ABSTRACT

THE IMPACT OF WORKING MEMORY CAPACITY ON CATEGORY LEARNING

by Krista D. Carlson

The current study investigated the influence of working memory (WM) capacity on ability to learn rule-based (RB) and information-integration (II) categories. Using stimuli varying on 4 binary dimensions, Experiment 1 replicated the results of Decaro, Thomas and Beilock (2009): with an 8-trial learning criterion, high WM participants outperformed low WMs on RB tasks, but low WMs outperformed high WMs on II tasks. With a stricter learning criterion of 16 trials, however, the advantage of low WMs disappeared. II response modeling showed that high WMs used the optimal II strategy more over time, while low WMs persisted in using unidimensional rules. Experiment 2 examined WM’s effect on category learning using stimuli with continuous dimensions, making category membership harder to distinguish. Results showed II learners took fewer blocks to reach criterion (BTC) as their visual WM increased, while complex rule learners took less BTC as their verbal WM increased.
THE IMPACT OF WORKING MEMORY CAPACITY ON CATEGORY LEARNING

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A prominent model of categorization put forth by Ashby and colleagues suggests that novel category learning can be attributed to multiple systems operating simultaneously (Ashby, et al., 1998). Termed *competition between verbal and implicit systems*, or COVIS, this theory holds that category learning is accomplished through an explicit system that relies on hypothesis testing and an implicit one that depends on procedural learning (Ashby & Ell, 2001; Maddox & Ashby, 2004). Although learners exhibit an initial bias towards using the explicit system, this system is generally optimal only for rule-based (RB) categories, the members of which are identified through easily verbalized rules concerning separable relevant characteristics or dimensions (Ashby & Ell, 2001; Waldron & Ashby, 2001). The implicit system is required for the learning of information-integration (II) categories, in which values of multiple relevant dimensions must be taken into account before making a classification decision. Learning in these types of structures has been described as a kind of nonanalytical stimulus-response mapping and appears to draw on neural structures involved in motor learning (Ashby & Ell, 2001).

In an initial test of the COVIS theory, Waldron and Ashby (2001) had participants perform a concurrent numerical Stroop task while categorizing stimuli best classified by both rule-based and information-integration strategies. The Stroop task is a classical verbal working memory task and would serve to interfere with other tasks simultaneously performed that, too, draw on those same working memory resources. Since successfully utilizing the explicit system for category learning in a rule-based structure requires focusing one’s attention solely on the single relevant dimension and the values that signal category membership, the Stroop task would interfere with learning in this condition. In contrast, learning in the information-integration condition would not be affected as this type of learning draws on procedural mechanisms that do not require explicit attention. Waldron and Ashby (2001) found support for the two systems view, in that the learning of simple rule-based categories was impaired relative to the learning of information integration categories when performed concurrently with a Stroop task. Zeithamova and Maddox (2006) replicated this finding using a different kind of stimuli, adding further support to the two-system view as well as granting it a measure of generalizability. Thus, manipulations that are known to affect verbal, explicit processing selectively impair rule-based learning but do not impede information integration performance. To document a double
dissociation, Maddox & Ashby (2004) reviewed evidence demonstrating decrements in
information integration learning when feedback was absent or delayed and when the location
associated with a particular response was switched (see also Ashby & Ell, 2001). Both feedback
and response location influence the stimulus-response association vital to procedural learning.

Adding working memory

Although a fair amount of research addresses the COVIS two-system theory of category
learning, relatively little work has been done regarding the relationship between successful
category learning and working memory ability. Working memory (WM) refers to the capacity of
an individual to maintain, manipulate and focus on information relevant to current goals (Kane,
Bleckley, Conway & Engle, 2001; Engle, 2002; DeCaro, Thomas and Beilock, 2008; Salthouse
& Pink, 2008). It is often linked to the concept of executive functioning, which Jurado and
Rosselli characterize as referring to the abilities of “attentional control, planning, set-shifting and
verbal fluency” (2007). Given this definition, it seems that WM ability might influence how
successfully an individual identifies and maintains the salient attributes of a stimulus.

To investigate this idea, DeCaro, Thomas and Beilock (2008) used stimuli developed
from Waldron and Ashby (2001), to observe the categorization performance of high and low
WM individuals on both rule-based (RB) and information integration (II) categories. They found
that participants with high WM demonstrated superior performance on RB categories using an 8-
trial learning criterion (the same learning criterion used by Waldron & Ashby, 2001); on the
other hand, low WM participants outperformed high WMs on II categories. These rather
counter-intuitive results suggested the intriguing possibility that, for some tasks, more working
memory may not be advantageous. For the II categories, high WM participants may have been
focusing all of their attention on utilizing the default explicit, rule-based category strategies to
which the COVIS system is initially biased, rather than abandoning them in favor of nonexplicit
ones (Waldron & Ashby, 2001). Low WM participants, being more prone to distractibility, may
have sampled a greater variety of strategies, leading them to eventually identify the correct one,
unlike their higher WM counterparts (DeCaro et al., 2008).

Despite the intriguing implications of these results, a subsequent commentary by Tharp
and Pickering (2009) raised concerns regarding the methodology by which they were obtained.
The set of 16 stimuli used by Decaro et al. (2008) varied on 4 binary dimensions (see Figure 1
and Table 1); given their discrete nature, using one-dimensional rules could result in up to 75
percent classification accuracy even when the optimal strategy (i.e., the strategy that affords maximum accuracy of 100%) was a more complex information integration one. Using even more complex verbal rules enabled accuracies of up to 87.5 percent (see Table 2). Given that up to 12 stimuli could therefore be classified properly using one-dimensional strategies, and the criterion for learning was 8 correct categorizations, participants could be identified as learners in the information-integration condition without actually employing the optimal strategy. Further complications arose from the fact that stimuli were sampled with replacement, allowing for multiple classifications of the same stimulus to count towards the learning criterion.

