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Whichever Way you Choose to Categorize, Working Memory Helps you Learn

Stewart Craig and Stephan Lewandowsky

The University of Western Australia

Stephan Lewandowsky

School of Psychology

University of Western Australia

Crawley, W.A. 6009, AUSTRALIA

lewan@psy.uwa.edu.au

URL: http://www.cogsciwa.com

Abstract

There has been growing interest in the relationship between the capacity of a person's working memory, and their ability to learn to categorize stimuli. While there is evidence that working memory capacity (WMC) is related to the speed of category learning, it is unknown whether WMC predicts which strategies people use when there are multiple possible solutions to a categorization problem. To explore the relationship between WMC, category learning, and categorization strategy use, 173 participants completed two categorization tasks and a battery of WMC tasks. WMC predicted the speed of category learning, but it did not predict which strategies participants chose to perform categorization. Thus, WMC does not predict which categorization strategies people use but it predicts how well they will use the strategy they select.

Whichever Way you Choose to Categorize, Working Memory Helps you Learn

Different people classify the environment in very different ways. What a referee classifies as a foul in a football game is often different from a spectator's classification. Similarly, when deciding whether a late-night stranger poses a threat, some people may base their classification on age whereas others might focus on body strength or build. This diversity of classification techniques is frequently observed in the laboratory. Despite near identical training, people often use different strategies to categorize items (e.g., Johansen & Palmeri, 2002; Lewandowsky, Roberts, & Yang, 2006; Little & Lewandowsky, 2009; Nosofsky, Palmeri, & McKinley, 1994; Sewell & Lewandowsky, 2011b; Yang & Lewandowsky, 2003, 2004).

The diversity of strategies is readily illustrated by Nosofsky et al.'s (1994) replication of Medin and Schaffer's (1978) seminal categorization task. Participants were trained to associate five items with category A, and four items with category B. Each item varied on four binary dimensions. After extensive training, participants classified seven new items. The classifications of these new items provided insight into the strategies participants were using to categorize. Nosofsky et al. (1994) found that while some participants categorized items using an exemplar strategy, others applied simple one-dimensional rules.

Similarly, Yang and Lewandowsky (2003, 2004) had participants classify stimuli that varied on two continuous dimensions and one binary dimension. During training, the binary dimension, termed *context*, was not predictive of category membership. Despite being presented with exactly the same training items, different participants used strikingly different strategies to categorize the items. Some participants classified the items based on the context cue. Others ignored context, relying only on the two continuous dimensions to classify items.

Cognitively, those various strategies can be considered distinct psychological representations of an identical category space (Medin & Schaffer, 1978). In the task by Yang and Lewandowsky (2004), participants who utilized the context cue responded as if they partitioned the two-dimensional category space into two distinct and independently-represented regions. In contrast, participants who ignored the context cue responded as if they represented the category space as a single integrated area. In computational models, these different strategic representations are typically expressed through different parameter values (Medin & Smith, 1981; Nosofsky & Johansen, 2000; Yang & Lewandowsky, 2004). At a behavioral level, different strategies are observed as different classification responses to an identical set of new items.

The marked differences in people's categorization strategies has led to a growing awareness of the need to analyze categorization behavior at the individual level (Lee & Webb, 2005; Maddox, 1999; Navarro, Griffiths, Steyvers, & Lee, 2006). However, while there have been post-hoc attempts to model the variation in strategies, it remains unclear what factors lead people toward one or the other strategy.

Intriguingly, performance during category learning has been found to be a poor predictor of strategy choice (Little & Lewandowsky, 2009; Sewell & Lewandowsky, 2011b; Yang & Lewandowsky, 2004). For example, in the study by Yang and Lewandowsky (2004), training performance was virtually identical between participants who used the context cue (mean proportion correct .84) to partition the problem and those who ignored context (.82). This result has been replicated with both deterministic (Sewell & Lewandowsky, 2011b) and probabilistic (Little & Lewandowsky, 2009) categorization environments. As long as people learn enough about the task to acquire *some* successful strategy, performance may not predict *which* strategy is chosen.

This article commences the search for potential predictors of strategy choice in categorization. We choose to focus on the role of working memory capacity (WMC).

Working memory (WM) is a central cognitive system that provides temporary storage and active manipulation of information (Baddeley, 1986). WMC is highly correlated with general fluid intelligence (Kane, Hambrick, & Conway, 2005) and performance in other cognitive domains, such as reading comprehension (Daneman & Carpenter, 1980), sentence comprehension (Daneman & Carpenter, 1983) and reasoning (Kyllonen & Christal, 1990). Additionally, there is evidence that WMC is related to the speed of category learning on a range of categorization tasks (DeCaro, Thomas, & Beilock, 2008; DeCaro, Carlson, Thomas, & Beilock, 2009; Erickson, 2008; Lewandowsky, 2011). WMC is a particularly plausible candidate predictor of strategy choice for three reasons. First, the fact that WMC is related to speed of category learning suggests that working memory may also contribute in other ways to classification performance. Second, the processing and storage attributes of WMC and categorization provide possible cognitive links between WMC and strategy use in categorization. In many categorization theories, incoming stimuli are converted into a psychological representation. This representation is then actively processed, typically in comparison to previously encountered stimuli (Erickson & Kruschke, 1998; Kruschke, 1992; Nosofsky, 1986; Stewart, Brown, & Chater, 2002), or some boundary resulting from application of a rule (Ashby & Townsend, 1986; Erickson & Kruschke, 1998). Temporary representation and processing of information are key characteristics of WM. In addition, attentional control, thought to be a key component of WM (Conway, Tuholski, Shisler, & Engle, 1999; Cowan, 1988; Engle, 2002; Kane, Bleckley, Conway, & Engle, 2001), equally plays a key role in many theories of categorization (e.g. Erickson & Kruschke, 1998; Kruschke, 1992, 2001; Kruschke & Johansen, 1999; Love, Medin, & Gureckis, 2004). For example, incorporating an ability to control how attention is directed toward stimulus dimensions dramatically improves the performance of categorization models on a range of tasks (Kruschke, 1992, 2005; Nosofsky, 1986).

In addition to clear theoretical links between WMC and categorization processes, there is a third reason to expect that WMC might predict strategy choice in categorization: WMC has been found to predict strategy choice in other domains. In memory tasks, participants with higher WMC are more likely than low-WMC participants to report using "deeper" encoding strategies rather than surface strategies (Bailey, Dunlosky, & Kane, 2008; Dunlosky & Kane, 2007; Friedman & Miyake, 2004; Kaakinen & Hyönä, 2007; Turley-Ames & Whitfield, 2003). These deeper encoding strategies include creating visual images, or creating stories to link items. To illustrate, Dunlosky and Kane (2007) had participants complete a measure of WMC, an operation-span task. The operation-span task requires participants to remember a series of words interspersed with arithmetic equations. After each series of words, Dunlosky and Kane asked participants what strategy they used to encode the items. The proportion of trials on which participants reported using a deeper encoding strategy was positively related to participants' WMC ($r = .30$).

The relationship between WMC and encoding strategies is further illuminated by studies that sought to bring strategies under experimental control. Turley-Ames and Whitfield (2003) manipulated strategy use by teaching participants to use a rehearsal strategy. They found that teaching participants to repeat to-be-remembered words aloud increased WMC more for those who had low WMC scores prior to training than those who already had a high WMC. The fact that the training benefit was limited to participants who had low initial WMC suggests that high-WMC individuals may have already been using the effective strategy prior to training (see also McNamara & Scott, 2001; Swanson, Kehler, & Jerman, 2009). Similarly, Cokely, Kelley, and Gilchrist (2006) used a part-list cuing paradigm to explore the relationship between WMC and strategy use. At training, 12 cue words were presented alongside 12 to-be-remembered items. At recall, participants were presented with only 6 of the cue words. The participants were told to recall all 12 to-be-remembered items, but specifically instructed not to report the remaining 6 cue words. Incorrectly recalled cue words were treated as intrusions. Initially, high-WMC individuals had higher recall performance but also produced more intrusion errors than low-WMC individuals. After initial testing, participants were trained to use an effective encoding strategy; specifically, they were taught to use a story to link the cues to the to-be-remembered words. After strategy training, both correct recall *and* the number of intrusions increased for low-WMC participants. Cokely et al. argued that prior to training, high-WMC individuals had already selected a strategy that allowed for better performance, at the expense of more intrusion errors. Hence, any explicit training only benefited low-WMC participants, increasing both performance and intrusion errors.

These results clearly link WMC to encoding strategies in memory tasks, suggesting that WMC may also contribute to strategy choice in categorization. There is, however, an important difference between these precedents in memory research and categorization: Whereas in memory tasks higher WMC is related to the use of more successful strategies—as evidenced by higher memory performance—in categorization, as noted earlier, different strategies are often unrelated to success of training.

Thus, the research to date presents an intriguing platform from which to initiate our investigation, without however providing sufficient confidence for exact predictions: On the one hand, WMC is clearly related to category learning performance, and WMC has also been implicated in mediating successful strategy use during memory encoding. On the other hand, choice of categorization strategy has often been found to be unrelated to performance during training. It is thus conceivable that WMC might not mediate strategy choice in categorization; however, in the absence of any known predictor, an investigation of WMC is clearly warranted on the basis of the memory results and its relationship with category learning.

Method

The aim of the present study is to explore the relationship between WMC and strategy use in categorization. In addition, we explore the relationships between WMC and category learning, and category learning and categorization strategy choice. Participants completed a battery of WMC tests (Lewandowsky, Oberauer, Yang, & Ecker, 2010) and two different categorization tasks known to elicit a range of categorization strategies. The first task, taken from Medin and Schaffer (1978, Experiment 2), has consistently produced a range of strategies. The most popular of these are two rule-based strategies and an exemplar-based strategy (Johansen & Palmeri, 2002; Nosofsky et al., 1994; Palmeri & Nosofsky, 1995). The second task, taken from Medin, Altom, Edelson, and Freko (1982, Experiment 4), was designed to explore sensitivity to correlated cues. Thus, the task constituted a proxy for others in which some (but not all) people were found to be sensitive to correlated cues (Yang & Lewandowsky, 2003, 2004). Each categorization task included a training session in which participants received feedback on categorization decisions. The training session was interspersed with periodic transfer trials. On the transfer trials, participants categorized new generalization items, thus permitting identification of the strategy each participant applied to the task.

