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Does Working Memory Load Influence the Prioritization Effect by Affecting the Consistency of Attention?

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Abstract

The way working memory, attention, and long-term memory interact is an important question given the role these cognitive systems play in many tasks. In this paper, we present a study examining prior counterintuitive results that show that prioritization of some stimuli aids learning but hurts performance at a delayed test. In this study, we use eye tracking to measure attention consistency, to examine the effect of prioritization and working memory load on recall accuracy. The goal was to assess two possible explanations of the negative effect of prioritization on a delayed test. Our results indicate that prioritization reduces response time and increases accuracy during learning of associations. However, the negative effect of prioritization on a delayed test is replicated with participants showing higher accuracy for non-prioritized items during testing. Measures of attention shifting and consistency impact learning performance but do not explain the negative prioritization effect at test.

Keywords: eye tracking; working memory; prioritization; attention; association leaning

Prioritization is a fundamental cognitive strategy in which individuals devote their cognitive resources to processing some stimuli before others. It is expected that prioritization yields more efficient encoding of information by minimizing distraction from irrelevant or less crucial information and subsequently enhances learning through interactions with attention and memory (Chun & Turk-Browne, 2007). However, it has been observed that prioritization does not necessarily enhance the retention of information and does not improve memory recall all the time (Williamson & Moss, 2022). This finding leads to the questions of when prioritization is effective for learning, and what are the underlying mechanisms that influence its effect on learning?

Previous findings emphasize the importance of attention and working memory in prioritization (Myers et al., 2017; Ravizza & Conn, 2022). For example, some explanations of prioritization discuss the importance of internal attention to select items from memory to prioritize in working memory (Myers et al., 2017). In the time-based resource sharing theory of working memory, items are maintained in working memory via attentional refreshing (Barrouillet & Camos, 2021), and prioritized items might be more likely to be selected to be maintained using this attentional refreshing mechanism. This prior research supports the idea that people can successfully prioritize some information in working memory using attention resources.

However, in an association learning task, Williamson and Moss (2022) found that although prioritizing some items allowed people to respond faster and more accurately during initial learning, at a delayed test, those prioritized items were recalled at lower rates than non-prioritized items. One proposed explanation from this prior work was related to skill acquisition that interfered with recalling the items later at a delayed test. However, another potential mechanism is related to the consistency of attention (Unsworth & Miller, 2021) to prioritized items during learning. The current experiment was designed to examine whether consistency of attention or skill acquisition is a better explanation of these prior results.

Prioritization in an Association Learning Task

Williamson and Moss (2022) introduced a prioritization manipulation into an association learning task that has been used to examine contributions of reinforcement learning and working memory to the learning of associations (Collins & Frank, 2012). In their study on prioritization, participants engaged in an association learning task where they had to learn the correct key press ("A," "S," or "D") for different stimuli via trial and error. Each category consisted of 3, 4, or 6 stimuli (i.e., set size), and correct key presses were rewarded with points with more points being awarded for stimuli designated as prioritized. The learning phase entailed presenting participants with blocks of different set sizes and some images were designated for prioritization with blue borders (1 prioritized item in set size 3, 2 items in set size 4, and 3 items in set size 6 blocks). Within a block, participants saw 3-6 items from a single category in random order with each item being presented 13 times. Following this learning phase, after a delay, participants completed a surprise testing phase, where all previously encountered images were tested individually in random order, with no feedback provided. The primary result of concern here is that prioritized item-key associations were recalled at a lower rate than non-prioritized items in the testing phase for set sizes 3 and 4.

Williamson and Moss (2022) describe a skill acquisition framework that can explain these results. This framework emphasizes the transfer of declarative-based memory to procedural memory in which learning associations after some trials result in an automatic process of responding via procedural memory instead of relying on declarative memory retrieval for producing answers. This explanation is consistent with the ACT-R theory of declarative memory

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(Anderson et al., 2004) in which the likelihood of retrieving a declarative memory is based on the frequency and recency with which it has been perceived or retrieved. Well-learned associations would become proceduralized via a process called production compilation in ACT-R into production rules eliminating the need for the declarative representation to be retrieved later in a block of trials. Because these associations were not being strengthened by memory retrieval, they were less available to use during testing. The proceduralized responses available during learning were also not available at test because the task changed from learning associations in a category-based block to testing on all stimuli presented in random order. Proceduralized representations could be specific to the category learning context, which is supported by research showing that when the test is presented in the same category-by-category manner as learning, then accuracy is higher (Newlin & Moss, 2020). This skill acquisition explanation explains reduced response accuracy for prioritized items at test by the decrease in retrieval attempts that happens after an association is proceduralized in the learning phase.