These issues suggested a need for replication of this study with certain methodological changes: a stricter 16-trial learning criterion, which would eliminate the possibility that participants using verbal rules could be classified as learners in the II categories; and a change in the manner of stimulus sampling, allowing for no replacement sampling within a 16-trial block. One additional virtue of sampling the stimuli from the 16 without replacement within learning “blocks” was that different decision strategies could be diagnosed using the participant response patterns. This new method of sampling would also make strategy analysis possible by permitting the clearer differentiation of the predictions of the different II and RB strategies (Table 2).

In Experiment 1 we replicate DeCaro et al., (2008) but with two important modifications to the methodology. First, to be deemed a ‘learner’ we increase the requisite number of trials to be classified correctly in a row from 8 to 16. Second, trials are organized into 16 trial blocks within which stimuli are sampled from the total set without replacement. To forecast the results, we find that while high WMs reach learner status of the RB categories more quickly than lows whether the criterion is 8 or 16 trials, for the II categories they take more trials than low WMs to reach the 8 trial criterion, and fewer trials than low WMs to reach the 16 trial criterion. We discuss potential explanations for this crossover finding, including the possibility that the specific information integration task of Waldron & Ashby (2001) does not necessary recruit the procedural learning module in all cases. Following this somewhat equivocal set of results, we plan to use category distributions that i) sample stimulus dimensions continuously so that, in theory, an infinite number of exemplars per category is possible, and ii) structure the information integration learning condition in such a way as to preclude the effectiveness of simple and/or tractable complex verbal rules. We describe the methodology for that experiment following the presentation of Experiment 1 results and discussion.
Experiment 1

Method

Participants

Thirty participants were obtained through the Miami University research participation pool, 16 of whom scored in the highest quartile on a previously administered working memory span screening task; the remaining 14 scored in the lowest quartile. Participants received either course credit or payment for their participation, neither of which depended on performance achieved.

Working Memory Screening

We computed an individual participant’s working memory score by averaging their absolute scores on the Automated Reading Span (Arspan) and Automated Operation Span (Aospan) tasks. The Arspan and Aospan tasks test memory for letter series while completing a concurrent task (DeCaro et al., 2008). In the Arspan, participants must determine whether sentences are semantically and syntactically correct and then click “true” or “false;” each sentence is followed by a letter to be held in memory for 800 ms. Following a set of such trials, 12 letters are shown on the screen and participants must select the presentation order of all the letters they remember. The Aospan task is similar, except that the sentences are replaced by simple, completed arithmetic problems; here, the participant must judge whether the given solution is “true” or “false.”

Stimuli

Participants were asked to correctly place sixteen stimuli in either category A or category B. The stimuli were square in shape, and varied on four dimensions, each dimension having two levels (see Table 2): background color (yellow or blue); foreground symbol color (red or green); number of symbols (one or two); and symbol shape (circle or square).

For rule-based or explicit categories, only one stimuli dimension was relevant, e.g. “All stimuli with green symbols belong in category A, all stimuli with red symbols in category B.” For integration-information or implicit categories, category membership was more complex. One level of each of the three stimuli dimensions (the fourth was disregarded) was given a value of one; its partner or opposite was assigned a value of -1, (e.g., if “green” was assigned a value
of one, “red” would be assigned -1). Then, the three dimension values were summed for each stimuli; those with a sum greater than zero belonged in category A, those with a sum less than zero in category B.

**Procedure**

After giving informed consent, participants began the computerized categorization program. They were instructed to place the stimuli into either category A or category B. Each participant completed four categorization tasks, two in which the optimal rule was an explicit verbal statement (R), and two in which the optimal rule was implicit (I). Four different category sequences (RIRI, IRIR, RIIR, IRRI) were counterbalanced across participants. For each category, participants saw a maximum of thirteen cycles of the entire set (no replacement) of 16 stimuli; if they discovered the optimal categorization rule, two full cycles with one hundred percent categorization accuracy were required before they could continue on to the next category.

After completing the categorization task, participants were asked to complete several forms, including seven-point Likert scales on perceived performance pressure, perceived importance of task, and perceived performance; a mood/mental state inventory; a handedness inventory; a demographics form; and a form asking them to explicitly state the “steps and processes” they used while completing the categorization task. Participants were debriefed following completion of the forms.

**Results and Discussion**

**Category Learning**

We contrast learning performance using two different ‘learning criteria’, the one in DeCaro, et al., (2008) and a stricter one of 16 trials correct in a row. That is, we defined a category as learned if a participant achieved a particular criterion of consecutive correct trials. In the first analysis, identical to that performed by DeCaro, Thomas and Beilock (2008), the criterion was 8 consecutive correct trials; in the second, we increased the criterion to 16 correct consecutive trials. For each category, participants received a score reflecting how many trials it took for them to reach the appropriate criterion. Within the same criterion group (8 or 16), we averaged the scores for the two RB and II categories, respectively. Therefore, each participant had a set of four scores: the number of trials needed to reach the 8 criterion for RB and II, and
the number of trials needed to reach the 16 criterion for RB and II. If the participant did not “learn” a particular category as defined by the criterion, he or she received a score of 208 for that category (the maximum amount of trials possible in the 13-block session). Also, the data from those participants whose scores fell 2 standard deviations above or below the mean of that of their WM group in a particular category structure were omitted in the analyses. One high WM and 2 low WM were excluded from both the 8 and 16-trial criterion analyses.