Participants

The participants were 173 (118 female, mean age = 20.99 years) volunteers from the University of Western Australia campus community. Participants received either partial course credit for an undergraduate psychology course, or $30 for their participation in the experiment.

Apparatus and Procedure

Each participant completed two different categorization tasks and a battery of four working memory tasks, divided over either two ($n = 30$) or three sessions ($n = 143$) of 30 to 60 mins. The categorization and WMC tasks were administered by a Windows based computer, using a MATLAB program created with the aid of the Psychophysics toolbox (Brainard, 1997; Pelli, 1991).

Categorization Tasks

The first categorization task used a category space originally designed by Medin and Schaffer (1978), and since termed the *5-4* task (Smith & Minda, 2000). Participants were presented with a series of stimuli that varied on four binary features. Each stimulus had to be assigned to one of two categories, A or B. Nine of these items were presented during training, and the remaining seven items were presented as transfer stimuli. The dimensional values of all stimuli are shown in Table 1, along with responses to the transfer items for popular strategies. Previous studies using the same category space have consistently identified three strategies to be most popular amongst participants (Johansen & Palmeri, 2002; Nosofsky et al., 1994; Palmeri & Nosofsky, 1995). Two of these three strategies are logical rule-based strategies based on either the first or third dimension. Participants using a rule on the first dimension (R1) categorize all transfer items as category A if the item has a value of 1 on the first dimension, or category B if the item has a value of 2. In training, this rule is consistent with 7 of the 9 training items. The rule strategy on the third dimension (R3) is equivalent, except that the strategy is based on the third rather than the first dimension. The third popular strategy is an exemplar-based strategy (EX). Exemplar models, which categorize based on summed similarity comparisons to training items, typically produce the exemplar strategy when presented with the MS1978 category space (Medin & Schaffer, 1978). We use the theoretical terms, rule and exemplar, only as descriptive names for the transfer responses. While we assume these strategies correspond to different category representations, we make no assumptions as to the processes underlying these representations. Although participants were presented with all 7 transfer items, following Johansen and Palmeri (2002), we focus on only five of these seven items (see Table 1). The remaining two items are non-diagnostic in distinguishing between the three primary strategies. With these two items removed, the difference between the R1, R3, and EX strategies is highlighted by the low or negative correlations between the response profiles for the three strategies, at $r = -.67$, $r = .17$, and $r = .17$, for the correlations between the R1 and R3 strategies, the R1 and EX, and the R3 and EX strategies respectively.

The second categorization task, designed by Medin et al. (1982), we term the *correlated-cues* task. Participants were trained to categorize 8 training stimuli composed of four binary dimensions, and were tested on 8 new transfer stimuli. The category structure and popular strategies are given in Table 2. Three popular strategies were expected to be used in this task (Medin et al., 1982; Nosofsky et al., 1994). One expected strategy is a correlated-cues strategy (CC)—perfect training accuracy can be obtained by observing the correlation between the third and fourth dimensions. If the value on the third and fourth dimensions match, then the item is in category A, if the value on these dimensions mismatch, then the item is in category B. The two other expected strategies were rules on the first (R1) or second (R2) dimensions. As in the 5-4 task, the difference in the popular strategies is highlighted by the low or negative correlations between the CC, R1, and R2 response profiles, at $r = -.50$, $r = -.50$, and $r = 0$ for the relationships between the CC and R1 strategy, the CC and R2 strategy, and the R1 and R2 strategies respectively.

Stimuli were instantiated in two different ways: One set of stimuli was designed to represent rocket ships that varied on four binary dimensions: (a) the size of the nose (large or small); (b) the size of the wings (large or small); (c) the shape of a porthole (circle or oval); and (d) the size of the tail. The second set of stimuli was presented to participants as “alien blood cells”. The alien blood cells were made up of a small circle, designed to represent a cell nucleus, surrounded by a large circle, designed to represent the cell wall. These stimuli varied along (a) the color of the cell wall (red or blue); (b) the color of the cell nucleus (black outline, filled with black or white); (c) the size of the cell wall (small or large); and (d) a the number of cell walls (single or double).

Participants were randomly assigned to one of two randomization groups, which differed only with respect to the assignment of stimulus set to categorization task, the assignment of pictorial stimulus dimensions to conceptual dimensions, and the order of trials. Participants in one randomization group (group A) were presented with alien blood cell stimuli in the 5-4 task and rockets in the correlated-cues task, and vice versa for the other randomization group (group B). The mappings of pictorial stimulus dimensions to conceptual dimensions are shown in Table 3. To minimize “method variance,” all participants within a randomization group were shown an identical random sequence of training and transfer trials, although the order of categorization tasks across sessions remained invariant; all participants completed the 5-4 task prior to the correlated cues task.

Categorization trials began with the presentation of a fixation cross, “+”, in the center of the screen for 500 ms. A stimulus was then presented centrally, with the words, “Is this rocket?” or “Is this alien blood cell?” shown above and the category options, “Type A” and “Type B” shown below the stimulus. Participants made their category selection by pressing either the “z” key (labeled “A”) or the “/” key (labeled “B”).

During training trials, feedback consisting of the word *CORRECT* or *WRONG* was presented after each response for 1300 ms. No feedback was presented during transfer trials. For both categorization tasks, participants completed 32 blocks of training, each involving a single presentation of each training stimulus. Three identical transfer tests were interspersed throughout training, after Blocks 4, 16, and 32. Each transfer item was presented once per transfer block.

Participants who completed three sessions did the 5-4 task in the first session and the MS1982 task in the third session.[1] Participants who did two sessions completed both the 5-4 followed by the correlated-cues task, in the first session.

WMC Tasks

To minimize task-specific variance associated with individual WMC measures (Lewandowsky et al., 2010; Oberauer, 2005), a battery of four WMC tasks were used to measure WMC. The WM tasks were an operation span task (OS), a sentence span task (SS), a spatial short-term memory task (SSTM), and two memory updating tasks (MU1 and MU2). Participants first completed either the MU1 task or the MU2 task, depending on whether they were tested over three or two sessions respectively, followed by the OS, SS, and SSTM task, in that order. The MU1, OS, SS, and SSTM tasks are part of a thoroughly tested WMC battery; because full details of these four tasks can be found in Lewandowsky et al. (2010), we survey them only briefly here. The MU2 task is not part of the WMC battery and was included to collect data for an unrelated study.

Memory updating - MU1. The MU1 task was designed by Salthouse, Babcock, and Shaw (1991), and adapted for testing purposes by Oberauer, Süß, Schulze, Willhelm, and Wittmann (2000). The task required participants to (a) store a series of numbers in memory, (b) mentally update these numbers based on a series of arithmetic operations, and (c) recall the updated numbers.

In each trial, three to five frames were presented on the screen that each contained a random digit. Successive arithmetic operations, (e.g., '+4' or '-3') were then presented in the frames, one at a time. Participants were instructed to mentally update the memorized content of each frame until their memory for the final values was probed after the last update operation. Not all frames were necessarily updated on all trials and a single frame could be updated multiple times during a single trial. There were a total of 15 trials. Initial digits, operations and prompt orders were generated randomly; however, all participants were presented with the same randomized sequence.

Memory updating 2 - MU2. The alternative memory updating task was a combined version of a modified Sternberg task (Oberauer, 2001; Sternberg, 1969) and an item-location binding task (Oberauer & Vokenberg, 2008). During each trial, words were sequentially presented in each of four frames on the screen. The aim of the task was to remember the last word that was presented in each of the frames.

At the beginning of each trial, four frames were presented in a row across the screen, each containing a word. These initial words remained on screen for 6 s. For the remainder of a trial, new words appeared in one of the frames, for 2 s each, and participants had to mentally replace the memorized contents of that frame with the new word. The identity of the frame varied across updating steps. After a varying number of updating steps, memory for the final contents of the frames was tested by presenting a probe word, accompanied by a“?”, in each frame in turn. Participants had to decide whether the presented word was the last word to be shown in that frame, using the "/" key for *yes* and the "z" key for *no*. Two of the four test items on each trial were old probes, for which the correct response was *yes*. One was a new probe, for which the correct response was *no*. Finally, one word was a "lure," which had been presented but replaced by updating step. The correct response for the lure was *no*. Participants completed four practice trials, followed by 42 experimental trials. Three self-paced breaks occurred at regular intervals throughout the task. See Hanich (2009) for further details.

Operation span - OS. The OS task was originally designed by Turner and Engle (1989). On each trial, a series of arithmetic equations were presented (e.g. $4 + 3 = 7$).

Each equation was followed by a consonant that had to be memorized. Participants judged the equation for correctness and memorized the consonants for later recall. A given trial involved between 4 and 8 unique consonants, which participants had to recall immediately after presentation in the original order. There were 15 trials total, with 3 trials for each set size. Participants were told to strive for 85% accuracy on the equation judgements. All participants received an identical random sequence of consonants, equations, and trials.

Sentence span - SS. The SS task was nearly identical to the OS task, except that instead of judging correctness of an equation, participants judged the meaningfulness of sentences (cf. Daneman & Carpenter, 1980). Two versions of the task were used, SS-A, and SS-B, which differed only with respect to the difficulty of the sentences. (SS-A and SS-B corresponded, respectively, to the sentences used in Experiment 1 and 2 of Lewandowsky et al., 2010; see their paper for details). Participants who received the SS-A task also received the MU-1 task whereas the SS-B task was administered to the people who received the MU-2 task. Set sizes ranged from 3 to 7 consonants. In all other respects, both versions of the SS task were identical to the OS task.

Spatial short-term memory - SSTM. The SSTM task, based on a task from Oberauer (1993), involved memorization of the spatial location of circles in a 10×10 grid. On each trial, a series of solid black circles was presented, one-by-one, in various grid locations. The grid was then briefly removed from the screen, before it reappeared. Participants used the mouse to indicate the memorized location of the dots in any order by clicking in the corresponding grid cells. There were 30 trials, 6 for each of set sizes 2 through 6. Scoring was based on relative rather than absolute position (see Lewandowsky et al., 2010, for details).

Results

Working Memory Performance

Span scores from the SS and OS tasks were calculated by averaging the proportion of correctly recalled letters. There was no significant difference between the mean span scores from the SS-A ($M = 0.64, SD = 0.19$) and SS-B ($M = 0.67, SD = 1.5$) tasks, $t(166) = 0.79, p > .05$, thus both sets of scores were combined into a single set of SS scores for the remainder of the analysis.