An alternative mechanism for this negative effect of prioritization on test performance is a consistency of attention explanation. According to this explanation, increasing the set size reduces the consistency of attention on each stimulus since participants need to switch their attention from one item to another during a restricted time to be capable of maintaining a representation of the associations in working memory and accessible long-term memory. Consistency of attention has been defined as the stability of attention during a task and can be seen as a distinct concept from the intensity of attention (Unsworth & Miller, 2021). Levels of consistency are potentially influenced by factors including working memory capacity, and it has been found that consistency of attention, as measured by pupil dilation, reduces attention lapses and increases learning in a paired-associates task (Unsworth & Miller, 2021). In another study, the impact of sustained attention has been shown to result in profound memory recall (Rahgosha, Hadinezhad, & Hosseini, 2023; Rahgosha, Hadinezhad, Hosseini, et al., 2023). In another study prioritization by covert spatial attention shifts was examined, with both trial-by-trial fluctuations of sustained attention and prioritization via covert spatial attention having an impact on long-term memory accuracy (deBettencourt et al., 2021). However, prioritizing some stimuli to maintain them in working memory may decrease the consistency of attention and interfere with long-term learning by promoting frequent switches of attention back to and between prioritized items.

Just as allocating attention and other cognitive resources to problem solving may interfere with long-term learning due to limited cognitive capacities such as working memory (Sweller, 1988), prioritizing items in working memory may interfere with retaining those items in declarative memory. There are a number of potential mechanisms by which this may occur, but one possible mechanism can illustrated within the time-based resource-sharing (TBRS) theory of working memory (Barrouillet & Camos, 2021). The TBRS theory states that working memory traces vanish gradually as attention switches away from them such that maintaining an item in working memory relies on a process of attentional refreshing to reactivate a decaying memory trace. As described by the TBRS theory, cognitive load can be manipulated by manipulating either the number of elements to be maintained or the time allowed to process them, where cognitive load = Nt / T. In this formula, N corresponds to the number of items that should be processed, t represents the amount of time required for processing each single stimulus, and T is the total amount of time given to refresh all items. The cognitive load would be increased if N or t are increased while T is kept constant (Barrouillet & Camos, 2021). Other research has shown that attentional refreshing alone is unlikely to improve long-term memory for that information, but instead the action of elaborative processes may be required in addition to refreshing (Bartsch et al., 2018). Therefore, if items were refreshed to maintain them in working memory but not maintained in activated state long enough for elaborative processes to improve long-term memory, then they may be accessible from working memory without improving long-term memory. Non-prioritized items may not be maintained in working memory (or at least be less likely to be maintained) and instead retrieved from long-term memory in this case. This allocation of resources may succeed in making prioritized items more accessible in the short-term while making them less accessible than non-prioritized items at a delayed test.

Current Study

In the current study, the goal was to attempt to measure shifts of attention between stimuli by providing a task environment that encouraged overt attention shifts measurable with eye tracking instead of the covert attention shifts that might underly performance in the task as it is traditionally used. To this end, all stimuli to be learned for a block of the task were present on the screen during the entire block as shown in Figure 1. Prioritized items were marked with a blue border, and one item was specified by a red border as the item to which participants should respond on the current trial. Upon response, there was a 500-ms inter-trial interval before the red border appeared around another item. This inter-trial interval may be a time when participants would shift attention to other stimuli to aid in maintenance.

Eye tracking was used for measuring the number of times participants began to fixate on one of the stimuli, with each stimulus serving as region of interest (ROI). The goal was to measure how often attention switched between each ROI and how long the ROI was attended on each switch. Each stimulus in Figure 1 is an ROI. Gaze data was collected during each block of the learning phase of the study and segmented into fixations. Each time the ROI being fixated on was changed, an entry into a new ROI was recorded (e.g., switching from looking at the top-left ROI to the top-middle ROI was an entry into the top-middle ROI). All consecutive fixations falling within the same ROI were summed together to obtain a measure of how long attention was maintained on that ROI before attention was switched to another ROI. Two protentional measures of consistency were considered: number of entries into an ROI, and the mean duration of attention on each ROI (i.e., summed fixation time divided by the number of entries into the ROI).