8-trial criterion. A 2 (category structure: RB, II) x 2 (WM group: low, high) mixed ANOVA was used to analyze the number of trials needed to reach the criterion for learning. This analysis revealed a main effect of category structure F(1,22)=65.77, p<.001 alongside a significant WM group x category structure interaction, F(1,22)=4.11, p=.05. For RB categories, individuals with high WM reached the learning criterion in fewer trials (M=15.97, SD=5.26) than did low WM individuals (M=24.42, SD=9.97). With the II categories, however, we found the reverse: high WMs needed more trials (M=97.33, SD=52.89) to reach the criterion than low WMs (M=73.25, SD=26.36) (Figure 2). These results therefore replicate the findings of DeCaro et al. (2008).

16-trial criterion. We examine next the performance of the two WM groups when a more difficult learning criterion is employed. Once again, a 2 (category structure: RB, II) x 2 (WM group: low, high) mixed ANOVA was used to analyze the number of trials needed to reach the learning criterion. This identified main effects of both category structure, F(1,25)=565.50, p<.001, and WM group, F(1, 25)=8.16, p<.01 with the II condition requiring more trials to learn than the RB structure, replicating several similar studies (e.g., Maddox & Ashby 2001, Waldron & Ashby, 2001). However, unlike with the 8 trial criterion, high WMs outperformed low WMs in both the RB (low WM: M=34.54, SD=12.27; high WM: M=27.40, SD=7.77) and II (low WM: M=200.58, SD=10.93; high WM: M=168.43, SD=42.97) categories (Figure 3). Therefore, the advantage demonstrated by low WM participants in II category structures at the 8 trial criterion does not persist as the learning criterion becomes more stringent.

Taken together, these results suggest that the two WM groups may rely on different types of learning strategies. Indeed, a 2 (WM group: low vs. high) x 2 (criterion level: 8 vs. 16) ANOVA demonstrated a significant WM x criterion level interaction, F(1, 24)=16.22, p<.001. In order to investigate this more thoroughly, we performed a strategy analysis of the learner response patterns. Within Table 2 are listed various plausible decision strategies that a learner
may employ to learn the information integration structure. As can be seen, several RB strategies allow for 75-87.5% accuracy in the II categories. Since stimuli were sampled without replacement within a block we can assess which of these strategies provides the best account of the learner response patterns.

**Strategy Analysis**

**Process.** Participant responses to each stimulus were compared to those generated by each of the models listed in Table 2: the optimal information-integration model and nine rule-based models of one-, two-, or three-dimensional complexity. If the response of the subject and a particular model agreed on a trial, this agreement was given a value of 1, otherwise 0. In this manner, the total response agreements for each model were summed for each 16-stimuli block. Then, for each block, the model accounting for the maximum number of agreements received a weight of 1. In the case that multiple models “tied” for maximum number of agreements, each of those tying models was given a weight of 1 divided by the number of ties for that particular block. For example, if three models accounted for a maximum of 10 agreements within a block, each of those models received a weight of 1/3 for that block. The weights accrued by the different strategies were summed for each block and converted to proportions for analysis.

**Findings.** The strategy analysis revealed that while high WM participants sampled a variety of strategy types, both RB and II ones, low WM participants relied predominantly upon one-dimensional RB ones (Figure 4), which may account for their apparent performance decrement under the 16-trial criterion. Moreover, high WMs use of the optimal strategy increases in a significantly linear fashion over time $F(1,14)=13.03$, $p<.01$, while that of the low WMs does not, $F(1,11)=3.32$, $p>.05$. This suggests that the high WMs may have been using the gradual stimulus-response association central to the procedural learning of the implicit system.

The heavy reliance of low WMs on one-dimensional strategies when classifying the discrete stimuli devised by Waldron and Ashby (2001) suggests that the low WMs may be perseverating on simple strategies. While this serves them well by allowing them to exit more quickly when the learning criterion is only 8, it adversely affects performance when the criterion is increased to 16 (see DeCaro, Carlson, Thomas & Beilock, 2009 for further details). The idea that lower WM leads to perseveration on simple heuristic reasoning strategies fits more with the conception of what cognitive control or executive functioning enables (Lezak, Howieson & Loring, 2004). What is needed to more effectively investigate the relationship between WM and
category learning is a category structure that prevents the possibility of simple heuristic responding as a means of learning.

**Experiment 2**

Although the strategy analysis of Experiment 1 does indicate that high WMs are learning the optimal information-integration strategy over training and implementing it in a manner consistent with procedural learning, the discrete nature of the four-dimension stimuli allows for the possibility that learning could be accomplished through an incredibly complex rule-based strategy. To discount this possibility, we utilize a category training procedure whereby stimulus dimensions are sampled continuously, and one in which the information-integration condition cannot be solved by simple or even moderately complex verbal rules.

The general recognition randomization technique (GRRT) of Ashby and Gott (1988) allows for both of these characteristics. Often the structure of the categories in this paradigm has been likened to the structure of natural categories (Rosch, 1978) in that exemplars are randomly distributed throughout the stimulus space, often around a best example, and the boundaries between categories may not be easily discernable. This is accomplished by defining a category structure by a probability distribution. In classic applications (Ashby & Gott, 1988; Ashby & Maddox, 1992; Maddox & Ashby, 1993; Thomas, 1998), category exemplars are constructed using stimulus values sampled from multivariate normal distributions. That is, a category is defined by the mean and variance-covariance parameters that describe the distribution. Consider the stimuli shown in Figure 5. There are two possible dimensions of variation, size of the circle and orientation of the radial line. Figure 7 displays exemplars of two categories that are bivariate normally distributed with a strong correlation between the sampled dimensions. The dimensions of the plot are the stimulus attributes, that is, size and orientation; a point represents a specific category exemplar whose size, for example, is the sampled x-value and orientation is the sampled y-value. In principle, any exemplar in the space can be produced, thus giving rise to continuous dimensions and possibly overlapping category structures. Category A exemplars reside above the diagonal line whereas B exemplars are below it. In this particular structure, the optimal ‘rule’ or boundary that best separates the two categories is the line $y = x$. In other words, the optimal strategy that yields the best classification performance is to classify a stimulus as an ‘A’ if its orientation exceeds its size ($y > x$). Given that these dimensions are not commensurable, this structure qualifies as an information-integration task. Learning in this
condition has been shown to require the procedural, implicit process of COVIS (reviewed in Maddox & Ashby, 2004). We adapt this methodology to a rule-based structure (Figure 6) and use the information-integration structure of Figure 7 in an attempt to more accurately assess the relationship between working memory capacity and category learning.