Scores for the MU1 and MU2 were calculated as an individual's mean proportion correct across trials. The mean score from the MU1 task ($M = 0.56, SD = 0.19$) was lower than for the MU2 ($M = 0.88, SD = 0.08$); $t(166) = 8.75, p < .001$. Scores on the MU2 task were therefore adjusted by subtracting the difference between the mean scores on the two tasks (.32). After this adjustment, the scores on the MU1 and MU2 tasks were combined and treated as a single memory updating (MU) score for the remainder of the analysis.[2]

Nineteen participants were removed from analysis as they did not attend all experimental sessions. Scores on each of the tasks were z-transformed and averaged across the four tasks to yield a single composite measure for each individual (zWMC) (Ackerman, Beier, & Boyle, 2005; Engle, Carullo, & Collins, 1991; Salthouse et al., 1991). One participant was removed from the analysis because their score fell more than 3 standard deviations below the mean zWMC. Two further participants were removed because their performance during the last four blocks of a category learning task was less than or equal to 50% correct. The final analysis included observations from 151 participants.

Category Learning

Averaged block measures were calculated by taking the mean proportion error across sets of 8 consecutive blocks (i.e., one measure was obtained for Blocks 1 to 8, another for Blocks 9 to 16, and so on). A square-root transformation was applied to the proportion error scores to correct apparent skew. The resultant average learning curves for the 5-4 and correlated-cues tasks are shown in Figure 1.

Two separate 2×4 mixed-design ANOVAs with randomization group (A or B) as a between-groups factor, and the four levels of block scores as a within-group factor, were conducted on the two tasks. A Greenhouse-Geisser correction was used to correct for violations in sphericity. For the 5-4 task there was a significant effect of block, $F(2.12,\ 447) = 221.02$, $MSE = 3.05$, $p < .001$, $\eta_p^2 = .60$, and of randomization condition, $F(1,\ 149) = 5.57$, $MSE = 0.37$, $p < .05$, $\eta_p^2 = .04$. The latter effect arose from better performance for Group B. The interaction between both variables was also significant, $F(2.12,\ 447) = 8.63$, $MSE = 0.12$, $p < .001$, $\eta_p^2 = .06$. For the correlated-cues task there was also a significant main effect of block, $F(2.72,\ 447) = 268.09$, $MSE = 3.60$, $p < .001$, $\eta_p^2 = .64$, and of randomization type, $F(1,\ 149) = 5.92$, $MSE = 0.47$, $p < .05$, $\eta_p^2 = .04$, except that this time it reflected better performance for Group A. There was no significant interaction, $F(2.72,\ 447) = 1.91$, $MSE = 0.27$, $p > .05$.

In addition to confirming the obvious presence of learning, the analyses revealed that whichever group was presented with rockets—Group B in the 5-4 task and Group A in the correlated-cues task—performed better than those presented with the alien blood cell stimuli. As Group A and B differed with respect to the stimuli used in each task, but not task order, this observed group effect likely reflects an effect of stimulus type. As the effects of stimulus type were small and of little theoretical interest, data from both stimulus groups were combined for the remaining analyses.

Relationship Between Category Learning and WMC

Descriptive statistics for the WMC measures are shown in Table 4. Structural equation modeling (SEM) was used to explore the relationship between category learning and WMC. SEM was employed as it allowed for comparisons between theoretical models of the relationship between WMC and category learning across tasks. In addition, the use of SEM reduced the impact of task-specific variance through the extraction of largely measurement-error-free latent variables.

We proceed by first extracting separate WMC and category learning latent variables by fitting two measurement models to the WMC and category learning data, respectively. These latent variables represent, respectively, an error-free measure of the shared variance between the WMC tasks and between measures of category-learning performance. Finally, to determine the covariance between the WMC and category-learning latent variables, we combine the two measurement models into a full structural model.

We first fit the WMC measurement model. Scores from the four tasks, OS, SS, SSTM, and MU, were used as four manifest variables that were predicted by a single latent variable (termed WMC). The fit of the measurement model was excellent, $\chi^2(2) = 1.6, p > .05$, comparative fit index, $CFI = 1$, root mean square error of approximation, $RMSEA = 0$, and standardized root-mean-square residual, $SRMR = 0.018$. The standardized regression weights for the manifest variables are shown in Table 4.

We next fit two different category learning measurement models, each involving the composite block scores from the preceding analysis as manifest variables. For one model, scores for the 5-4 and correlated-cues tasks were loaded onto a single latent variable, for the other model the proportion error scores loaded onto two separate latent variables, one for each task. To allow for a good fit, the correlation between error terms for adjacent blocks and blocks with a gap of one were freely estimated, thereby capturing the expected autocorrelations across stages of learning. The fit of both the one-factor model, $\chi^2(10) = 5.6, p > .05$, $CFI = 1$, $RMSEA = 0$, and $SRMR = 0.0294$, and the two-factor model, $\chi^2(9) = 2.9, p > .05$, $CFI = 1$, $RMSEA = 0$, $SRMR = .0099$, was excellent. The two-factor model did not significantly improve the fit over the one-factor model,

$\chi^2(1) = 2.7, p > .05$, thus we consider only the one-factor model. The standardized regression weights for the grouped learning blocks, in order of training blocks, were .41 .49 .59, and .54 for the 5-4 task, and .53, .52, .68, and .63 for the correlated-cues task. All standardized regression weights were significant at $p < .001$.

To explore the relationship between WMC and the rate of category learning, the latent *WMC* and *Learning* variables were combined into a structural model. The full model, with standardized regression weights, is shown in Figure 2. The fit of the model was good, $\chi^2(43) = 35.00$, $CFI = 1$, $RMSEA = 0$, and $SRMR = .0504$. The relationship between the *WMC* latent variable and the latent category learning variable was significant $-.49$, ($p < .001$). The strong negative relationship between the WMC latent variable and the category learning latent variable suggests that higher WMC was associated with fewer category learning errors across training for both categorization tasks.

Categorization Strategies

5-4 Task

As in Johansen and Palmeri (2002), the two non-diagnostic transfer items were removed from the analysis of the 5-4 task (see Table 1). These two items were poor at discriminating between transfer strategies, being classified in category A at close to ceiling, at 88.74% and 11.26% at the final transfer block, for items 1111 and 2122, respectively. Additionally, these items did not differentiate between the three most popular transfer strategies. Figure 3 shows the proportion of participants using each transfer profile for the three transfer tests for the 5-4 task. In the figure, each horizontal bar represents a possible sequence of responses to the transfer items. For example, the transfer profile $AAAAB$ identifies a sequence in which the first four transfer items were placed in category A, and the final transfer item was placed in category B. The order of the transfer items corresponds to the order that the items are presented in Table 1. Only transfer profiles used by at least two participants are shown in Figure 3.

The distribution of transfer profiles is consistent with previous studies using the same category space (e.g., Johansen & Palmeri, 2002; Nosofsky et al., 1994; Palmeri & Nosofsky, 1995). From the figure, the most popular strategies were the rule strategies on dimension one (R1) and dimension three (R3), and the exemplar strategy (EX). Given the popularity and the easily identifiable nature of the R1, R3, and EX strategies in both the present study and previous studies (Johansen & Palmeri, 2002; Nosofsky et al., 1994; Palmeri & Nosofsky, 1995), we focus on these strategies for the 5-4 task for the majority of the remaining analysis.

Consistent with Johansen and Palmeri (2002), the use of transfer profiles shifted across training. As in Johansen and Palmeri (2002), early in training, at the Block 4 transfer phase, the rule strategies, R1 and R3, were most popular. However, by Block 32, the R1 and R3 strategies had decreased in popularity, with the exemplar (EX) strategy becoming the modal response profile.

Correlated-Cues Task

Transfer profiles for the three transfer phases from the correlated-cues task are presented in Figure 4. The distribution of strategies used in the correlated-cues task differed from the expected strategies presented in Table 2. While many participants utilized the perfectly predictive correlated-cues strategy, CC, few participants utilized a rule on either the first or second dimension. In contrast to expectations, many participants utilized an alternative strategy.

Inspection of generalization profiles for the two randomization groups, shown in Figure 5, revealed that this alternative strategy was almost exclusively used by participants in randomization Group A, those presented with rocket stimuli in the correlated-cues task. Discussions with participants and inspection of the category space revealed that the alternative strategy relied on cues that were unique to the rocket stimuli: Participants using that strategy relied on the size of the wings to indicate whether the porthole or nose was used to determine category membership. If the wings had a value of 1 (corresponding to large wings), then the nose was used to determine category membership such that if the nose was large, the item was placed in category A, and if the nose was small, the item was placed in category B. Alternatively, if the wings had a value of 2 (corresponding to small wings), then the porthole was used to determine category membership, such that if the porthole was round, the item was placed in category A, and if the porthole as oval, then the item as placed in category B. Little, Nosofsky, and Denton (in press) have suggested that stimuli with spatially separated dimensions, such as the rockets, may encourage serial processing of stimulus dimensions. In contrast, stimuli with spatially overlapping dimensions, such as the alien blood cells, may engender more parallel processing. This meshes well with the alternative strategy, where participants appeared to check the wings to decide whether to check the nose or porthole to make a classification.

It is noteworthy that the porthole dimension was irrelevant in that it provided no information beyond that available from the nose of the rocket. In previous studies, people have been found to partition category spaces into independent parcels of knowledge, sometimes leading to the utilization of irrelevant cues (Yang & Lewandowsky, 2003, 2004; Lewandowsky et al., 2006). This partitioning behavior is termed *knowledge partitioning.* In the alternative strategy, people seemed to partition the category space based on the value of the wings, leading to the utilization of the overall-irrelevant porthole cue. We therefore term the alternative strategy the knowledge partitioning (KP) strategy. The correlation between the response profiles for the CC and KP strategies was $r = 0$.

