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Brief article

Individual differences in category learning: Sometimes less working memory capacity is better than more ☆

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Abstract

We examined whether individual differences in working memory influence the facility with which individuals learn new categories. Participants learned two different types of category structures: *rule-based* and *information-integration*. Successful learning of the former category structure is thought to be based on explicit hypothesis testing that relies heavily on working memory. Successful learning of the latter category structure is believed to be driven by procedural learning processes that operate largely outside of conscious control. Consistent with a widespread literature touting the positive benefits of working memory and attentional control, the higher one's working memory, the fewer trials one took to learn rule-based categories. The opposite occurred for information-integration categories – the lower one's working memory, the fewer trials one took to learn this category structure. Thus, the positive relation commonly seen between individual differences in working memory and performance can not only be absent, but reversed. As such, a comprehensive understanding of skill learning – and category learning in particular – requires considering the demands of the tasks being performed and the cognitive abilities of the performer.
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1. Introduction

Categorization allows us to divide the world into meaningful parts – a key component of skill learning and performance. Perhaps not surprisingly then, category learning has garnered attention across diverse areas of cognitive science ranging from the study of expert knowledge structures (Chi, Feltovich, & Glaser, 1981) to research examining how individuals extract consistencies from diverse sets of stimuli (Barsalou, 1983). Although a significant amount of work has been devoted to understanding the cognitive and neural mechanisms supporting category learning (Ashby & Maddox, 2005; Thomas, 1998), little work has considered how individual differences in cognition may influence the facility with which one discovers category structures. Such work is important, as skill learning and performance does not solely depend on the demands of the task being performed, but on the ability of the learner as well (Beilock & Carr, 2005). Toward this end, in the current work we ask how individual differences in the cognitive construct of working memory impact the learning of different types of category structures. Given the central role that working memory plays in complex cognition (Engle, 2002) and the vital role that categorization plays in the acquisition and representation of information in memory (Ashby & O'Brien, 2004), the relation between individual differences in working memory and category learning is important to explore and – as will be seen below – not as straightforward as one might initially imagine.

1.1. Working memory

Working memory can be thought of as a short-term system involved in the control, regulation, and active maintenance of a limited amount of information with immediate relevance to the task at hand (Miyake & Shah, 1999). It can also be thought of as an individual difference variable – meaning that some people have more of this construct and some have less. Although, investigations of the link between working memory and behavior have spanned diverse areas of cognitive science, most of this work has yielded surprisingly similar conclusions regarding its role in high-level performance – the more working memory capacity individuals have at a given time, the better performance will be on the types of reasoning, problem solving, and comprehension tasks encountered in both the confines of the laboratory and the complexity of the real world (Conway et al., 2005).

Given a scientific literature that emphasizes the positive aspects of working memory and attentional control (Miyake & Shah, 1999), one might suppose that higher working memory individuals should always outperform their lower working memory counterparts. Nonetheless, there are situations in which individual differences in working memory are not predictive of behavior. In syllogistic reasoning for example,

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when the goal is to decide whether a conclusion follows logically from given premises, performance does not differ as a function of working memory when the believability of the conclusion is consistent with logic (e.g., *Premises*: all mammals can walk. Dogs are mammals. *Conclusion*: dogs can walk). In contrast, when logic is in conflict with believability, higher working memory individuals outperform their lower capacity counterparts (e.g., *Premises*: all mammals can walk. Dolphins are mammals. *Conclusion*: dolphins can walk). In this second example, the conclusion is valid, but not believable, and thus providing the correct response requires reliance on demanding logical reasoning processes. The more working memory individuals have to support such processes, the better their performance (De Neys, 2006; Evans, 2003; Stanovich & West, 2000). In the first case, the complex reasoning associated with higher working memory capacity does not inform behavior over and above more associatively driven processes thought to run largely outside working memory.

Although the above mentioned work is informative regarding individual differences in cognitive control and its relation to reasoning processes, it is important to note that the pattern of data reported above – and in a large majority of work to date – shows working memory differences on some problems (e.g., where complex hypothesis testing or reasoning processes are needed for successful performance), and a lack of working memory differences on others (e.g., where demanding computations are not necessary for accurate performance). In the current work we ask whether, for certain tasks, the relation between individual differences in working memory and performance may not just be absent, but *reversed*. To do this, we turn to the category learning literature. Although the learning of certain category structures is thought to be based on complex hypothesis testing and thus likely relies heavily on working memory, there are also category structures for which instantiating demanding reasoning processes may not only be useless, but detrimental.