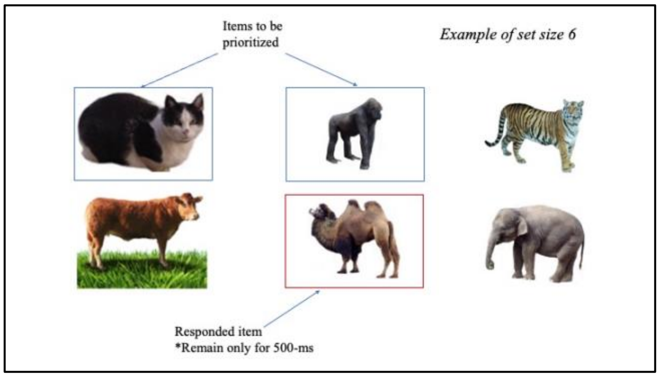

Figure 1: Example of a block in the learning phase

We hypothesized that while prioritization enhances performance during learning, our results would replicate the effect that prioritization decreases performance at test. Second, the decrease in performance at test for prioritized items will be explained by measures of attention consistency. The skill acquisition and the attention consistency explanations make different predictions about what should be observed in the eye tracking data.

For the skill acquisition hypothesis, there should be fewer attention shifts to prioritized stimuli if they are proceduralized faster than non-prioritized stimuli. In addition, the number of shifts to stimuli would be weakly positively correlated with memory at test because each of these shifts would reflect retrieval of the item from memory (at least before the item is proceduralized).

The attention consistency explanation predicts that more frequent shifts of attention to an item with each shift being of lower duration would be negatively associated with memory accuracy at test. Prioritization would affect consistency which in turn affects test performance. In other words, there is a negative effect of prioritization on consistency of attention and this mediates the relationship between prioritization and test accuracy.

To sum up, we tried to examine which of these explanations best accounts for the decreased accuracy of prioritized items at a delayed test by examining the effect of prioritization on attention consistency measured via eye tracking.

Method

Design

The association learning task was composed of a learning phase, followed by a testing phase which occurs after a delay. During the learning phase, the set size (3, 4, 5, and 6) and whether an item was prioritized were manipulated within participants.

For the learning phase of the association learning task, 20 categories of stimuli were used with six different images available for each category. In total, there were 20 blocks containing between 3 and 6 images from a single category. There were five blocks at each level of set size (e.g., a block may contain different animals while another other block consists of different types of fruit). The task was to learn the associations between three keys on the keyboard (A, S, and D) and each stimulus in a block. In each block, two items were prioritized and awarded twice as many points for correct responses as did non-prioritized items.

For the delay, participants completed the operation span task (Unsworth et al., 2005). which lasted 10-20 minutes (M = 16). The task is designed as a measure of working memory capacity, but it was used here primarily as a delay between learning and test, and therefore, the data from this task are not reported in this paper.

Participants

Based on the prioritization effect during the testing phase reported by Williamson and Moss (2022), a power analysis was conducted based on monte carlo simulations of the interaction effect between prioritization and set size in this prior study. This power analysis that yielded a sample size requirement of N = 50 for a significance level of $\alpha = 0.05$ with power of 0.80. A sample of 65 undergraduate students completed the study for course credit or for payment.

An a priori exclusion criterion was adopted to exclude participants who did not perform well on the learning task. Participants who had mean accuracy below 75% for set size three during the last three trials of blocks during the learning phase were excluded (N = 3). This criterion was the same as that used by Williamson and Moss (2022).

During exploration of the data, two additional participants were excluded for low quality data. One participant responded to more than 70% of testing trials in under 300 ms. The other participant failed to respond within the 1.5-s time limit on more than 70% of testing trials. These exclusions resulted in a final sample of 60 participants.

Procedure

During a block of the learning phase, all images for that block always remained on the screen and two of them were specified, using blue borders around them, as the items that need to be prioritized as shown in Figure 1. The locations for prioritized items were randomized across blocks. Participants had 1.5 s to respond to that image and were then provided with correct/incorrect feedback via audio during a 500-ms intertrial interval before another stimulus was randomly selected to be responded to. Feedback was 0 points for incorrect responses, 1 point for correct responses to nonprioritized items, 2 points for correct responses to prioritized items, and a buzzing sound for when the participant did not press a key. The block continued until all stimuli had been presented 13 times.

Prior to the start of the learning blocks, participants completed a practice block to learn the task. They were provided with a set of three images and attempted to learn associations. They only proceed to the main experiment after reaching 80% accuracy for each of the three stimuli over the last five presentations of each stimulus. Instructions for the task were repeated after all stimuli had been presented ten times without meeting criterion. This practice procedure ensured that participants understood the instructions.

