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Removing the Frontal Lobes: The Effects of Engaging Executive Functions on Perceptual Category Learning

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Abstract

The present study examined the impact of engaging frontal-mediated, working memory processes on implicit and explicit category learning. Two stimulus dimensions were relevant to categorization, but in some conditions a third irrelevant dimension was also presented. Results indicated that, in both implicit and explicit conditions, the inclusion of the irrelevant dimension impaired performance by increasing the reliance on sub-optimal unidimensional strategies. With three-dimension stimuli a striking dissociation was observed between implicit and explicit category learning when participants performed the sequential working memory task. With explicit category learning, performance was impaired further and there was an increased use of sub-optimal unidimensional strategies. However, with implicit category learning, the performance impairment decreased and there was an increased use of optimal strategies. These findings demonstrate the paradoxical situation in which learning can be improved under sequential-task conditions and have important implications for training, decision making, and understanding interactive memory systems.

Humans are remarkably accurate at making highly complex decisions using processes that are outside conscious thought. For example, expert radiologists accurately determine whether x-rays are normal or abnormal, but often cannot describe their decision process verbally. In contrast, other decisions require a great deal of verbal thought and often require working memory (WM) and executive attention. For example, when investing in stocks, an expert broker will analyze a company's previous earnings and potential for future growth. When making complex decisions using either approach, extraneous information in the decision process (e.g., movement artifacts in x-rays or anomalies in corporate earnings) often harms performance. Identifying methods for mitigating the impact of extraneous information would have broad implications for learning, training, and decision-making.

It is well established that performance of a secondary, extraneous task often leads to performance decrements on a primary task (Pashler & Johnston, 1998), which is often explained as capacity limitations within WM (Navon & Miller, 2002; Tombu & Jolicoeur, 2005). Recent work demonstrates that primary tasks with greater WM requirements are more vulnerable to secondary-task interference (Beilock & Carr, 2001). For example,

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Maddox and colleagues (Maddox, Ashby, Ing, & Pickering, 2004; see also Waldron & Ashby, 2001; Zeithamova & Maddox, 2006 , 2007) found that the inclusion of a sequential WM task performed 500ms after the presentation of corrective feedback impacted rule-based (RB) category learning, but did not impact information-integration (II) category learning. This supports the hypothesis that RB category learning relies to a greater extent on WM because the corrective feedback must be linked with the response that was made. In contrast, WM is not required when learning II categories because the response is linked automatically with the feedback. This finding is consistent with multiple-systems theories of category learning (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Erickson & Kruschke, 1998; Smith, Patalano, & Jonides, 1998). For example, the COmpetition between Verbal and Implicit Systems theory (COVIS; Ashby et al., 1998), proposes two distinct systems: an explicit hypothesis-testing system that mediates RB category learning (see Figure 1A) and relies on WM and attention, and an implicit procedural-based system that mediates II category learning (see Figure 1B) and relies on reinforcement-based learning processes. These systems are thought to have different neuroanatomical bases, with the hypothesis-testing system mediated to a greater extent in frontal cortices, and the procedural-based system relying more on posterior regions of the striatum (Ashby et al., 1998; Filoteo et al., 2005; Nomura et al., 2007; Seger & Cincotta, 2002).