Predicting Strategy Choice

We next explored whether participants' choice of strategy could be predicted by WMC or category learning performance. For the 5-4 task, we grouped participants into three groups on the basis of the generalization profile they used in the final transfer block. Participants using the exemplar strategy were placed into an EX group (for "EXemplar"; $n = 24$). Participants using the R1 and R3 strategies were grouped into a single strategy group, RU (for "Rule Use"; $n = 27$). Combining the rule strategies was necessary for running a discriminant analysis. The sample size for the combined rule group, but not individual rule groups, met sample size guidelines for discriminant analysis (Hair, Black, Babin, & Anderson, 2010). Further, the decision to combine the rules strategies was guided by the assumption that there were no individual differences that led participants toward either rule strategy. In support of this assumption, the rules strategies were structurally equivalent; for both rule strategies, category responses were based on a single stimulus dimension on which seven of the nine training items were consistent with the rule. Additionally, there was a lack of difference in WMC between participants using the R1 and R3 strategies, $t(19.85) = 0.55$, $p > .1$. The remaining participants were placed into an *Other* group ($n = 100$). For the correlated-cues task, participants were grouped into the popular CC ("correlated cues"; $n = 46$) and KP ("knowledge partitioning"; $n = 35$) strategies, with the remaining participants being placed into an *Other* group ($n = 70$). Table 5 shows the mean zWMC scores and mean square-root transformed proportion error for each of the strategy groups for both tasks.

Discriminant analyses were used to explore whether WMC or category learning performance predicted strategy choice. Discriminant analysis is best understood as an isomorph of MANOVA, and it is used when predicting group membership from measured variables. Discriminant analyses are highly robust against variations in group sizes (Tabachnick & Fidell, 2007). Two discriminant analyses were run for each of the two categorization tasks. The first discriminant analysis tested whether final strategy choice could be predicted by WMC and training performance. The second discriminant analysis tested whether use of a popular strategy could be predicted by WMC and training performance across any of the three transfer blocks.

5-4 Task

For the 5-4 task, the square-root transformed mean proportion error across the final eight blocks and zWMC scores were included as independent variables. Strategy choice (EX, RU, and Other) on the final transfer test was included as the dependent variable. Box's M was calculated: a non-significant value of Box's M indicates that homogeneity of variance-covariance matrices is not violated. Based on recommendations (Tabachnick & Fidell, 2007), Box's M was judged at a highly-conservative α level of .001. Box's M was not significant, $F(6,\ 41332.52) = 1.37, p > .1$.

Two discriminant functions were calculated. Each discriminant function represents a linear combination of the two predictor variables (Tabachnick & Fidell, 2007). The first function is calculated to account for the maximum between-group variance. The second function is calculated to account for the maximum amount of the remaining between-group variance. Overall, Wilks' Lambda indicated that together the functions accounted for a significant amount of variance, (Wilks' Lambda = .93, $\chi^2(4) = 10.16, p < .05$), and were thus able to discriminate between the strategies. The second function alone did not account for significant variance, Wilks' Lambda = 1.00, $\chi^2(1) = .02, p > .05$. The first and second functions accounted for 99.8% and 0.2% of the discriminating power in strategy use respectivly.

Exploring the individual predictors, proportion error had loadings of .99 and $-.15$ on the first and second function, respectively. By contrast, zWMC had a loadings of $-.16$ and .99 on the first and second function, respectively. As the first function accounted for the majority of the discriminating power, these loadings suggest that proportion error during training was better able to a discriminate between the groups than zWMC. Six contrasts were run to determine which strategy groups the predictors were able to discriminate between. Proportion error differentiated the EX strategy from the RU strategy ($t(148) = 3.20, p < .01$), and the EX strategy from the Other strategies ($t(148) = 2.28, p < .01$), but not the RU from the Other strategies ($p > .1$). zWMC did not significantly discriminate between any of the strategy groups ($p > .1$).

The preceding analysis suggests that WMC did not determine which strategy people ultimately used (i.e., in the final transfer block) in the 5-4 task. It is possible, however, that participants with a higher WMC may not tend toward specific popular strategies at the end of training, but may nonetheless be more likely to use *any* of the popular strategies at any time during training. Accordingly, we next explore whether WMC might differentiate participants who used a popular rule or exemplar strategies at *any* of the three transfer blocks from those who *only* used the Other strategies.

For the 5-4 task, a discriminant analysis was run, with participants who only used Other strategies across all transfer blocks in one group ($n = 56$), and those who used at least one of the R1, R3, or EX transfer strategies at one or more transfer blocks in another group ($n = 95$). Square-root transformed proportion error across the final eight blocks and zWMC were input as predictor variables. Box's M was not significant at $\alpha = .001$, $F(3,\ 460911.07) = 2.88, p > .01$ One discriminant function was calculated. The function did not significantly discriminate between participants who used popular strategies and those that used Other strategies, Wilks' Lambda = .99, $\chi^2(2) = .21, p > .1$.

Correlated-Cues Task

Equivalent discriminant analyses were conducted for the correlated-cues task. For the correlated-cues task, proportion correct was not included in the analysis because stimulus type was highly correlated with strategy use: The CC and KP strategies were predominantly used by participants presented with alien blood cells (randomization group A) and rockets (randomization group B) respectively (see Figure 5). Exploration of the randomization groups uncovered performance differences; on both categorization tasks, participants presented with rockets performed better during training than those presented with alien blood cells. If training performance were to predict strategy use, it would be unclear whether this relationship was due to differences in strategy representations or the different stimulus types. We therefore excluded training performance from the discriminant analyses for the correlated-cues task, and explored only whether zWMC could predict strategy choice.

A discriminant analysis was run with zWMC scores entered as a predictor variable and transfer strategy (CC, KP, and Other) entered as the dependent variable. Box's M was not significant, $F(2,\ 40853.44) = 2.67, p > .05$. One discriminant function was calculated. Wilks' Lambda was not significant, Wilks' Lambda = .99, $\chi^2(2) = 2.05, p > .1$. Thus, zWMC was unable to discriminate between CC, KP, and Other strategies.

A discriminant analysis was used to determine whether zWMC could discriminate between those who used Other strategies across all transfer blocks ($n = 67$), and those who used the CC or KP strategy at one or more transfer blocks ($n = 84$). Box's M was not significant, $F(1,\ 64320.88) = 1.53, p > .1$. The discriminant function did not significantly discriminate between the participants who used popular strategies and those who did not, Wilks' Lambda = .99, $\chi^2(1) = .12, p > .1$.

In summary, for both tasks, WMC was unable to discriminate between strategy choices at the final training block, nor did WMC predict whether participants would use a popular strategy at any of the transfer blocks. Training performance discriminated between strategy choice for the 5-4 task. We next explored whether a participants' tendency to shift their strategy choice across transfer blocks was related to their WMC.

Strategy Shifting and WMC

Some theories of working memory suggest that WMC is a measure of people's ability to control and focus attention toward task-relevant information (Conway et al., 1999; Engle, 2002; Kane & Engle, 2000; Kane et al., 2001; Rosen & Engle, 1997). It is possible that people with higher WMC may not tend toward particular strategies, but may instead be better at selecting and focusing on a particular categorization strategy. Accordingly, we explored whether WMC or training performance predicted the number of times participants shifted their transfer strategy.

With three transfer phases, participants could either (a) use the same strategy at all transfer phases, (b) shift their strategy once, or (c) shift their strategy twice. Participants who shifted to a new strategy, and then back to their original strategy, were counted as making two shifts. To allow for possible response errors across transfer blocks, we counted a shift as making two or more responses that differed from the previous transfer strategy. Mean zWMC scores and mean square-root transformed proportion error across the final eight blocks for both categorization tasks are shown in Table 6.

5-4 Task

For the 5-4 task, a discriminant analysis was run with zWMC and the square-root transformed proportion error across the final eight training blocks included as independent variables. The dependent variable was the number of strategy shifts, none, one, or two. Box's M was not significant, $F(6,\ 215075.79) = .52, p > .1$. Together the functions significantly discriminated between the number of shifts, Wilks' Lambda = .93, $\chi^2(4) = 10.50, p < .05$, but that the second function alone did not account for a significant amount of variance, Wilks' Lambda = .99, $\chi^2(1) = 0.21, p > .1$. The two functions accounted for 98.0% and 2.0% of the discriminating power respectively.

Proportion error and zWMC had loadings of .97 and $-.49$ on the first function respectively, and .23 and .87 on the second function respectively. Contrasts for proportion error indicated that participants that made two shifts had significantly lower error than participants who made no shifts, $t(148) = 2.93, p < .01$ or one shift, $t(148) = 2.60, p < .05$. Proportion error did not discriminate between participants who made no shifts or one shift ($p > .1$). For zWMC, none of the shift groups were significantly discriminated ($p > .1$).

Correlated-Cues Task

A discriminant analysis was also run to explore shifting behavior for the correlated-cues. Once again, zWMC and proportion error across the final eight blocks of the correlated-cues task were included as predictors. The dependent variable was the number of shifts: none, one or two. Box's M was not significant, $F(6,\ 196409.967) = 1.50, p > .1$. The ability of the two functions to discriminate between the three groups was bordering on significance, Wilks' Lambda = .94, $\chi^2(4) = 9.305, p = .054$. The second function did not significantly discriminate between the shift groups, Wilks' Lambda = 1.00, $\chi^2(1) = .51, p > .1$. The first and second functions accounted for 94.6% and 5.4% of the discriminating power respectively.

Proportion error and zWMC loaded on the first function at .998 and $-.316$ respectively, and loaded onto the second function at .056 and .949 respectively. Contrasts indicated that proportion error significantly discriminated the two shift group from the no shift group $t(148) = 2.47, p < .05$, and the one shift group, $t(148) = 2.71, p < .1$, but not the no shift and one shift groups ($p > .1$). The zWMC scores did not significantly discriminate between any of the groups ($p > .1$).

Simplicity Analysis

The analyses so far failed to find any relationship between WMC and categorization strategy; WMC did not predict strategy choice or shifts on either of the two categorization tasks. One limitation of these analyses was that participants were aggregated into strategy groups. By grouping people, we lost detailed information about individual response profiles. For this final analysis we therefore converted all individual transfer profiles into a continuous measure; namely, simplicity scores.

It has been suggested that people may categorize items by reducing a category space into the "simplest" clustering of objects, as defined by a minimum description length measure (Chater, 1999; Feldman, 2003). We used a model from Pothos and Chater (2002) to measure the simplicity of participants' categorization strategies. Using this simplicity model, Pothos and Bailey (2009) found that simplicity scores predicted category preferences for each of the seven transfer items on the 5-4 task. We extend the analysis from Pothos and Bailey (2009) by computing the simplicity scores at the individual, rather than the aggregate level.