After the learning phase, the operation span task was presented following the procedure of Unsworth et al. (2005). After the delay task, participants completed a surprise testing phase. During the testing phase, all images from the learning phase were presented one at a time in random order with no accuracy feedback provided. Each image was presented four times with a 1.5-s response time limit and a 500-ms intertrial interval. The stimuli were not presented as blocks during the testing phase and participants were instructed to press the correct key that they learned earlier in the experiment.

Analysis Approach

All analyses were conducted with generalized linear mixed effects models. Random intercepts for participants and items were included. Random slopes for all within-participant and within-item manipulations were also included. If the model did not converge or reported a singular fit, then the random effects structure was simplified by removing random slopes that accounted for little variance (Matuschek et al., 2017).

Results

Prioritization in the Learning Phase

Accuracy and response time both were examined during the learning phase to investigate the prioritization effect. Based on previous work with this association learning task, larger set sizes should be associated with lower accuracy and longer response times (Collins & Frank, 2012). In addition, prior work with the prioritization variant of this task found that prioritization affected response time during learning more so than it affects accuracy (Williamson & Moss, 2022). Mean accuracy for the learning phase is shown in Figure 2. Using a generalized linear mixed model to examine accuracy including set size and priority condition as predictors, the results indicated that prioritized items were responded to more accurately than non-prioritized items, $z = 2.59$, $p = .009$ and that larger set sizes had lower accuracy, $z = -13.13$, $p < .001$. There was not a significant interaction between set size and prioritization.

Mean correct response time is shown in Figure 3. A linear mixed effects model with set size and priority condition showed that a larger set size was associated with slower response times, $t = 10.58$, $p < 0.001$, and prioritized items were responded to faster than non-prioritized items, $t = -4.87$, $p < 0.001$. There was no interaction between set size and prioritization.

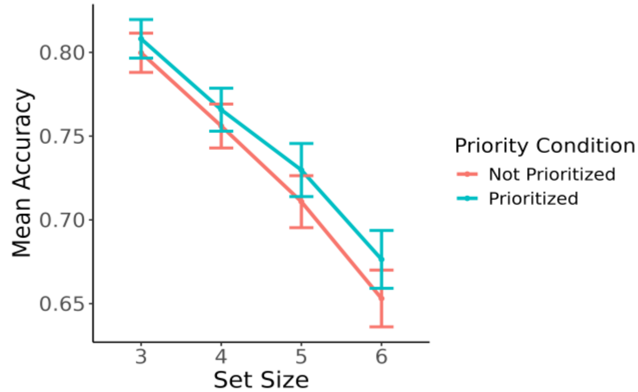

Figure 2: Mean accuracy during the learning phase. Error bars indicate one standard error of the mean.

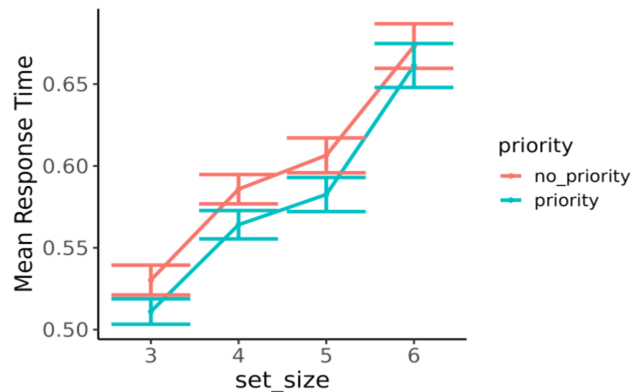

Figure 3: Set size Versus response time for prioritized and non-prioritized stimuli.

Prioritization in the Testing Phase

Accuracy in the testing phase is shown in Figure 4. Prioritization and set size were used to predict accuracy in a generalized mixed effects model. Increasing set size was associated with increasing accuracy, $z = 3.01$, $p = .002$, and prioritized items were recalled at a lower rate than non-prioritized items, $z = -2.02$, $p = .04$. There was no interaction between priority and set size. Testing response time was also examined in a similar model, and prioritized items had slower response times, $t = -2.22$, $p = .03$.