Method

Participants
Eighty-one participants were obtained through the Miami University research participation pool, 42 of whom completed a complex rule categorization task; the other 39 completed an information-integration categorization task. Working memory (WM) capacity was treated as a continuous variable in study 2, so participants with WM scores across the spectrum took part. Assessment of the individual difference measures (Rspan, Ospan, Sspan, Handedness Inventory and Cognitive Style Inventory) took place prior to the category learning task. All participants received course credit for their participation.

Stimuli
Stimuli were circles of varying size intersected with lines of varying orientation (see Figure 5). Stimuli were created by following the GRRT paradigm (Ashby and Gott, 1988). Values of the two stimulus attributes (circle diameter and angle of line) were sampled from a bivariate distribution randomly, and then created using a MATLAB program running the Psychophysics Toolbox (Brainard, 1997). The resulting category structures can be represented by scatterplots, with each point representing a stimulus and lines denoting the optimal categorization decision boundary. Figures 6 and 7 represent the complex rule-based (CR) and information-integration (II) structures, respectively, to be used in this study. The axes represent values of the two stimulus dimensions, circle diameter and line angle. The lines drawn within the plot represent the optimal decision boundary that, when used, affords the maximum percent correct. In the case of the complex rule-based condition, this boundary is equivalent to an exclusive-or structure: “if both large and high angle, or both small and low angle, classify as a B member, otherwise, classify as an A”. This task was chosen because in previous research (e.g., Thomas, 1998, Mauldin & Thomas, 2009), its overall difficulty is roughly the same as that of the current information-integration structure.

Procedure
In the first session, after giving informed consent participants completed three working memory tasks, as well as a handedness inventory, inventory of cognitive style, and demographic questionnaire. In addition to the two working memory tasks used in Experiment 1, we included a primarily visual working memory measure, the Symmetry Span (Engle, 2005). Evidence suggests that visual working memory capacity may be dissociable from verbal working memory capacity (Gevins & Smith, 2000; Miyake, et al., 2001) and hence may be more appropriately relatable to performance in the information-integration tasks given its reliance on visual integration. The measures used in DeCaro, et al., (2008, 2009) are considered to be verbal working memory measures (Conway, et al., 2005).

The Edinburgh Handedness Inventory (HI, Oldfield, 1972) assesses to what degree an individual is dominantly left or right-handed. Handedness scores are thought to indicate the degree to which an individual exhibits interhemispheric interaction, with less strongly-right handed and left-handed individuals displaying more integration than strong right-handers (Christman, 1993). In support of this, strongly right-handed individuals have been shown to be disadvantaged on memory measures thought to rely upon interhemispheric communication (Propper, Christman & Phaneuf, 2005; Lyle, McCabe & Roediger, 2008). Lastly, the cognitive style inventory (V-V, Heckler, Childers, & Houston, 1993) indicates to what degree an individual uses visual or verbal processes when carrying out mental tasks. Some participants completed the HI and V-V assessments by hand, while others completed a computerized version using MediaLab. Participants were debriefed following completion of all 6 components of the session.

For the categorization component of the experiment, after giving informed consent participants were randomly assigned to one of the two category structures, and completed four blocks of classification trials, 280 trials per block, in each of two sessions. Sessions took place at least 2.5 hours apart, but most participants completed their sessions on consecutive days, depending on availability. Participants were debriefed following their second session.

**WM span tasks.** Participants completed three WM span tasks: the Arspan and Aospan, described in Study 1, and the Symmetry Span (Engle, 2005, Unsworth, et al., 2005). In the Symmetry Span, participants were first asked to recall the locations of red squares in various 4 x 4 grids composed of black cells; these grids were presented on a computer screen. Each grid was presented for 650 ms, with a delay of 500 ms between each grid. Following presentation of the
grids, participants were asked to indicate the placement of each of the red squares, in presentation order, by clicking on a blank grid. Next, participants evaluated whether various patterns made by black cells in 8 x 8 grids exhibited left-right symmetry. They responded by clicking “yes” or “no” and received feedback regarding their accuracy. The final part of the Symmetry Span combined memory for the sequence of red cells with symmetry judgments by alternating these two tasks (Engle, 2005; Erickson, 2008). The order of the three span tasks was counterbalanced across participants.

**Handedness Inventory.** The Edinburgh HI lists 12 common actions whose performance is impacted by an individual’s degree of left or right-handedness (Oldfield, 1972). For each action, an individual was asked whether he always used the right or left hand (values of 2 and -2, respectively), generally used the right or left hand (values of 1 and -1, respectively), or either hand (value of 0). The twelve values were summed and divided by the absolute value of the sum to obtain the handedness score of each participant, which could range from -100 to +100. Negative values indicated left-hand dominance, while positive values indicated right-hand dominance, while the magnitude of the scores indicated the degree of dominance. Therefore, an individual with a score of 25 would be considered more right-hand dominant than someone with a score of -60, but less right-hand dominant than someone with a score of 85.

**Cognitive Style Inventory.** The V-V asks individuals to indicate their level of agreement with 20 statements that assess the degree to which they rely upon visual or verbal processes in completing tasks, as well as the frequency at which they perform activities that rely predominantly on either visual or verbal mechanisms. Participants scored their agreement with each statement using a 5-point Likert scale, where a value of 1 corresponded to “Strongly Disagree” and 5 to “Strongly Agree.” Overall V-V scores were obtained by summing the values of each score (or reverse score, depending on the phrasing of the question; this ensured that all values were similarly valenced). Values could range from 20 to 100, with higher values suggesting a more visual cognitive style.