1.2. Category learning

How do individuals learn to classify the stimuli they encounter? There is a growing body of evidence suggesting that individuals draw upon multiple processing modes in learning different types of category structures (Zeithamova & Maddox, 2006). For instance, *rule-based* categorization tasks can be optimally solved using a verbalizable, logical rule. Rule-based category learning is thought to be accomplished by explicit hypothesis testing that relies heavily on working memory. In support of this idea, several studies have shown that the addition of a secondary demanding task impairs rule-based learning in comparison to control conditions in which no dual-task is present (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). In contrast, *information-integration* categorization tasks require learners to integrate stimulus values across multiple dimensions prior to making a categorization decision. This is thought to involve procedural learning mechanisms that identify stimulus–response mappings between category members and a correct response (for a review, see Ashby & Maddox, 2005; Ashby & O'Brien, 2004).

The processes used to learn rule-based and information-integration category structures are thought to operate simultaneously, competing throughout learning,

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with that most suited for the task at hand eventually winning out (Ashby & Maddox, 2005; Zeithamova & Maddox, 2006). Specifically, when presented with a categorization task, individuals attempt to test explicit hypotheses about the category structure while at the same time integrating complex feature information and learning stimulus–response mappings based on this information. Initially, there is a bias toward explicit hypothesis testing, and when an explicit rule is discovered (e.g., in a rule-based task), it dominates the categorization task (Zeithamova & Maddox, 2006). But when a simple rule does not lead to accurate performance (e.g., in information-integration tasks), procedural learning wins out.

Given that rule-based categorization demands the explicit testing of category feature combinations, and that such processes likely rely on the types of controlled attention abilities believed to be at the heart of working memory (Engle, 2002), it seems logical that individual differences in working memory will moderate the learning of rule-based category structures. In contrast, because information-integration category structures are not as reliant on explicit hypothesis testing, one might assume no relation between individual differences in working memory and performance – just as when believability and logic point in the same direction in the reasoning work presented above (De Neys, 2006; Evans, 2003; Stanovich & West, 2000). It has been suggested, however, that explicit hypothesis testing may actually harm performance on information-integration categorization tasks by limiting the ability of procedural learning processes to take over (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Markman, Maddox, & Worthy, 2006). To the extent that individuals higher in working memory more readily employ complex hypothesis testing and reasoning, then one might very well find a relation between working memory capacity and information-integration category learning – but in the opposite direction of that seen for rule-based tasks. Such a finding would underscore the idea that a comprehensive understanding of learning and performance not only requires considering situations in which more working memory capacity will lead to better performance but also when it will lead to worse. Moreover, it would highlight the need to address individual differences in category learning – a topic that has been largely ignored in this literature to date.

In the current work, we build upon the ideas that (a) individual differences in working memory carry implications for the ability to utilize complex hypothesis testing and reasoning processes (Conway et al., 2005; Dougherty & Hunter, 2003; Gaissmaier, Schooler, & Rieskamp, 2006) and (b) performance on rule-based versus information-integration categorization tasks may differ as a function of the ability to successfully hypothesis test (Ashby et al., 1998), to explore how working memory capacity relates to category learning. To our knowledge, little work has considered how individual differences in cognitive constructs such as working memory influence the facility with which one discovers different category structures. Moreover, although it has been suggested that different types of category learning may be mediated by different neural circuitry (for a review, see Ashby & Ell, 2001), no study has demonstrated a double-dissociation between category structures and individual difference variables that supports a multiple systems perspective. Finally, given the plethora of work demonstrating a positive relation between working memory capacity and complex cognitive behaviors ranging from reasoning to problem solv-

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ing (Conway et al., 2005), demonstrations that this relation may not only be absent but *reversed* are important for developing theories of executive control that take into account the multifaceted nature of the tasks individuals encounter.

2. Current experiment

Individuals learned two types of category structures: *rule-based* and *information-integration*. To the extent that working memory supports hypothesis generation and testing, the higher one's working memory, the faster one should learn rule-based categories. Such a result would be consistent with the abundance of research demonstrating a positive relationship between working memory and performance (Conway et al., 2005). However, the very capacity limitations associated with less working memory may be just what is needed to optimally learn information-integration categories. If so, the lower one's working memory, the more optimal learning may be on this task.

2.1. Method

2.1.1. Participants

Undergraduate students ($N = 71$) at a large Midwestern University served as participants.