Simplicity of an observed classification—represented by the transfer profile—is expressed as a code length, in bits, required to represent this classification. The model represents a category space as the set of inequalities of the distances between items. For example, given three items, X, Y, and Z, the model uses one bit to represent each of the inequalities between the inter-item distances (e.g., whether $\|X - Y\| < \|X - Z\|$, where $\| \ldots \|$ represents an appropriate distance metric). In the absence of any classification, the stimulus ensemble is represented by the full set of all possible pairwise inequalities, and the simplicity score represents the total number of such inequalities. When a classification is present, the representation can be potentially simplified because stimuli in different categories need not be represented by their own inequalities—instead, they are collectively represented by the relationship between categories. The total number of bits required to represent a classification is thus the summed individual inequalities (within a category), plus some number of bits required to define the categories, plus some number of bits required to correct errors (i.e., account for pairwise inequalities that run counter to those expected on the basis of category membership). See Pothos and Chater (2002) for a full description of the model. For each participant, we computed the simplicity of the category space for the training and transfer items together, where the categories were defined by the correct responses to the training items and by an individual's chosen transfer profile.

As shown in the left panel of Figure 6, participants tended toward the simpler strategies. Simplicity scores for the 5-4 task were significantly related to the frequency of strategy use, $r(30) = -.41, p < .05$. The R1 and R3 strategies had the lowest simplicity, and the EX was the fourth simplest strategy. There was still no relationship between WMC and strategy choice. The cube-root transformed simplicity measure was not significantly related to the WMC latent variable, $r = -.14, p > .1$.

Simplicity scores were likewise calculated for the correlated-cues task and are shown in right panel of Figure 6. The two popular profiles, KP and CC were eliminated from the computation of the correlation as their proportion of use was 9.44 and 12.46 standard deviations above the mean proportion of use respectively. The relationship between the simplicity scores and frequency of strategy use just failed to reach significance, $r(252) = -.12$, $p = .067$. As the distributions of participant's simplicity scores appeared bimodal, we used a non-parametric Spearman's correlation, instead of SEM, to compare simplicity scores for the correlated-cues task with participants' zWMC. The correlation was not significant, $r_s(149) = .15, p > .1$.

Overall, the simplicity analysis provided some support for the notion that people preferred simpler classifications over complex ones. However, the simplicity analysis again failed to uncover any relationship between WMC and categorization strategy.

Discussion

Limitations and Concerns

Before addressing the implications of our findings, we first consider some limitations and possible concerns. Notwithstanding the final simplicity-based analysis, a lingering concern might involve the aggregation of strategies for the main analysis. This concern can be allayed by noting that we also explored numerous other measures to characterize the strategies in disaggregated analyses, for example, by representing each participant's strategy as a single number, namely the Hamming distance calculated by summing the number of response mismatches between that person's chosen transfer profile and the nearest popular (exemplar or rule) strategy. None of these attempts uncovered any significant association between WMC and strategy.

A second concern may be whether the failure of our WMC measure to discriminate between strategies could be due to a lack of power. In addressing this concern, we point to the fact that WMC predicted category learning for both categorization tasks, which renders an omnibus "lack of power" criticism less forceful. Conversely, we were able to relate strategy choice to other variables, including simplicity of a transfer pattern and category learning performance (for the 5-4 task). These significant results suggest that the study would have had sufficient power to detect a relationship between WMC and strategy choice had it been present.

In the present study we measured WMC using a range of WM tasks. Scores from these tasks were combined to produce a single WMC measure. All measures loaded highly onto a single WMC latent variable (standardized regression weights all $\geq .46$). In contrast to our treatment of WMC as a single variable, some theories of WM do not subscribe to the idea that WM is a unitary system (e.g., Baddeley & Hitch, 1974). In particular Baddeley and Hitch's influential WM model implicates separate systems for storing verbal and visual-spatial information. While the issue of whether WM is a unitary or a modular system remains unsettled, our conclusions regarding WMC were based on a mix of verbal and spatial tasks, suggesting that even if WM is best considered modular, our tasks likely spanned multiple modules.

Finally, some may question whether the present category structures were sufficiently complex to detect differences in WMC across strategies. While more complex strategies might exist in other category structures, the present results suggest that higher WMC individuals may not necessarily select these more complex strategies, even if they offered a training advantage. The simplicity scores revealed that participants opted for a range of strategies of varying complexity. Yet, higher WM participants did not tend to use more complex strategies; no relationship was found between simplicity scores and WMC. Further, in the 5-4 task, participants using the RU strategy performed worse in training than those using the EX strategy. As we discuss below, the higher performance for the exemplar strategy likely represented a training advantage for the EX over the RU strategies. Despite this apparent training advantage, higher WMC individuals were not more likely to opt for the “better” EX strategy. While it is possible that higher WM individuals are *better* at representing more complex strategies, the present results suggest that higher WMC individuals are not more likely to *select* more complex representations.

Summary of Findings and Theoretical implications

Our study yielded four principal findings: (a) WMC predicted category learning, (b) strategy choice was partially predicted by learning performance, (c) strategy choice was not predicted by WMC, and (d) simpler strategies tended to be used more frequently than complex strategies. We now take up those four results in turn.

WMC was related to a common category-learning factor across two different categorization tasks: The higher participants’ WMC, the greater their accuracy across training in both the 5-4 and correlated-cues tasks. This positive relationship between WMC and categorization performance across tasks is consistent with recent work that suggests that not only is WMC positively related to category learning performance, but that this positive relationship exists irrespective of strategy type (e.g., DeCaro et al., 2009; Lewandowsky, 2011).

We also observed a relationship between category learning performance and strategy use. In both tasks, participants with higher training accuracy had more stable transfer patterns, showing fewer strategy shifts. In the 5-4 task, participants with higher training accuracy were more likely to select the exemplar, EX, strategy than an Other strategy or either of the two rule, RU, strategies. This later finding stands in contrast to the results of some previous studies exploring strategy choice in categorization (Little & Lewandowsky, 2009; Sewell & Lewandowsky, 2011b; Yang & Lewandowsky, 2004). The discrepancy most likely arose from the fact that the RU strategies required memory for exception stimuli. Recall that seven of the nine training items could be classified correctly by applying the rule, whereas the remaining two items, one in each category, were exceptions that were inconsistent with the rule. As in previous studies, participants using the RU strategies acquired some memory for the exception items (Johansen & Palmeri, 2002; Palmeri & Nosofsky, 1995; Nosofsky et al., 1994), obtaining an overall mean accuracy of 85% across the final eight blocks—higher than the 78% permitted by application of the rule without memory for exceptions. However, accuracy on the exception items during the last 8 blocks was considerably lower in the RU (65%) than the EX group (91%); $t(42.23) = 3.69, p < .001$. The fact that RU participants struggled to learn the exceptions explains their lower accuracy overall. This link between learning and strategy use is of marginal theoretical interest here. It is not surprising that learning performance, a highly domain-specific measure, is predictive of other facets of performance within the same domain.[3]

Of greater theoretical interest is the potential relationship between WMC, a domain-general and stable cognitive construct (Klein & Fiss, 1999), and strategy use. The fact that we found no such relationship for either of the tasks is therefore quite revealing. As WMC has previously been linked to strategy choice (Cokely et al., 2006; Bailey et al., 2008; Dunlosky & Kane, 2007; Turley-Ames & Whitfield, 2003; Unsworth & Spillers, 2010), we expected at the outset that WMC might also predict strategy choice on categorization tasks. However, to date the relationship between WMC and strategy choice has been predominantly explored within memory tasks, where on average, participants with higher WMC select more effective memorial strategies (Bailey et al., 2008; Cokely et al., 2006; Dunlosky & Kane, 2007; Turley-Ames & Whitfield, 2003; Unsworth & Spillers, 2010). It is possible that WMC may not aid participants in finding better strategies on tasks for which item recall is not the primary goal. Consistent with this notion, Bröder (2003) likewise failed to find a relationship between WMC and choice of decision-making strategies. The results of the present study showed that WMC was associated with better performance in category learning, but was not related to the choice of categorization strategy.

How is it that WMC might influence the success with which a strategy is used but not its choice in the first place? One possibility is that WMC influences the learning of associations between stimuli and categories, but does not directly influence which associations are formed. In some theories of working memory, the ability to form cognitive associations, or *bind* information, is considered a key determinant of WMC (e.g. Oberauer, Süß, Wilhelm, & Sander, 2007; Oberauer & Vokenberg, 2008). In some categorization models, the ability to bind information is critical to obtaining accurate category learning performance (Erickson & Kruschke, 1998; Kruschke, 1992; Kruschke & Johansen, 1999). In such models, a learning parameter controls the speed at which associations are formed between stimuli and categories. Fitting the exemplar model

ALCOVE (Kruschke, 1992) to individual's category learning behavior, Lewandowsky (2011) found that the parameter controlling the speed of learning of associations between stimuli and their category membership was positively related to participants' WMC. This link between the association learning parameter and WMC suggests that WMC may improve categorization performance by mediating the speed at which associations are formed between specific stimuli and categories.

In the present study, participants preferred "simpler" strategies overall. For the 5-4 task, simplicity was significantly correlated with the frequency of strategy use. For the correlated-cues task, the correlation between simplicity and frequency of strategy use approached, but did not quite reach, significance. This preference for simpler categorization strategies has been observed in previous tasks using Pothos and Chater's (2002) model of simplicity. For a range of category structures, Pothos and Chater (2002) found that the strategies that participants reliably selected were the strategies that the simplicity model rated as the simplest. Similarly, Pothos and Close (2008) found that the simplicity model accurately predicted participants' preference towards a unidimensional or multidimensional classification. Colreavy and Lewandowsky (2008) added a dimensional attention into the simplicity model, finding that when attention was directed toward the correct dimension, the simplicity model predicted participants' strategy preferences.

These results are all consonant with the *simplicity principle*; that is, the idea that when presented with some data about the world, people prefer the simplest representation of those data (Chater, 1999; Feldman, 2003). The simplicity principle has shown considerable success in a variety of contexts. Using a Boolean description length measure, Feldman (2000) found that the speed of learning of the six categorization problems from Shepard, Hovland, and Jenkins (1961) was directly related to the minimum Boolean description length required to represent the six category structures. Similarly, using minimum-description length (MDL, Rissanen, 1978), Fass and Feldman (2002) were able to predict strategies for category structures with continuous dimensions. The simplicity principle is also implicitly incorporated into Bayesian theories of categorization (Chater & Brown, 2008; Tenenbaum, 1999). In Bayesian models of categorization, hypotheses about the structure of a category space are updated as people sample exemplars. As more exemplars are sampled, simpler hypotheses remain more consistent with the data than do complex strategies, increasing the preference for such the simpler strategies (Tenenbaum, 2000).