**Categorization task.** In the categorization task, stimuli were presented one-by-one on a computer screen; participants were asked to classify each stimulus as a member of either category A or category B, gradually learning to discriminate between the two classes. The “z” or “Z” key was used to make a category A response, while the “/” key indicated a B response.
Following each classification response, participants received feedback of either “Correct” or “Incorrect” depending on their accuracy. In the event that they hit a wrong key, “Invalid Response” was displayed on the screen. After feedback, participants progressed to the next trial by hitting the spacebar. In the absence of response from a participant, the program advanced to the next stimulus after four seconds.

After completing the categorization task, participants were asked to complete several computerized forms using MediaLab, including seven-point Likert scales on perceived performance pressure, perceived importance of task, and perceived performance; a mood/mental state inventory; a handedness inventory; a demographics form; and a form asking them to explicitly state the “steps and processes” they used while completing the categorization task. Participants were debriefed following completion of the forms.

Results and Discussion

Individual Difference Variables. Each participant received a score on five individual difference (ID) variables: the performance-based IDs, Rspan, Ospan and Sspan; and the non-performance based IDs, handedness (HI) and cognitive style (V-V).

Descriptive Statistics. The mean, median, standard deviation, range, maximum and minimum of each ID variable is recorded in Table 3.

For handedness scores, the minimum and maximum values of -100 and 100, respectively, indicate the presence of both completely left-hand dominant and completely right-hand dominant individuals amongst the participants. However, the value of -100 applied to only one participant, while the value of 100 applied to 25 participants. In fact, a HI score of less than 0 (indicating a left-hand bias) occurred only 5 times. To compensate for the negative skew these 5 scores produced, the data were transformed. The transform process was as follows: the values were reflected around zero, and then a constant was added so that the smallest value was equal to one. We then took the square root of these transformed values, and these square roots were then subtracted from another constant such that the largest value transformed value became the smallest. This last step preserved the original order of the scores. Specifically, the data were transformed using the following equation:

\[ HI_{\text{transformed}} = 15.18 - \sqrt{(-HI_{\text{original}} + 101)} \] (1)
Correlations. Correlations between the five IDs are presented in Table 4. As expected, the correlation between the Rspan and Ospan was significant, \( r(79)=0.41, p<0.01 \); as an individual’s Rspan score increased so did his Ospan score. In addition, the correlation between Sspan and V-V score approached significance, \( r(79)=0.194, p=0.081 \), suggesting that scores on the Sspan increased as cognitive style became more visual. The remainder of the correlations did not approach significance.

Category Learning.

Selection of learning criterion. Before examining how a participant’s scores on the individual difference variables relate to his or her ability to learn either of the Gaussian category structures, it was necessary to define what level of performance we considered indicative of learning in this paradigm. For analysis, each of the eight 280-trial blocks of stimuli were further divided into seven 40-trial blocks, resulting in 56 40-trial blocks total for analysis. A participant was considered to have demonstrated learning within a 40-trial block if he made 26 correct categorizations, thus achieving 65% accuracy within the block. Maddox and colleagues have also used this 65% criterion to indicate category learning (Zeithamova & Maddox, 2007). Although this criterion seems a bit low at first glance, actually the binomial probability or probability of achieving 26 out of 40 correct categorizations by chance is 0.0403. However, to ensure that individuals who reached 65% accuracy only once by chance were not incorrectly classified as learners, our learning criterion required two instances of 65% accuracy or better within a 280-trial overall block. Specifically, it required that 65% accuracy be reached in at least two out of three consecutive 40-trial blocks, therefore accounting for any fatigue that might have been experienced by the learner. Under this criterion, 47 of the 81 participants showed evidence of learning (20 in the CR category group, 27 in the II category).

Individual difference variables and frequency of learning. To begin to assess the relationship between learning and the individual difference variables, we examined frequency tables. We constructed a 2 (category structure: CR vs. II) x 2 (median group: below vs. above) frequency table for each of the five ID variables, where the numbers inside each cell indicate how many learners scored above or below the median within each category group. Using a median split to create a grouping variable insured that the groups in which we identified learners had equal numbers of subjects. Table 5 summarizes the 5 frequency tables.
An examination of the counts presented in Table 5 demonstrated that of the five individual difference variables, only Sspan and HI median group membership suggested even moderately sizeable differences in counts between the four groups of learners. For the Sspan groups, the frequencies were not significantly different, $\chi^2 (1, N=81)=1.705, p>.05$. The frequencies in the HI groups, on the other hand, resulted in differences that approached significance, $\chi^2 (1, N=81)= 3.071, p=.08$.

**Median group and BTC.** A series of 2 (category structure: CR, II) x 2 (ID median group: below ID median, above ID median) factorial ANOVAs were used to analyze the average number of blocks needed to reach the criterion for learning for each of the 5 ID measures in turn. The results of these analyses are presented below.

A main effect of category group existed across all five of the ID ANOVAs, with II learners taking fewer trials to reach criterion ($M=14.04, SD=10.80$), than did CR learners, ($M=21.75, SD=14.97$). As these descriptive statistics are constant across all five ANOVAs, they will be omitted from the individual discussions.

**Rspan.** A factorial analysis with Rspan median group as the ID between subjects factor revealed the significant main effect of category structure, $F(1, 43)=5.857, p=.02$, and a significant main effect of Rspan median group, $F(1,43)=6.764, p=.013$, but no significant interaction effect, $F(1, 43)=.204, p>.05$. Learners whose Rspan score was above the median took fewer blocks to learn ($M=13.13, SD=11.42$) than did those whose Rspan score fell below the median ($M=21.33, SD=13.70$) (see Figure 8).