2.1.2. Procedure

Category learning task. Participants completed the categorization task individually on the computer. Individuals were instructed to place each stimulus into either category A or category B by pressing one of two keys on the keyboard. Immediate feedback was given on each trial, with the words ''correct'' or ''incorrect'' appearing directly below the stimulus. Participants completed four sets of 200 trials each, separated by rest periods during which they were informed that they would be learning a new rule. The four sets included two different rule-based tasks (R) and two different information-integration tasks (I), with one of each category structure occurring in the first two sets of trials (first block) and the other in the last two sets (second block). Thus, four orders were possible (i.e., RIRI, IRIR, RIIR, IRRI) and counterbalanced across participants. The order of the specific tasks within each category structure (e.g., which rule-based task came first) was randomized across participants as well. All participants performed the same four categorization tasks.

Categorization stimuli were adapted from Waldron and Ashby (2001). Each was a square with either one or two symbols embedded within it. Sixteen stimuli were constructed by taking the factorial combination of four dimensions, two levels each: square/background color (yellow or blue), embedded symbol shape (circle or square), symbol color (red or green), and number of embedded symbols (1 or 2). The two types of categorization structures, rule-based and information-integration, used all 16 stimuli but differed in the mapping from stimuli to responses.

Rule-based categories were one-dimensional (e.g., ''If the embedded symbol is a circle, choose category A; if the symbol is a square, choose category B''), affording

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an easy verbalizable strategy. Because previous studies (e.g., Waldron & Ashby, 2001) found no differences in performance depending on the dimension selected to be relevant, symbol color was randomly chosen as the relevant dimension for one rule-based task and symbol shape for the other.

Information-integration categories involved three dimensions. One dimension was randomly selected to be irrelevant (background color for one information-integration task and number of embedded symbols for the other). Each binary value of the other three dimensions was randomly assigned either a -1 or a $+1$ (e.g., a green symbol $= -1$ and a red symbol $= +1$); the three remaining relevant dimensions were labeled X, Y, and Z. Stimuli were categorized according to the following rule: If $\text{value}(X) + \text{value}(Y) + \text{value}(Z) > 0$, respond category A, otherwise respond category B (Waldron & Ashby, 2001). Information-integration categories cannot usefully be described by simple verbal rules. Instead, dimensional values must be integrated at a pre-decisional stage, presumably without access to conscious awareness (Ashby & Maddox, 2005).

Following categorization, participants filled out a question regarding how much pressure they felt to perform at a high level, ranging from 1 (very little performance pressure) to 7 (extreme performance pressure). Previous research has demonstrated that feelings of performance pressure impact category learning (Markman et al., 2006). Thus, we were interested in ensuring that such perceptions did not differ as a function of individual differences in working memory.

Working memory tasks. Finally, individuals completed two commonly used measures of working memory counterbalanced in order: a modified Operation Span (Turner & Engle, 1989) and a modified Reading Span (Daneman & Carpenter, 1980). The Automated Operation Span (Aospan; Unsworth, Heitz, Schrock, & Engle, 2005) and Automated Reading Span (Arspan) were both performed individually on a computer and require participants to remember a series of letters while performing a concurrent task. Maintaining information in the face of interference is thought to be at the heart of working memory (Engle, 2002).

In the Aospan, participants judge whether a math problem yields a true or false answer. Individuals view an equation on the screen (e.g., "$(1 * 2) + 1=?$") and are instructed to press the mouse button after they have solved it. The equation is then replaced by a number, which participants judge as either the correct or incorrect equation answer by clicking a "true" or "false" screen box. Next, a letter is presented (800 ms) for later recall. After a series of equation-letter trials, 12 letters are presented and individuals are asked to select the letters they remember, in the correct order. To prevent letter rehearsal, participants are given a limited amount of time to solve and respond to the math equation, determined by their performance speed during a series of practice trials. Individuals are instructed to keep accuracy above 85% and feedback (i.e., equation accuracy and letter response) is provided. The Arspan is similar to the Aospan. However, rather than judging equation accuracy, participants are asked to read a sentence (e.g., "Stacey stopped dating the light when she found out he had a wife.") and verify whether or not it makes sense. In both the Aospan and the Arspan, participants view 75 total trials in random order, with 15 sets of 3–7 trials each. Lastly, participants were thanked and debriefed.