COVIS assumes that the two systems compete during learning, with one system eventually winning control of the response. Importantly, COVIS assumes that there is an initial bias toward the hypothesis-testing system and unidimensional rules (Bruner, Goodnow, & Austin, 1956; Shepard, Hovland, & Jenkins, 1961). Thus, regardless of the nature of the optimal categorization rule (RB or II) people will start by testing verbal rules that are based on a single dimension. One implication of this architecture is that any manipulation that increases the number of possible rules could increase the WM requirements of the task (Ellenbogen & Meiran, 2008; Kruschke, 1992), and thus, should increase the amount of time spent testing verbal rules. To our knowledge, this prediction has not been tested previously. We test this prediction by examining conjunctive (CJ) RB and II category learning of three-dimensional stimuli that consisted of single lines (see Figure 2) that varied along two relevant dimensions-- length and orientation, and a single irrelevant dimension-- horizontal spatial position (i.e., where it appeared on the computer screen). Participants had to learn either CJ or II categories (Figures 1A and 1B, respectively) when the irrelevant dimension was either fixed (2D conditions) or varied (3D conditions) across trials. We predicted that the inclusion of a third, irrelevant dimension would result in poorer performance in the CJ-3D condition relative to the CJ-2D condition, and poorer performance in the II-3D condition relative to the II-2D condition because participants would spend more time testing unidimensional rules before transitioning to CJ rules or II rules. To anticipate, this prediction was supported in the data.

This architecture also makes an additional, counterintuitive prediction with respect to II learning and secondary task effects. If a secondary sequential task engages WM processes during processing of the feedback, participants should be less inclined to use rules and would be better able to disengage from the hypothesis-testing system thereby allowing the procedural-based system to learn the II task (i.e., in the II-3D-WM condition vs. the II-3D condition). This would lead to the paradoxical effect of enhanced II learning under secondary sequential task conditions. In essence, the addition of the secondary task would behaviorally limit the contribution of the frontal lobes by overly engaging WM processes during the processing of the corrective feedback, thus allowing the procedural-based system to operate without competition. On the other hand, a secondary WM task that behaviorally removes the contributions of the frontal lobes should further tax the hypothesis-testing system leading to an even greater performance decrement for CJ learning (i.e., in the CJ-3D-WM condition relative to the CJ-3D condition).

Methods

Participants

A total of 205 undergraduates from the University of Texas, Austin, participated. All participants had normal or corrected to normal vision. Participants were tested in one of the six conditions and each received course credit for the study. To ensure that participants achieved a minimal level of learning, individuals who did not achieve at least 50% accuracy in the final block of trials were not included in the analyses. For the II conditions, this process resulted in 21 (0 dropped) participants in the II-2D condition, 33 (3 dropped) participants in the II-3D condition, and 37 (2 dropped) participants in the II -3D-WM condition. For the CJ conditions, this resulted in 20 (3 dropped) participants in the CJ-2D condition, 40 (4 dropped) participants in the CJ-3D condition, and 41 (1 dropped) participants in the CJ-3D-WM condition.

Stimuli and Stimulus Generation

Stimuli consisted of single lines that varied in length and orientation on a trial-by-trial basis in the 2D conditions, and in length, orientation, and spatial location in the 3D conditions. In all cases, the length and orientation were the relevant dimensions. The stimuli and stimulus generation algorithm are detailed in Figure 1. The parameter values for the categories in the CJ and II conditions are shown in Table 1.

Procedure

Category Learning Task—Each of the six conditions consisted of 6, 100-trial blocks. Participants were told that they would see a single line that would appear somewhere on the computer screen and that they had to categorize the stimulus into either Categories A or B. They were informed that each category was equally likely and that high levels of accuracy could be achieved. On each trial, a stimulus appeared and remained on the screen until the participant generated a response by pressing one of two keys that were labeled "A" or "B". For the conditions that did not include the sequential WM task (i.e., the CJ-2D, CJ-3D, II-2D, and II-3D conditions), corrective feedback was provided for 500 ms following a response and the next trial was initiated following a 2-s ITI. For the conditions that included the sequential WM task, corrective feedback was also provided for 500 ms following a response, but instead of the 2-s ITI, WM trials followed the feedback (see below).