**Ospan.** A similar analysis using Ospan median group as the ID between subjects factor demonstrated the main effect of category structure, $F(1,43)=.4.337, p=.043$, but no effect of median group, $F(1,43)=.171, p>.05$, and no interaction between the two, $F(1,43)=.497, p>.05$. (see Figure 9).

**Sspan.** When Span median group became the between subject ID variable, there was once again the significant main effect of category group, $F(1,43)=5.898, p=.018$, as well as a main effect of Sspan median group that approached significance, $F(1,43)=3.694, p=.061$. Those who had higher Sspan scores took fewer blocks to learn ($M=14.43, SD=13.11$) than those with lower Sspan scores ($M=20.08, SD=12.88$) No significant interaction existed between the two, $F(1,43)=.095, p>.05$. However, a closer examination of the means (see Figure 10), suggests that for the II learners only, median group membership may affect how quickly an individual reached
the learning criterion. A simple effect analysis revealed an effect that approached significance: within the II category group, those who scored above the median on the Sspan took fewer blocks ($M=9.09$, $SD=6.36$) to achieve learning, $F(1,43)=2.931$, $p=.094$, than did those who scored below the median ($M=17.44$, $SD=12.04$).

**Handedness.** With handedness as the between subjects ID variable, the only main effect was that which existed between category groups, $F(1,43)=4.737$, $p=.035$. Neither a main effect of handedness median group $F(1,43)=.323$, $p>.05$, nor an interaction effect, $F(1,43)=.367$, $p>.05$, were present. However, Figure 11 suggests that for those individuals scoring below the median (less right-hand bias), category structure may have had an impact on learning. A simple effects test of category structure for those scoring below the median approached significance, $F(1,43)=3.404$, $p=.072$. Individuals with less right hand bias learned the information-integration structure more quickly ($M=10.75$, $SD=12.06$) than the complex rule ($M=21.82$, $SD=14.63$).

**Cognitive Style.** Overall, the results of the analysis of variance with V-V score as the between subjects ID variable were quite similar to those obtained with handedness, with only the main effect of category structure on blocks to criterion approaching significance, $F(1,43)=3.931$, $p=.054$. Once again, analysis demonstrated neither a main effect of V-V median group, $F(1,43)=.015$, $p>.05$, nor an interaction, $F(1,43)=.364$, $p>.05$ (see Figure 12).

**Individual difference scores and BTC.**

To examine whether an individual’s actual score on each of the 5 ID variables predicted how many blocks they took to reach the learning criterion, we conducted several regression analyses, considering the CR and II category groups separately. Handedness scores were once again transformed using an equation similar to Equation 1, with appropriate changes in the constants.

**Rspan.** For those in the CR group, the relationship between Rspan score and BTC approached significance, $t(18)=-1.982$, $p=.063$. As Rspan score increased, BTC decreased. For the II group, the relationship between Rspan score and BTC did not approach significance, $t(25)=-1.463$, $p>.05$.

**Ospan.** The relationship between Ospan score and BTC were not related for either the CR group, $t(18)=-1.379$, $p>.05$ nor the II group, $t(25)=0.450$, $p>.05$.

**Sspan.** For the CR group, Sspan score did not affect BTC, $t(18)=-0.713$, $p>.05$. However, Sspan score and BTC were significantly related for the II group, $t(25)=-2.744$, $p=.011$. 

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As Sspan score increased, BTC decreased. Sspan score accounted for 23.1% of the variance in BTC for the II group.

**Handedness.** For the CR group, the transformed handedness scores predicted BTC, \( t(18) = -2.098, p = .05 \). As handedness increased (indicating more right-hand bias), BTC decreased. The relationship between handedness and BTC did not approach significance for the II group, \( t(25) = .03, p > .05 \).

**Cognitive Style.** Cognitive style did not predict BTC in either the CR group, \( t(18) = -0.155, p > .05 \) or the II group, \( t(25) = -0.782, p > .05 \).

**Correlations.** The correlations among the ID measures for the learners in each category group are presented in Table 6. Surprisingly, for the CR group, none of the correlations reached significance. The II group demonstrated a significant correlation between Rspan score and Ospan score, \( r(25) = .516, p = .006 \); as Rspan score increased, so did the Ospan score. The correlation between Sspan score and VV score approached significance, \( r(25) = .365, p = .061 \); Sspan scores increased as cognitive style became more visual. The correlation between Ospan and Sspan also approached significance somewhat, \( r(25) = .324, p = .099 \); as Ospan score increased so did Sspan score.

Taken as a whole, these results indicate that having higher working memory benefits an individual’s ability to learn categories requiring the use of both information-integration and complex rule strategies. It seems that having more spatial working memory is particularly important for successfully learning information-integration categories. This result makes sense given the fact that information-integration learning depends more upon implicit visual integration than verbal rules. In contrast, having more verbal working memory seems to have a stronger impact on complex rule learning than information-integration learning. This suggests that working memory has dissociable impacts upon learning, depending on whether an individual possesses more visual or verbal working memory.

It may be that the degree to which an individual is more or less right-handed has some interesting implications for learning, and it may produce different effects in the two category structures. Given that over half of our sample was maximally right-handed, however, and only 5 participants exhibited a left-hand bias, drawing conclusions based on handedness seems premature.
General Discussion

Both Experiments 1 and 2 demonstrate that having more working memory resources facilitates category learning. The more complex stimuli and rules used in Experiment 2 allow us to conclude that this advantage persists as category membership becomes more difficult to distinguish. The strategy analysis in Experiment 1 indicated that individuals with high working memory become more adept at learning the optimal information-integration strategy over time; Experiment 2 suggests spatial working memory may be what determines performance in a more complex information-integration task, and allows individuals to switch from an ineffective verbal, rule-based strategy to the optimal implicit, visual information-integration strategy. On the other hand, distinguishing category membership in a complex rule task seems to be benefited more by having higher verbal working memory.