It should be noted that simplicity accounted only for a modest amount of variance in strategy choice; clearly, many other relevant factors remain to be identified. One such factor may be the way in which people distribute their attention across dimensions at the outset of learning. In Yang and Lewandowsky (2004)'s study, the two prominent strategies were differentiated by whether or not participants utilized a specific "context" cue. With the exemplar model ALCOVE, Yang and Lewandowsky (2004) found that the only way to capture the two distinct categorization strategies was to adjust the model's initial distribution of attention to the context cue. This apparent linkage between attention and strategy choice turns out to have wider implications.

WMC and Attention in Categorization

In some theories of working memory, WMC is considered to be mediated by executive attention; that is, the ability to control and distribute attention in light of competing demands (Conway et al., 1999; Engle, 2002; Kane & Engle, 2000; Kane et al., 2001; Rosen & Engle, 1997). In these executive-attention theories, people with higher WMC are said to be better at directing their attention to task relevant information, and inhibiting attention to task irrelevant information. Attention is equally critical in many theories of categorization (e.g. Erickson & Kruschke, 1998; Kruschke, 1992, 2001; Kruschke & Johansen, 1999; Love et al., 2004; Nosofsky, 1986). Typically, attention here refers to *dimensional* attention; that is, the distribution of attention across stimulus features (Kruschke, 1992, 2005; Nosofsky, 1986). On a range of categorization tasks, including the 5-4 task, the ability to distribute attention dramatically improves the ability of models to account for behavior (Kruschke, 1992, 2005; Nosofsky, 1986). Moreover, the link between attention and strategy drawn by Yang and Lewandowsky (2004) has been observed repeatedly (Johansen & Palmeri, 2002; Sewell & Lewandowsky, 2011b; Yang & Lewandowsky, 2004); for example, in a replication of the 5-4 task, Johansen and Palmeri (2002) captured both the rule and exemplar strategies by changing the model's distribution of attention across the stimulus dimensions. Our own simulations of the present data with ALCOVE, not reported here, confirmed the need to have different distributions of attention to account for the rule and exemplar strategies in the 5-4 task. To capture the rule strategies, ALCOVE distributed almost all its attention to the critical stimulus dimension. Conversely, ALCOVE captured the exemplar strategy by distributing its attention more evenly across stimulus dimensions.

Notwithstanding the conceptual link between executive attention in WMC and dimensional attention in categorization, we found no evidence that these two types of attention are related. In the 5-4 task, the two rule strategies required all attention to be distributed toward a single dimension, with attention inhibited toward the remaining three dimensions. Despite the required attentional control, the use of rule strategies was not associated with higher WMC. These results are consistent with recent work by Sewell and Lewandowsky (2011a) who examined blocking and highlighting in a category learning task. In blocking and highlighting, early learning between cues and outcomes occludes subsequent learning of associations between new cues and the same outcomes (Kamin, 1969; Medin & Edelson, 1988, and see also Kruschke, 2005). Popular theories of blocking and highlighting implicate the distribution of attention as the cause of both behaviors (Kruschke, 2005; Kruschke & Blair, 2000). Mirroring the present results, Sewell and

Lewandowsky failed to find a relationship between WMC and blocking and highlighting behavior (although they again obtained the usual relationship between WMC and speed of learning).

Summary and Conclusions

The present study adds to the growing body of work exploring the relationship between WMC and categorization (Blair et al., 2009; DeCaro et al., 2008, 2009; Erickson, 2008; Lewandowsky, 2011; Tharp & Pickering, 2009). Consistent with previous work (e.g., DeCaro et al., 2009; Lewandowsky, 2011), WMC was related to participants' category learning performance—participants with higher WMC had higher categorization accuracy. However, in contrast to expectations, WMC did not predict participants' choice of categorization strategy in either of the two tasks. WMC may not influence which strategy a person chooses, but generally determines how well they use whichever strategy representation they select.

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Notes

[1] Participants who completed the 5-4 task and correlated-cues tasks in different sessions also completed (a) one additional transfer phase of the 5-4 task after the WMC tasks in the second session and (b) Raven's Standard Progressive Matrices (Raven, Raven, & Court, 2000) at the end of the first session. The responses to the extra transfer block were inspected but showed no effects of interest; as such we do not report the results of the extra tests here. The data from Raven's Standard Progressive Matrices were used for a separate study.

[2] Using Structural equation modeling (SEM) we confirmed that (a) WMC tasks all loaded onto a single WMC factor when the MU1 and MU2 tasks were combined, (b) that loadings on the WMC factor showed minimal change when the MU1 task was used alone, compared to when the MU tasks were combined, and (c) that the loadings of the combined MU tasks were comparable to previously reported loadings using the OS, SS, SSTM, and MU1 tasks (Lewandowsky et al., 2010). We therefore present only the analysis using a combined MU score.

[3] We did not relate learning performance to strategy use in the correlated-cues task because the type of stimuli—alien cells vs. rockets—turned out to be strongly associated with both.

Table 1

Category structure for training and transfer items used in the MS1978 task originally designed by Medin & Schaffer (1978). Each set of four digits represents a stimulus. For each stimulus, each of the four digits represents a binary stimulus dimension. The value of these number, 1 or 2, represents the cue value on the given dimension. The table also includes transfer responses for the three expected popular profiles, dimension-one rule (R1), dimension-two rule (R3), and exemplar (EX).

Category A	Category B	Transfer stimuli	R1	R3	EX
1112	1122	1221	A	B	A
1212	2112	1222	A	B	B
1211	2221	1111[a]	A	A	A
1121	2222	2212	B	A	B
2111		2121	B	B	B
		2211	B	A	A
		2122[a]	B	B	B

[a] Non-critical transfer stimuli. These items are removed from the analysis as in Johansen & Palmeri (2002).

Table 2

Category structure for training and transfer items used in the correlated-cues task originally designed by Medin et al. (1982). Each set of four digits represents a stimulus. For each stimulus, each of the four numbers represents a binary stimulus dimension. The value of these number, 1 or 2, represents the cue value on the given dimension. The table also includes transfer responses for the three expected popular profiles, correlated cues (CC), dimension-one rule, (R1), and dimension-two rule (R2); and the unexpected knowledge partitioning (KP) strategy

Category A	Category B	Transfer stimuli	CC	R1	R2	KP
1111	1212	2222	A	B	B	B
2111	2212	2211	A	B	B	A
1122	2121	2122	A	B	A	B
1222	2221	1211	A	A	B	A
		1112	B	A	A	B
		1121	B	A	A	A
		2112	B	B	A	B
		1221	B	A	B	A

Table 3

Association between pictorial stimulus dimensions and conceptual stimulus dimensions for the two randomization groups (group A and group B) for the 5-4 and correlated-cues task.

			Stimulus dimensions			
Group	Task	Stimuli	1	2	3	4
A	5-4	Alien cells	Size	Wall color	No. walls	Nucleus
	Correlated-cues	Rockets	Porthole	Tail	Wings	Nose
B	5-4	Rockets	Wings	Nose	Porthole	Tail
	Correlated-cues	Alien cells	No. walls	Nucleus	Size	Wall color

Table 4

Means, standard deviations, skewness, and kurtosis for memory updating (MU), operation span (OS), sentence span (SS), and spatial short-term memory (SSTM) tasks, along with standardized regression weights (SRW) for the WMC measurement model.

Measure	*M*	*SD*	Skewness	Kurtosis	*SRW*
OS	0.72	0.13	-0.70	3.36	.85
SS	0.65	0.17	-0.39	2.69	.68
SSTM	0.85	0.05	-0.29	3.04	.46
MU	0.58	0.17	0.20	2.90	.68

Table 5

Mean and SD zWMC scores and mean square-root transformed proportion error (Prop. E.) scores across final 8 blocks for each of the popular transfer strategies from the final transfer block: rule (RU), exemplar (EX), and Other for the 5-4 task, and correlated cues (CC), knowledge partitioning (KP), and Other for the correlated-cues task. In addition, the table includes M and SD zWMC scores for any popular strategy and only other strategy use across all transfer blocks.

				zWMC		Prop. E.	
Task	Transfer block	Strategy	n	*M*	*SD*	*M*	*SD*
5-4	Final	RU	27	0.013	0.93	.33	.21
		EX	24	0.073	0.61	.21	.15
		Other	100	-0.021	0.75	.34	.19
	All	Popular	82	0.004	0.76	.31	.18
		Other	69	-0.005	0.77	.33	.21
Correlated-cues	Final	CC	46	0.113	0.60	.16	.14
		KP	35	-0.132	0.83	.19	.16
		Other	70	-0.009	0.82	.28	.20
	All	Popular	84	0.019	0.71	.17	.15
		other	67	-0.024	0.82	.29	.20

Table 6

Means and SDs *for* z*WMC and square root-transformed proportion error (Prop. Error) for the number of transfer strategy shifts (No. switches) made by participants across the three transfer blocks for both 5-4 and correlated-cues tasks. A strategy shift was counted as using a strategy that differed by two or more responses from the previous strategy.*

			zWMC		Prop. Error	
Cat. task	No. switches	n	M	SD	M	SD
5-4	0	27	0.059	0.82	0.271	0.19
	1	63	0.071	0.73	0.299	0.18
	2	61	-0.157	0.76	0.393	0.19
Correlated-cues	0	36	0.115	0.69	0.192	0.16
	1	65	-0.002	0.81	0.197	0.17
	2	50	-0.080	0.75	0.288	0.20

Figure Captions

Figure 1. Mean of square-root transformed proportion correct across grouped training blocks for 5-4 and correlated-cues categorization tasks separated by randomization group (Group A vs Group B). Training blocks were grouped by averaging training performance across sets of 8 blocks: Blocks 1–8, Blocks 9–16, Blocks 17–24, and Blocks 24–32. Error bars indicate 95% confidence intervals.