Secondary WM Task—Participants were administered the same WM task as that used by Maddox and colleagues (Maddox et al., 2004). On each trial, four digits (between 0 – 9) were sampled randomly (without replacement) and were displayed in 48-point type in a horizontal array for 500ms. A blank screen was then presented for 1000-msec followed by a single probe digit. The participant was asked to indicate with a key press whether it was one of the four numbers displayed in the array. The secondary, WM task was embedded within the category learning task for the CJ-3D-WM and II-3D-WM conditions using the sequence and timing depicted in Figure 2. For the WM task, the participant was informed that high levels of performance were possible and that they should respond as quickly and accurately as possible. If performance in the memory scanning task was below 90% accuracy at the end of any trial, the observers were told to increase their memory scanning accuracy. These notifications stopped once memory scanning accuracy was above 90%. Importantly, performance on the WM task was high in both the II-3D-WM (98.2%) and CJ-3D-WM (97.8%) conditions, suggesting that category learning differences across conditions were not due to differential attention to the WM task.

Model-Based Analyses

A strength of these tasks is that computational models have been developed to determine the type of strategy that the participant uses in learning the task. Four types of models were applied to the final block of data separately for each participant (the details of these models can be found in Maddox, 1999; Maddox & Ashby, 1993). One type of model assumes that the participant used a CJ rule. A second type of model assumes that the participant used a unidimensional rule (UD) based on one of the three stimulus dimensions (i.e., length, orientation, and in the 3D condition, spatial location). A third type of model assumes that the participant used a procedural-based approach (II) by performing an implicit integration of the length and orientation of the line, or an implicit integration of the length, orientation, and spatial location of the line (in the 3D condition). A fourth type of model assumes that the participant responded randomly (RR). Akaike's (Akaike, 1974) information criterion (AIC) was used to determine the model that provided the best account of the data. We then used binomial tests to contrast the proportions of participants whose data were best fit by each model in the various conditions.

Results

Irrelevant Dimension Effects on Category Learning Performance

Percent correct for the three CJ and three II conditions are displayed in Figure 3. To examine the impact of the third, irrelevant dimension on category learning, we conducted a 2 (Condition: 2D vs. 3D) × 2 (Category Type: CJ vs. II) × 6 (Blocks 1–6) mixed ANOVA that revealed a significant interaction between Condition and Block, $F(1,110)=9.2$, $p<.01$, $p_{rep}=.98$, $\eta^2 = 0.08$, and main effects of Block, $F(1,110)=129.5$, $p<.001$, $p_{rep}>.99$, $\eta^2 = 0.54$, and Condition, $F(1,110)=17.7$, $p<.001$, $p_{rep}>.99$, $\eta^2 = 0.14$. The interaction between Condition and Block was due to the learning slopes (block 6 accuracy - block 1 accuracy) being greater in the 2D condition as compared to the 3D condition (averaged across Category Type), $p<.002$, $p_{rep}>.99$. The main effect of block was due to the increase in learning across all conditions. Importantly, the significant main effect of Condition (averaged across Category Type) was due to greater accuracy in the 2D condition relative to the 3D condition, $p<.001$, $p_{rep}>.99$, indicating that the addition of the irrelevant dimension impeded performance. The lack of a significant Condition by Category Type interaction indicated that the effect of the third, irrelevant dimension was similar in the CJ and II conditions.

Table 2 displays the proportion of participants in the six conditions whose data were best accounted for by a CJ, UD, II or RR model. This table also includes the percentage correct for those participants whose data were best fit by the various models. The results were clear. For the CJ-2D condition, the majority of participants (.70) used a CJ approach when performing the task, but this proportion declined in the CJ-3D condition (.45), $p<.001$, $p_{rep}>.99$, and this appeared to be due to an increase in the use of UD rules in the CJ-3D condition (.23) relative to the CJ-2D condition (.10), $p<.05$, $p_{rep}=.96$. For the II-2D condition, most participants (.81) used an II approach but this proportion decreased in the II–3D condition (.52), $p<.001$, $p_{rep}>.99$, and there was a shift from there being no UD users in the II-2D condition to a larger proportion (.24) using a UD approach in the II-3D condition, $p<.05$, $p_{rep}=.95$.