Although in general results were favorable, questions remain, such as why more participants learned the information-integration category structure in Experiment 2 than the complex rule structure. This may be addressed through response modeling, which will reveal what kinds of strategies participants used and how these strategies changed over time. In addition, the effects of handedness hinted at in Experiment 2 warrant further investigation to determine whether non-right-handedness truly impacts category learning. Selective recruiting of left-handed individuals will allow for a clearer illustration of whether an effect of handedness exists.

If possessing higher working memory facilitates task-switching and implies better attentional control, individuals with higher working memory should respond more quickly and accurately to instructions communicating an optimal categorization strategy. If instructed to use an implicit gut-hunch strategy on an information-integration task rather than an explicit hypothesis-testing one, individuals with higher working memory should be able to abandon an explicit strategy (to which category learning is initially biased) and learn the optimal implicit rule. Further investigation will include an instructional manipulation, to determine whether relevant instruction facilitates category learning as a function of working memory ability. It will be interesting to see whether individuals with higher spatial working memory still exhibit superior information-integration learning after receiving relevant instruction; as has been shown in Experiment 2, their higher spatial ability should benefit information-integration learning, but the fact that the instructions are communicated “verbally” might possibly interfere.
Table 1. Stimulus dimensions.

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Value</th>
<th>Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>V=Symbol Color</td>
<td>-1</td>
<td>Red</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>Green</td>
</tr>
<tr>
<td>W=Background Color</td>
<td>-1</td>
<td>Yellow</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>Blue</td>
</tr>
<tr>
<td>X=Number of Symbols</td>
<td>-1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Y=Symbol Shape</td>
<td>-1</td>
<td>Circle</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>Square</td>
</tr>
</tbody>
</table>
Table 2. Possible strategies to classify information-integration stimuli belonging to category A and their accuracy.

<table>
<thead>
<tr>
<th>Strategy Type</th>
<th>Response Model</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimal</td>
<td>1) ((V+X+Y)&gt;0)</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>2) (V&gt;0)</td>
<td></td>
</tr>
<tr>
<td>One-Dimension</td>
<td>3) (Y&gt;0)</td>
<td>75%</td>
</tr>
<tr>
<td></td>
<td>4) (X&gt;0)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>5) (W&gt;0) or (Y&gt;0)</td>
<td></td>
</tr>
<tr>
<td>Two-Dimension</td>
<td>6) (W&gt;0) or (V&gt;0)</td>
<td>75%</td>
</tr>
<tr>
<td></td>
<td>7) (V&gt;0) or (Y&gt;0)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>8) (W&gt;0) or ((V&gt;0) and (Y&gt;0))</td>
<td></td>
</tr>
<tr>
<td>Three-Dimension</td>
<td>9) (V&gt;0) or ((W&gt;0) and (Y&gt;0))</td>
<td>87.5%</td>
</tr>
<tr>
<td></td>
<td>10) (Y&gt;0) or ((W&gt;0) and (V&gt;0))</td>
<td></td>
</tr>
</tbody>
</table>
Table 3. Mean, median, standard deviation, range, minimum and maximum for each individual difference variable.

<table>
<thead>
<tr>
<th>ID variable</th>
<th>Mean</th>
<th>Median</th>
<th>SD</th>
<th>Range</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rspan</td>
<td>44.80</td>
<td>46</td>
<td>16.26</td>
<td>67</td>
<td>4</td>
<td>71</td>
</tr>
<tr>
<td>Ospan</td>
<td>49.86</td>
<td>52</td>
<td>15.04</td>
<td>68</td>
<td>7</td>
<td>75</td>
</tr>
<tr>
<td>Sspan</td>
<td>21.11</td>
<td>21</td>
<td>8.46</td>
<td>38</td>
<td>4</td>
<td>42</td>
</tr>
<tr>
<td>HI</td>
<td>68.11</td>
<td>75</td>
<td>42.38</td>
<td>200</td>
<td>-100</td>
<td>100</td>
</tr>
<tr>
<td>V-V</td>
<td>65.88</td>
<td>66</td>
<td>8.54</td>
<td>51</td>
<td>29</td>
<td>80</td>
</tr>
</tbody>
</table>
Table 4. Overall correlations between individual difference variables.

<table>
<thead>
<tr>
<th>ID variable</th>
<th>Rspan</th>
<th>Ospan</th>
<th>Sspan</th>
<th>HI_Transform</th>
<th>V-V</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rspan</td>
<td>1</td>
<td>.410**</td>
<td>.082</td>
<td>-.003</td>
<td>.152</td>
</tr>
<tr>
<td>Ospan</td>
<td>.410**</td>
<td>1</td>
<td>.096</td>
<td>-.028</td>
<td>.067</td>
</tr>
<tr>
<td>Sspan</td>
<td>.082</td>
<td>.096</td>
<td>1</td>
<td>.066</td>
<td>.194†</td>
</tr>
<tr>
<td>HI_Transform</td>
<td>-.003</td>
<td>-.028</td>
<td>.066</td>
<td>1</td>
<td>.095</td>
</tr>
<tr>
<td>V-V</td>
<td>.152</td>
<td>.067</td>
<td>.194†</td>
<td>.095</td>
<td>1</td>
</tr>
</tbody>
</table>

** indicates significant correlations, \(p<.01\)

† indicates correlations approaching significance, \(.05<p<.1\)
Table 5. Frequency of learners in each median by category structure group for the 2 out of 3 learning criterion.