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3. Results

Working memory scores were calculated by summing the number of letters selected for all correctly selected sets. Averages across the two working memory measures ranged from 2 to 72 ($M = 45.49$, $SE = 1.9$). Eleven additional participants were tested but not included in the current work for failure to maintain above 85% accuracy on the math and sentence portions of the span tasks (Unsworth et al., 2005). However, including these participants did not change the pattern of results in any way. Moreover, working memory scores were not correlated with reports of perceived pressure ($M = 3.82$, $SE = .16$), $r = .13$, $p = .29$. Thus, it would be difficult to explain any of the working memory differences reported below by general differences in perceived pressure to perform well on our categorization tasks.

Our main dependent measure was the number of trials taken to learn category rules to criterion: eight correct trials in a row, log transformed due to positive skew in the distribution. Log transformations are a common method for normalizing data (Tabachnick & Fidel, 1996), including categorization data that is typically positively skewed (e.g., Waldron & Ashby, 2001). Individuals who successfully learned all four category rules (prior to the 200 trial max) and whose performance did not exceed two *SD* above the mean trials to criterion in each block were included in the current work. This exclusion criterion was designed to prevent extreme values in our distribution from unduly influencing the results (Tabachnick & Fidel, 1996).

We began by regressing trials to criterion on average working memory scores, category structure (rule-based versus information-integration, dummy coded), and their interaction. This regression resulted in a significant working memory × category structure interaction, $\beta = .609$, $t = 3.11$, $p < .01$. As can be seen in Fig. 1, for rule-based category structures, the higher one's working memory, the fewer trials one took to reach criterion, $\beta = -.236$, $t = -2.02$, $p < .05$. In contrast, for information-integration category structures, the higher one's working memory, the more trials one took to reach criterion, $\beta = .274$, $t = 2.36$, $p <. 03$.[1]

[1] An alternative approach to this analysis is to assess whether (i) the Pearson r between the average working memory scores and trials-to-criterion is significantly different from 0 (and negative) in the rule-based condition, (ii) the Pearson r between the average working memory scores and trials-to-criterion is significantly different from 0 (and positive) in the information-integration condition, and (iii) the two correlation coefficients differ from each other. Tests (i) and (ii) were confirmed: the Pearson r between (log) trials-to-criterion and the average working memory score in the rule-based task was $-.236$, $t(69) = -2.02$, $p < .05$, and the Pearson r between trials-to-criterion and the average working memory score in the information-integration task was .274, $t(69) = 2.36$, $p < .03$. To assess test (iii), we use the procedure described in Meng, Rosenthal, and Rubin (1992) which allows us to compare correlation coefficients which are "overlapping" in the sense that the same working memory variable participates in both correlation coefficients which may be correlated themselves because the same participants produced the trials-to-criterion outcome in each. By their procedure (see p. 173, Eqs. (1)–(4) in Meng et al. (1992)), the difference in the two Pearson r's is significant ($z = 3.075$, $p < .01$, two-tailed). The 95% confidence interval for the difference between the r obtained in the information integration task and the r obtained in the rule-based task is (.189, .854).

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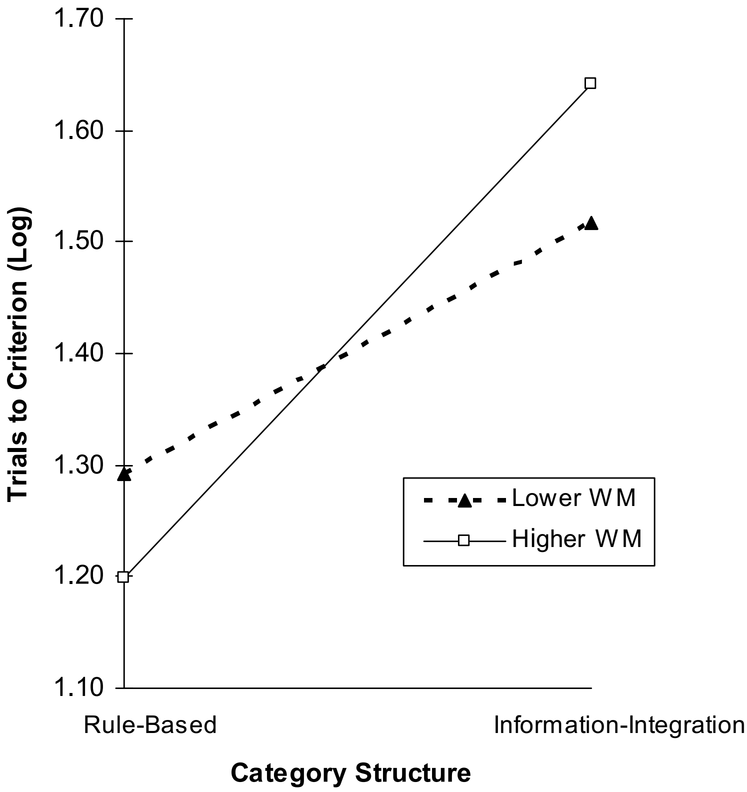