WM Effects on Category Learning Performance

To determine the impact of the secondary WM task, we conducted a 2 (Condition: 3D vs. 3DWM) × 2 (Category Type: CJ vs. II) × 6 (Blocks 1–6) repeated measures ANOVA that revealed a significant interaction between Condition and Category Type, $F(1,147)=7.0$, $p<.01$, $p_{rep}=.97$, $\eta^2 = 0.05$, and a significant main effect of block, $F(1,147) = 90.8$, $p < 0.001$, $p_{rep}>.99$, $\eta^2 = 0.38$; the latter indicating improved accuracy across blocks. The significant

Condition by Category Type interaction was characterized by improved performance in the II-3D-WM condition relative to the II-3D condition, $p<.01$, $p_{rep}=.97$, and no performance difference between the CJ-3D-WM and CJ-3D conditions (although there was a slight decline in performance in the CJ conditions when the WM task was added). This interaction was also highlighted by the fact that the II-3D and CJ-3D conditions did not differ significantly, $p=.55$, $p_{rep}=.66$, but accuracy in the II-3D-WM condition was significantly greater than in the CJ-3D-WM condition, $p<.002$, $p_{rep}>.99$.

The model-based analyses were also highly informative. The addition of the WM task in the CJ conditions resulted in a decline in the proportion of participants who used a CJ approach (.45 in the CJ-3D condition vs. .27 in the CJ-3D-WM condition), $p<.05$, $p_{rep}=.94$, with the shift in approach being distributed equally across UD and II approaches. In the II condition, there was an increase in the proportion of participants who used an II approach with the addition of the WM task (.52 in the II-3D vs. .65 in the II-3D-WM condition), but this difference was not significant, $p=.16$, $p_{rep}=.84$. However, there was a significant drop in the proportion of UD users in the II-3D-WM condition (.08) as compared to the II-3D condition (.24), $p<.05$, $p_{rep}=.94$.

Discussion

It is often the case that performing a secondary task negatively impacts performance on a primary task (Pashler & Johnston, 1998). This is especially so when both the primary and secondary task rely to a large extent on WM, and might even be particularly the case in the presence of additional distraction. But is it possible to demonstrate the opposite pattern--enhanced performance on one task while performing a secondary task? Such a finding would have important implications for theories of learning and decisionmaking, as well as approaches to training. This line of research also has important ecological implications since we often make complex decisions in the face of distracting information.

The present study demonstrated that the inclusion of a third, irrelevant dimension had a negative impact on CJ and II category learning, and the model-based analysis indicated that this was due to a decrease in the proportion of participants using II or CJ approaches in the respective conditions, and an increase in the proportion of participants using a UD approach. Thus, the addition of the irrelevant dimension impacted both CJ and II learning. However, the presence of a sequential WM task improved II category learning. The model-based analyses indicated that the II improvement was due to a decrease in the proportion of participants using a UD approach in the II task when the sequential WM task was present (and to a smaller extent, an increase in the proportion of participants using an II approach). Therefore, in some manner, including the sequential task behaviorally removed the frontal lobes by engaging WM processes so that the procedural-based system could control performance in the task. On the other hand, the presence of a sequential WM task had no effect on accuracy in the CJ conditions, although it did impair performance in the CJ-3D-WM condition relative to the II-3D-WM condition. The model-based analyses indicated that there was an even further decrease in the proportion of participants who used a CJ approach in the category learning task in the sequential WM condition. Thus, there was a crossover effect between condition (3D vs. 3D-WM) and category structure (CJ vs. II).

