

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