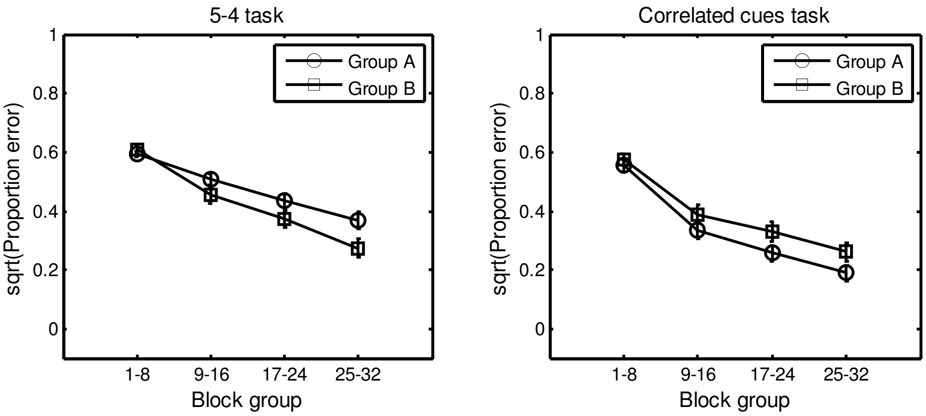
Figure 2. Structural equation model showing the relationship between working memory capacity (WMC) and learning. Manifest variables predicted by WMC are from the four WMC tasks, operation span (OS), sentence span (SS), spatial short-term memory (SSTM), and MU tasks. Manifest variables for learning rates are estimated mean proportion error scores across four groups of eight training blocks, blocks 1 to 8, blocks 9 to 16, blocks 17 to 24, and blocks 25 to 32 for the 5-4 and correlated-cues (Corr) tasks. Fit statistics for the model are $\chi^2(43) = 35.00$, $CFI = 1$, $RMSEA = 0$, and $SRMR = .0504$.

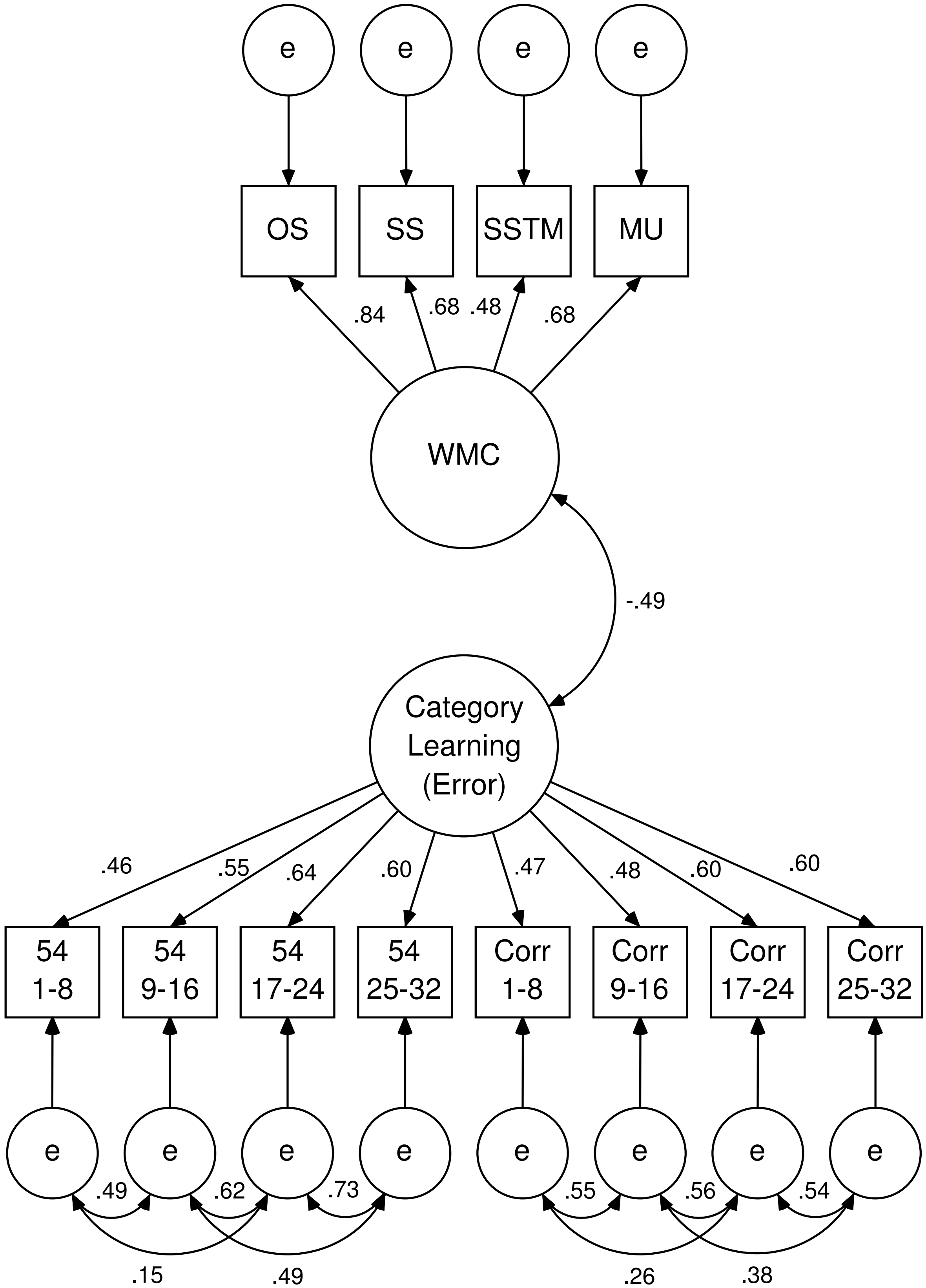
Figure 3. Proportion of use of generalization profiles for the 5-4 task for the three transfer blocks. Transfer blocks were presented after training blocks 4, 16, and 32. Each bar represents a possible sequence of responses to the five critical transfer items. Only profiles that were used by at least two participants at any transfer test are included in the figure. Popular strategies, R1, EX, and R3, are marked.

Figure 4. Proportion of use of generalization profiles for the correlated-cues task for the three transfer blocks. Transfer blocks were presented after training blocks 4, 16, and 32. Each bar represents a possible sequence of responses to the eight transfer items. Only profiles that were used by at least two participants at any transfer profile are included in the figure. Popular strategies, CC and KP, are marked.

Figure 5. Proportion of generalization profiles for the two randomization groups, A (top panel) and B (bottom panel), for the correlated-cues task. Only the final transfer block is included for each randomization group. Each bar represents a possible sequence of responses to the eight transfer items. Profiles that were used by at least one participant at any transfer profile are included. Popular profiles, CC and KP, are marked.

Figure 6. Relationship between the proportion of participants who used each strategy and their simplicity scores for the 5-4 (left) and the correlated-cues (right) categorization tasks. Simplicity scores are given in bits, as calculated using Pothos & Chater's (2002) model of simplicity. Scores for the two popular strategies for the correlated-cues task, CC and KP, are not shown as these were statistical outliers. The dotted lines represent the best fitting regression line. The correlation between simplicity and proportion of strategy use was significant for the 5-4 task, $r(30) = -.41, p < .05$, and approached significance for correlated-cues, $r(252) = -.12, p = 0.67$. See text for further details.


5-4 task
Correlated cues task
sqrt(Proportion error)
Block group
Group A
Group B
1-8
9-16
17-24
25-32
0
0.2
0.4
0.6
0.8
1


e
e
e
e
OS
SS
SSTM
MU
.84
.68
.48
.68
WMC
-.49
Category
Learning
(Error)
.46
.55
.64
.60
.47
.48
.60
.60
54
1-8
54
9-16
54
17-24
54
25-32
Corr
1-8
Corr
9-16
Corr
17-24
Corr
25-32
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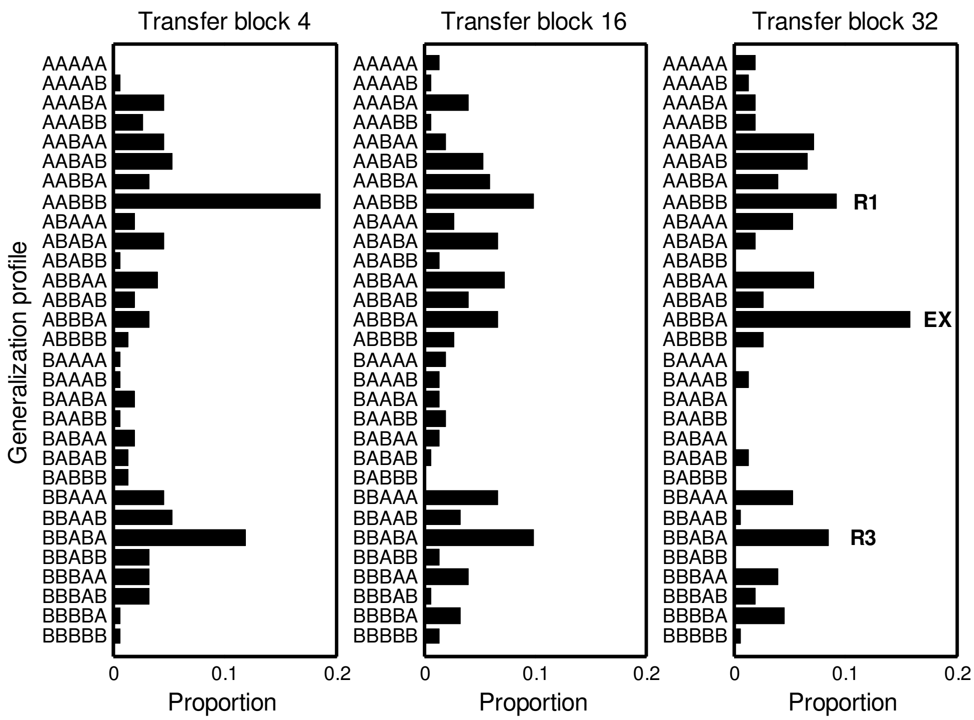
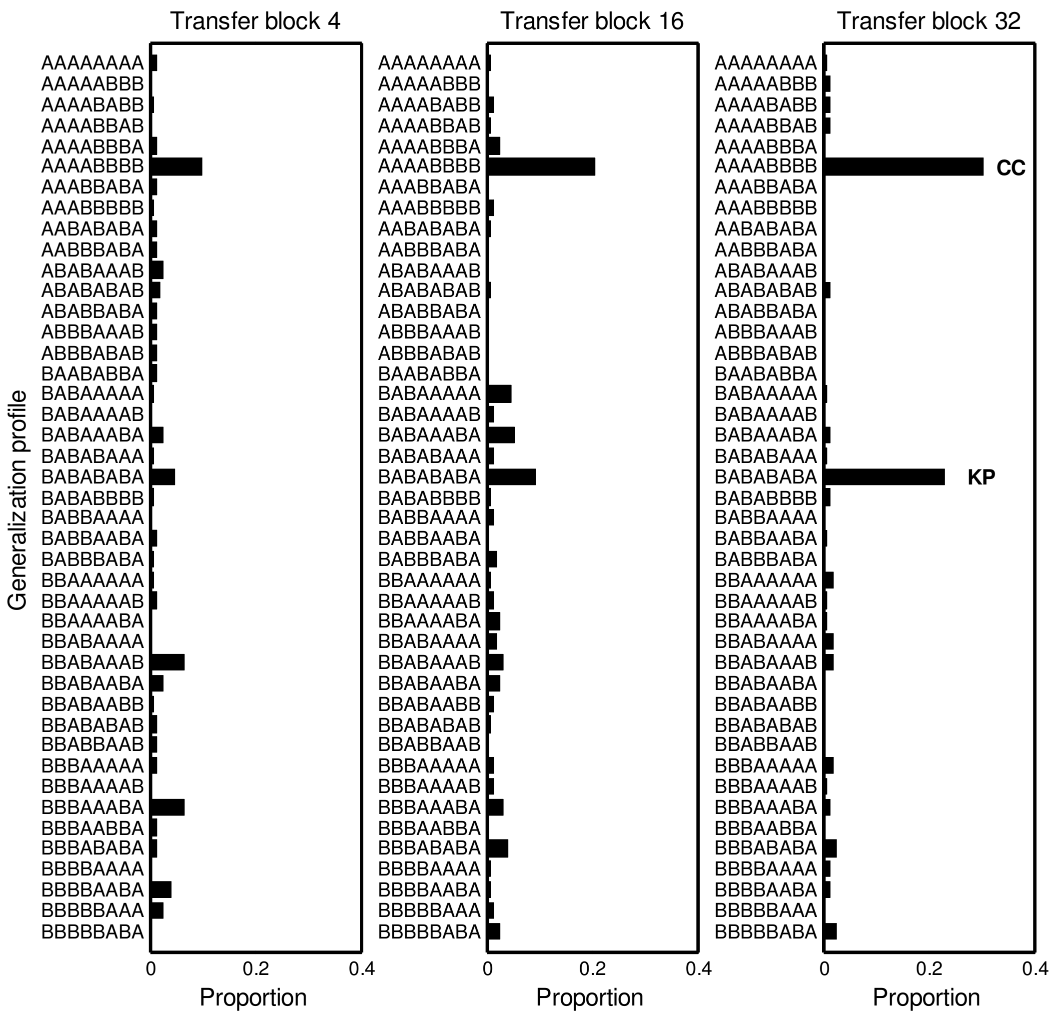