These results provide important insights into how category learning systems interact. As predicted by COVIS (Ashby et al., 1998), when learning II categories, participants appear to initially use verbalizable rules, and once they have exhausted the potential rules, they abandon a hypothesis-testing system and attempt to use more of a procedural-based approach. This transition will take place much earlier in the learning process (1) if the number of potential rules is minimized, such as in the II-2D condition, or (2) if the feedback processing component of the hypothesis-testing system is taxed to a great extent making it more difficult to use verbalizable rules, such as in the II-3D-WM condition. In contrast, II learning will be hindered if the number of verbalizable rules is increased and the hypothesis-testing system is not overly engaged, such as in the II-3D condition. This pattern of results is highly consistent with recent work demonstrating that participants will make use of procedural-based learning processes (as opposed to explicit processes) under secondary-task conditions when having to learn probabilistic sequences (Fu & Anderson, 2008), and other work demonstrating that individuals with greater WM capacity perform more poorly on II category learning tasks (Decaro, Thomas, & Beilock, 2008). In regard to this latter observation, it could be that individuals with greater WM capacity will inherently rely more on the use of rules when learning II tasks and will be less likely to abandon such an approach to use the procedural-based system.

Although this is one of the first studies to demonstrate improved II category learning with the performance of a sequential secondary task, it should be mentioned that other manipulations have also resulted in better II learning. Markman and colleagues (Markman, Maddox, & Worthy, 2006) demonstrated significantly improved II category learning when participants were under high social pressure as compared to a low pressure condition. In contrast, the opposite pattern was displayed when participants were asked to learn RB categories. This pattern of results was due to the increase in pressure overly engaging WM, thereby allowing participants to more quickly engage the procedural-based learning system when learning II categories.

Other studies have also demonstrated improved performance on a primary task as a result of performing a secondary task, particularly within the visuomotor domain (Laufer, 2008; Roche et al., 2007; Wulf, McNevin, & Shea, 2001). In addition, other studies have shown that procedural memory processes can be impaired on the serial reaction time task when explicit instructions are provided informing the participant to look for the sequence (Howard & Howard, 2001). These studies also provide evidence for multiple learning systems. An important distinction between many of those studies and the present study, however, is the underlying explanation for why such improvement occurs. Previous explanations of such effects have focused primarily on attentional processes (Pellecchia, 2005; Roche et al., 2007). For example, Roche and colleagues (Roche et al., 2007) argued that improvement in visuomotor learning during secondary task performance was due to the secondary task increasing the amount of attentional resources directed toward the stimulus in the primary task, thereby enhancing learning. In contrast, we argue that the sequential-task improvements we observed in II category learning had to do with the inherent competition between the hypothesis-testing system and the procedural-based system, with the sequential WM task engaging the hypothesis-testing system's processing of the feedback so that the procedural-based system could learn the categories.

Although we argue that the engagement of the hypothesis-testing system was mediated via WM, we also acknowledge that other executive function processes might have been enlisted (e.g., shifting of attention) that could have engaged the hypothesis-testing system during feedback processing. However, given the nature of the sequential secondary task, we feel that the mechanism by which the procedural-based system was allowed to dominate task performance in the II-3D-WM condition was through the engagement of the WM processes necessary for the hypothesis-testing system to process corrective feedback. This point also highlights another important distinction-- that between the use of a sequential secondary task and the use of a concurrent secondary task. Previous studies have demonstrated using either a sequential working memory task (such as the one in this study; Maddox *et al.*, 2004) or a concurrent secondary task (that is performed simultaneously during the categorization judgment; Waldron & Ashby, 2001; Zeithamova & Maddox, 2006) can differentially interfere with RB category learning as compared to II category learning. However, the processes that are disrupted in RB category learning by the sequential and concurrent tasks are likely different. As we have suggested, sequential secondary tasks likely interfere with the processing of corrective feedback. In contrast, concurrent tasks likely interfere with other processes, such as selective attention or the actual categorization judgment.