<table>
<thead>
<tr>
<th>Category Group</th>
<th>Median Group</th>
<th>CR</th>
<th>II</th>
</tr>
</thead>
<tbody>
<tr>
<td>2/3 65% RSPAN</td>
<td>Below</td>
<td>9</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Above</td>
<td>11</td>
<td>12</td>
</tr>
<tr>
<td>2/3 65% OSPAN</td>
<td>Below</td>
<td>9</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>Above</td>
<td>11</td>
<td>15</td>
</tr>
<tr>
<td>2/3 65% SSPAN</td>
<td>Below</td>
<td>8</td>
<td>16</td>
</tr>
<tr>
<td></td>
<td>Above</td>
<td>12</td>
<td>11</td>
</tr>
<tr>
<td>2/3 65% Hand</td>
<td>Below</td>
<td>11</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>Above</td>
<td>9</td>
<td>19</td>
</tr>
<tr>
<td>2/3 65% V-V</td>
<td>Below</td>
<td>9</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>Above</td>
<td>11</td>
<td>13</td>
</tr>
</tbody>
</table>
Table 6. Correlations among individual difference variables for learners in the complex rule and information-integration category structures.

<table>
<thead>
<tr>
<th>ID variable</th>
<th>Rspan</th>
<th>Ospan</th>
<th>Sspan</th>
<th>HI_Transform</th>
<th>V-V</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CR Group</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rspan</td>
<td>1</td>
<td>.249</td>
<td>.058</td>
<td>-.108</td>
<td>.357</td>
</tr>
<tr>
<td>Ospan</td>
<td>.249</td>
<td>1</td>
<td>-.089</td>
<td>.094</td>
<td>-.095</td>
</tr>
<tr>
<td>Sspan</td>
<td>.058</td>
<td>-.089</td>
<td>1</td>
<td>.187</td>
<td>-.040</td>
</tr>
<tr>
<td>HI_Transform</td>
<td>-.108</td>
<td>.094</td>
<td>.187</td>
<td>1</td>
<td>-.319</td>
</tr>
<tr>
<td>V-V</td>
<td>.357</td>
<td>-.095</td>
<td>-.040</td>
<td>-.319</td>
<td>1</td>
</tr>
<tr>
<td><strong>II Group</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rspan</td>
<td>1</td>
<td>.516**</td>
<td>.152</td>
<td>-.218</td>
<td>.123</td>
</tr>
<tr>
<td>Ospan</td>
<td>.516**</td>
<td>1</td>
<td>.324†</td>
<td>-.207</td>
<td>.020</td>
</tr>
<tr>
<td>Sspan</td>
<td>.152</td>
<td>.324†</td>
<td>1</td>
<td>.096</td>
<td>.365†</td>
</tr>
<tr>
<td>HI_Transform</td>
<td>-.218</td>
<td>-.207</td>
<td>.096</td>
<td>1</td>
<td>.009</td>
</tr>
<tr>
<td>V-V</td>
<td>.123</td>
<td>.020</td>
<td>.365†</td>
<td>.009</td>
<td>1</td>
</tr>
</tbody>
</table>

** indicates significant correlations, p<.01
† indicates correlations approaching significance, .05<p<.1
Figure Captions

Figure 1. The 16 stimuli adapted from Waldron and Ashby (2001) used in Study 1.

Figure 2. Average number of trials to reach 8-trial criterion, depending on category structure and working memory group. Error bars represent standard error.

Figure 3. Average number of trials to reach 16-trial criterion, depending on category structure and working memory group. Error bars represent standard error.

Figure 4. Proportion of strategy use (optimal, three-dimension rule, two-dimension rule, one-dimension rule) by strategy type and block for low and high working memory groups.

Figure 5. Two examples of the circle-line stimuli used in Study 2.

Figure 6. Information-integration category structure. Stimuli in category A are above the y=x decision bound; stimuli in category B are below.

Figure 7. Rule-based category structure. Stimuli in category A are in the upper right and lower left quadrants denoted by the decision bound; stimuli in category B are in the upper left and lower right quadrants.

Figure 8. Average number of blocks to reach learning criterion, depending on category structure and Rspan median group. Error bars represent standard error.

Figure 9. Average number of blocks to reach learning criterion, depending on category structure and Ospan median group. Error bars represent standard error.

Figure 10. Average number of blocks to reach learning criterion, depending on category structure and Sspan median group. Error bars represent standard error.

Figure 11. Average number of blocks to reach learning criterion, depending on category structure and handedness median group. Error bars represent standard error.

Figure 12. Average number of blocks to reach learning criterion, depending on category structure and V-V median group. Error bars represent standard error.
Figure 1
Figure 2

8 Trial Criterion

- Rule-based
- Information-integration

- High WM Group
- Low WM Group
Figure 3

16 Trial Criterion

Total Trials to Criterion

- Rule-based
- Information-integration

Category Structure

High WM Group
Low WM Group
Figure 4

Low WM Group

High WM Group
Figure 6
Figure 7.
Figure 8.

Average Blocks to Criterion

![Bar chart showing average blocks to criterion for Below Rspan Median and Above Rspan Median groups, with error bars indicating variability. The chart compares groups CR and II.]
Figure 9.

Average Blocks to Criterion

- Below Ospan Median
- Above Ospan Median

Ospan Median Group

Blocks to Criterion

CR
II
Figure 10.

Average Blocks to Criterion

- Below Sspan Median
- Above Sspan Median

CR
II

Sspan Median Group
Figure 11.

Average Blocks to Criterion

![Chart showing average blocks to criterion for Below Hand Median and Above Hand Median groups with error bars.]
Figure 12.

**Average Blocks to Criterion**

![Bar chart showing average blocks to criterion for different groups.](chart.png)

- **Vis_Verb Median Group**: Below and Above Vis-Verm Median
- **Values**: CR and II

**Axes**:
- **Y-Axis**: Blocks to Criterion
- **X-Axis**: Vis_Verb Median Group

**Legend**:
- CR
- II
References