Transfer block 4
Transfer block 16
Transfer block 32
Generalization profile
AAAAA
AAAAB
AAABA
AAABB
AABAA
AABAB
AABBA
AABBB
ABAAA
ABABA
ABABB
ABBAA
ABBAB
ABBBA
ABBBB
BAAAA
BAAAB
BAABA
BAABB
BABAA
BABAB
BABBB
BBAAA
BBAAB
BBABA
BBABB
BBBAA
BBBAB
BBBBA
BBBBB
R1
EX
R3
0
0.1
0.2
Proportion


Transfer block 4
Transfer block 16
Transfer block 32
Generalization profile
AAAAAAAA
AAAAABBB
AAAABABB
AAAABBAB
AAAABBBA
AAAABBBB
AAABBABA
AAABBBBB
AABABABA
AABBBABA
ABABAAAB
ABABABAB
ABABBABA
ABBBAAAB
ABBBABAB
BAABABBA
BABAAAAA
BABAAAAB
BABAAABA
BABABAAA
BABABABA
BABABBBB
BABBAAAA
BABBAABA
BABBBABA
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BBABBAAB
BBBAAAAA
BBBAAAAB
BBBAAABA
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BBBABABA
BBBBAAAA
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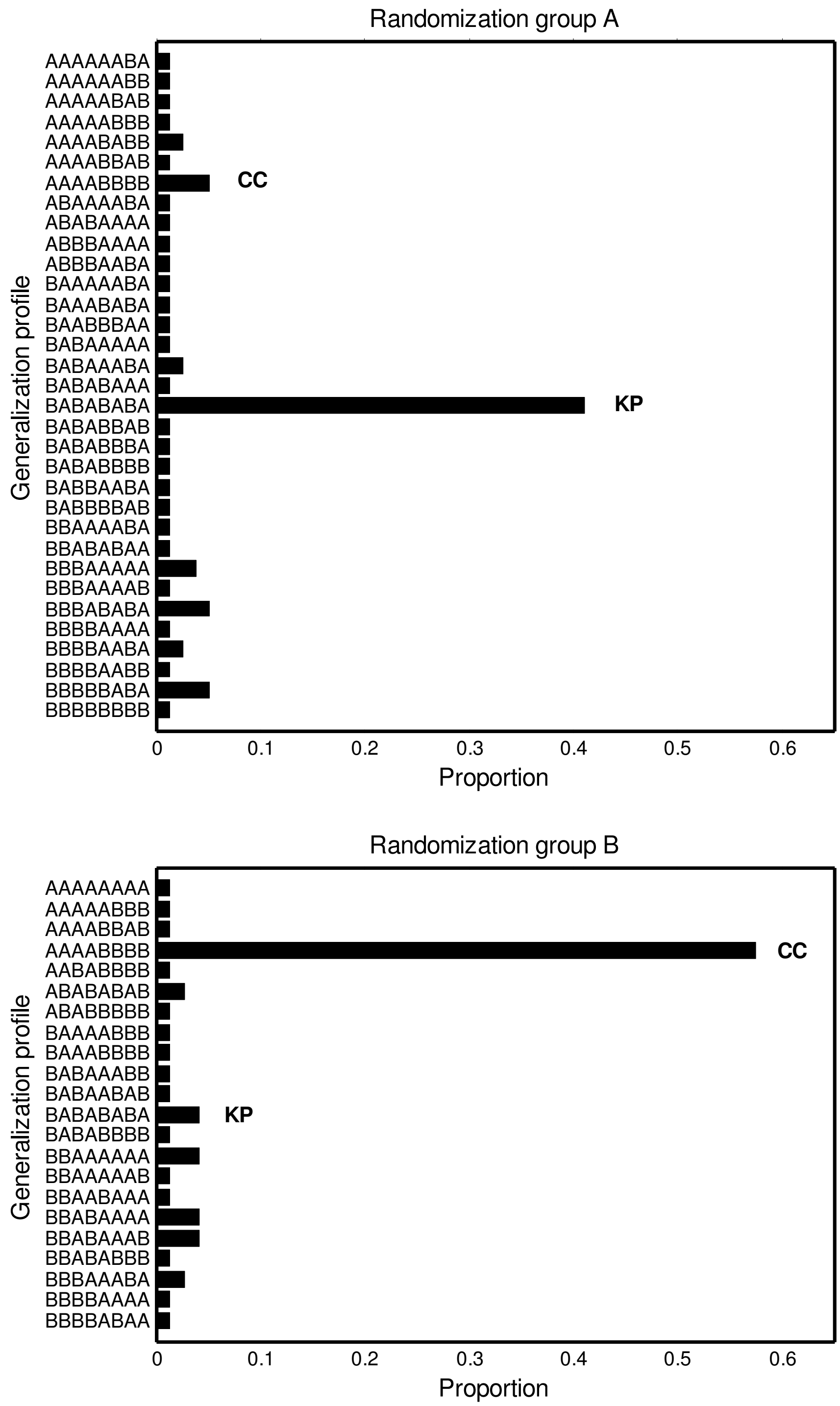
BBBBBAAA
BBBBBABA
CC
KP
0
0.2
0.4
Proportion


Randomization group A
Generalization profile
AAAAAABA
AAAAAABB
AAAAABAB
AAAAABBB
AAAABABB
AAAABBAB
AAAABBBB
ABAAAABA
ABABAAAA
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ABBBAABA
BAAAAABA
BAAABABA
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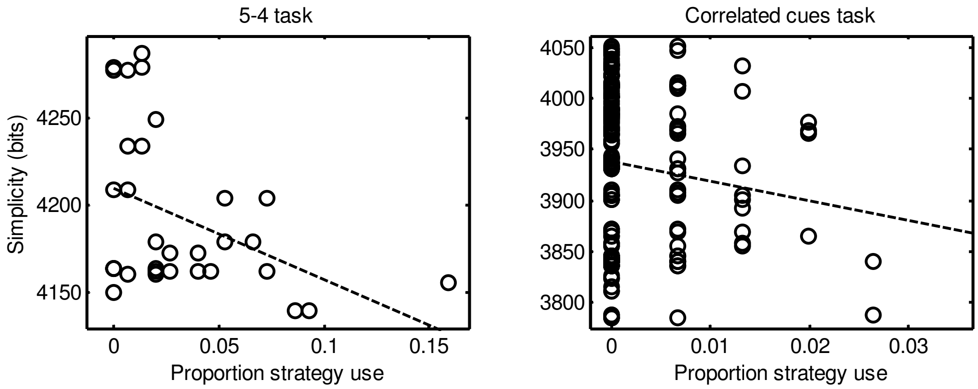
BBBBAAAA
BBBBAABA
BBBBAABB
BBBBBABA
BBBBBBBB
CC
KP
0
0.1
0.2
0.3
0.4
0.5
0.6
Proportion
Randomization group B
Generalization profile
AAAAAAAA
AAAAABBB
AAAABBAB
AAAABBBB
AABABBBB
ABABABAB
ABABBBBB
BAAAABBB
BAAABBBB
BABAAABB
BABAABAB
BABABABA
BABABBBB
BBAAAAAA
BBAAAAAB
BBAABAAA
BBABAAAA
BBABAAAB
BBABABBB
BBBAAABA
BBBBAAAA
BBBBABAA
CC
KP
0
0.1
0.2
0.3
0.4
0.5
0.6
Proportion


5-4 task
Simplicity (bits)
4250
4200
4150
0
0.05
0.1
0.15
Proportion strategy use
Correlated cues task
4050
4000
3950
3900
3850
3800
0
0.01
0.02
0.03
Proportion strategy use