An important distinction between our study and many previous secondary-task studies is methodological. Specifically, we demonstrated improved II category learning when we increased the number of potential verbalizable rules by adding an irrelevant dimension to the primary task, thereby requiring an increase in WM resources. Most other studies have manipulated the secondary task (e.g., Roche et al., 2007) in an attempt to determine at what stage of cognitive processing (e.g., attentional, perceptual, motor selection) the two tasks interfere. One potential reason that previous studies have not demonstrated improved performance under secondary-task conditions is that the resource limitations were not taxed to a large enough extent in the primary task, a possibility that has been considered in other studies (Ellenbogen & Meiran, 2008). Future work should consider the need to manipulate the primary task to observe dual-task improvement.

Finally, it is important to underscore that our findings could have important implications for training related issues, particularly when learning those tasks that likely rely on the procedural-based learning system. For example, based on our findings, it may be possible to enhance the training of radiologists by having them perform a secondary task while learning to read x-rays. Our results further suggest that such an improved training approach could be due to trainees quickly abandoning less-efficient verbal approaches to reading the scans so as to engage a more appropriate learning system.

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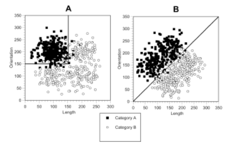

Figure 1.
Category structures used in the conjunctive, rule-based (A) and information-integration conditions (B). Solid lines denote the optimal decision bounds, and the open squares represent stimuli from category A, and the closed triangles represent stimuli from category B. Each "cluster" of stimuli was associated with a specific category. Each stimulus was created by converting the x value into a line length (measured in pixels), and the y value (after applying a scaling factor of π/500) into line orientation. The scaling factor π/500 was chosen to approximately equate the salience of line length and line orientation.

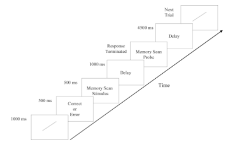

Figure 2.
Sequence of events for each trial in the rule-based and information-integration conditions with the working memory task (CJ-3D-WM and II-3D-WM conditions).

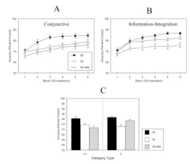

Figure 3.
Accuracy (percent correct) for each block of trials (in 100 trial blocks) for the conjunctive condition (A) and the information-integration condition (B) under two-dimension (2D), three-dimension (3D), and three-dimension working memory (3D-WM) conditions. Average accuracy for the two conjunctive and information-integration conditions averaged across all 600 trials (C). Error bars are standard errors of the mean.

Table 1

Category-distribution parameters for the length and orientation dimensions in the conjunctive rule-based and information-integration conditions. Note, for the working memory conditions (CJ-3D-WM and II-3D-WM), the irrelevant dimension (horizontal spatial location) had a mean of 150 and a standard deviation of 60.

	CONJUNCTIVE RULE-BASED				
Category	μ_l	μ_o	σ_l	σ_l	optimal accuracy
A	100	200	30	30	95%
B	100	100	30	30	95%
B	200	100	30	30	95%
B	200	200	30	30	95%
	INFORMATION-INTEGRATION				
Category	μ_l	μ_o	σ_l	σ_l	optimal accuracy
A	80	150	30	30	95%
A	150	220	30	30	95%
B	150	80	30	30	95%
B	220	150	30	30	95%

Table 2

Proportion of participants and corresponding accuracy levels (percent correct) for individuals whose data were best fit by a conjunctive model (CJ), unidimensional model (UD), information-integration model (II), or a random responding model.

		Conjunctive				Information-Integration		
		Condition				Condition		
Model		2D	3D	3D-WM		2D	3D	3D-WM
CJ	prop. of participants	.70	.45	.27		.19	.21	.27
	accuracy	88%	89%	88%		83%	75%	80%
UD	prop. of participants	.10	.23	.24		.00	.24	.08
	accuracy	73%	67%	65%		---	64%	65%
II	prop. of participants	.20	.30	.39		.81	.52	.65
	accuracy	80%	76%	81%		88%	83%	85%
RR	prop. of participants	.00	.03	.10		.00	.03	.00
	accuracy	---	52%	49%		---	.53	---