Fig. 1. Mean trials to criterion as a function of category structure and individual differences in working memory. Nonstandardized regression coefficients are plotted at ±1 *SD*.

4. Discussion

The higher one's working memory, the faster one learned rule-based categories. The opposite occurred for information-integration category structures. Both hypothesis testing and procedural learning are thought to be instantiated at the outset of any category learning task, with the former dominating successful rule-based categorization and the latter supporting information-integration learning (Maddox & Ashby, 2004). Thus, individual differences in cognitive control may influence which category learning process is most readily (and effectively) utilized. Higher working memory individuals' executive attention resources are thought to support successful hypothesis testing (Dougherty & Hunter, 2003). These same resources, however, seem to hinder learning of information-integration category structures.

The finding that the higher individuals' working memory, the slower they learned information-integration category structures may seem inconsistent with a scientific literature that emphasizes the positive benefits of working memory and attentional control (Beilock, Kulp, Holt, & Carr, 2004; Engle, 2002). However, as mentioned in Section 1, individual differences in working memory are not always predictive of performance. In reasoning for example, when a logically valid conclusion is also

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believable, no relation between working memory and performance is observed (De Neys, 2006; Stanovich & West, 2000). This is because the complex reasoning associated with higher working memory capacity does not inform behavior over and above more associatively driven processes that are thought to operate largely outside of working memory.

In the current work, we go beyond merely demonstrating a lack of a relation between individual differences and performance – showing that for tasks in which complex hypothesis testing may hinder effective learning, the higher one's working memory, the worse one performs. Optimal information-integration performance is thought to be based on proceduralized learning processes, and it has been suggested that the explicit hypothesis testing of category membership may actually inhibit ultimate learning (Ashby et al., 1998). The fact that those individuals highest in working memory performed the worst on this task suggests that higher working memory individuals may, at times, rely on complex computational processes that are not necessarily optimal for the task at hand. This counterintuitive finding demonstrates that the availability of executive attention resources can actually hinder the learning of tasks that rely more so on proceduralized processes and calls into question the utility of using the performance of higher working memory individuals as the universal benchmark for optimal performance across all tasks (De Neys, 2006; Stanovich & West, 2000).

Although investigations of the impact of secondary tasks on category learning can lend insight into the types of category structures that are heavily dependent on executive control resources (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006), the double-dissociation between category structure and working memory in the current work opens a window into category learning – and learning more broadly – in a way many dual-task studies do not. Indeed, previous work has shown that a secondary demanding task hurts rule-based category learning but spares information-integration learning (Waldron & Ashby, 2001). Yet, these types of secondary load studies have not shown the information-integration learning benefit seen for those lower in working memory in the current work. It may be that the addition of a demanding secondary task (e.g., numerical Stroop task; Waldron & Ashby, 2001) impacts one's ability to successfully encode the relevant stimulus features needed for procedural learning processes. Indeed, in the Waldron and Ashby study, the secondary task was concurrently displayed with the category stimulus to be encoded. Capitalizing on individual differences in working memory then may allow for the expression of procedural learning when individuals are able to encode the relevant stimulus features but are less able to apply rule-based reasoning processes to the stimuli they encode (e.g., individuals lower in working memory). By demonstrating systematic individual differences in learning various category structures we highlight that there is not always a positive relation between working memory and performance, thus underscoring the need to address individual differences in category learning – a topic that has been largely ignored in this literature to date.

In conclusion, individual differences in working memory influence the propensity with which individuals learn new categories, with the nature of the relation between working memory and category learning dependent on the demands of the task being

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performed. More specifically, in the learning of information-integration category structures, the positive relation commonly seen between individual differences in working memory and performance is not only absent, but reversed. Thus, a comprehensive understanding of category learning requires knowledge of the cognitive and neural substrates supporting the category structure being learned *and* consideration of how these processes interact with the cognitive abilities of the performer.

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