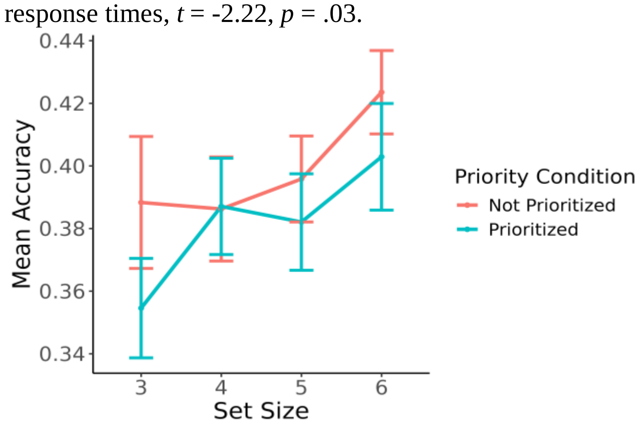

Figure 4: Mean accuracy versus set size for prioritized and non-prioritized stimuli.

Eye Tracking and Attention Consistency

Eye-tracking was used to examine the effect of consistency in our models as a mediator. The primary measures were number of entries into an ROI and consistency as described earlier. Table 1 shows the descriptive statistics for these measures. It appears that prioritization increased the number of shifts to an ROI (number of entries), but the amount of time fixating on those ROIs per shift is similar for both prioritized and non-prioritized items.

Table 1: Descriptive statistics for eye-tracking measures.

Set Size	Number of Entries		Total Fixation duration (s)		Consistency (s / entry)	
	N-P	P	N-P	P	N-P	P
3	12.98 (7.4)	13.62 (7.9)	15.08 (14.0)	16.11 (14.1)	1.32 (2.2)	1.31 (1.8)
4	15.40 (9.2)	17.08 (10.4)	14.80 (14.3)	16.43 (15.0)	0.92 (1.0)	0.96 (1.0)
5	16.21 (10.1)	17.61 (11.8)	14.71 (15.0)	16.33 (16.7)	0.85 (0.6)	0.86 (0.7)
6	18.28 (11.5)	20.27 (12.4)	15.19 (13.9)	17.21 (16.1)	0.78 (0.4)	0.84 (0.8)

N-P = non-prioritized, P = prioritized, SD in parentheses

The primary research question was whether the skill acquisition hypothesis or the attention consistency hypothesis is a better explanation of the decreased accuracy of prioritized items during the testing phase. As described earlier, for the skill acquisition hypothesis, there should be fewer attention shifts to prioritized stimuli if they are proceduralized faster than non-prioritized stimuli and a positive correlation between shifts and memory. The attention consistency explanation predicts that more frequent shifts of attention to an item with each shift being of lower duration would be negatively associated with memory accuracy at test.

First, the consistency measure was examined, priority condition and set size were included as predictors in a linear mixed effects model predicting consistency. Higher set sizes led to lower consistency, b = -0.14, t = -10.88, p < .001, but priority condition was not associated with consistency, b = 0.03, t = 1.35, p = .17. Consistency was then added to the model predicting test accuracy from set size and priority condition reported earlier, but it was not a significant predictor of test accuracy, z = .40, p = .68. Consistency was further tested as a mediator of priority's effect of test accuracy, but there was not a significant mediation relationship, p = .70. The lack of an effect of prioritization on consistency as well as the lack of mediation is not consistent with either explanation.

The number of entries into an ROI was examined next using a similar approach. As set size increased, the number of entries increased, b = .18, t = 14.45, p < .001, and prioritized items had more entries than non-prioritized items b = .13, t = 5.37, p < .001. However, when number of entries was added to the model predicting test accuracy from set size and priority condition, it was not associated with test accuracy, z = -1.06, p = .28. Number of entries was further tested as a mediator of priority's effect of test accuracy, but there was not a significant mediation relationship, p = .30. The positive effect of prioritization on number of entries is consistent with the attention consistency explanation, but there was not a mediation of the effect of priority on test performance as that explanation would predict.

Even though the eye tracking measures of attention shifting did not impact testing accuracy, their impact at learning was assessed. One possibility is that the task just was not good at measuring these attention shifts because the shifts of attention were still occurring covertly. First, the consistency measure was added to the model examining learning accuracy. Increasing consistency was associated with lower learning accuracy, z = -3.81, p < .001. Priority and set size were still significant predictors in this model. Consistency also did not mediate the effects of either priority or set size on learning accuracy.

The number of entries measure was also examined by adding it to the original learning accuracy model. Increasing number of entries was associated with decreased learning accuracy, z = -5.25, p < .001. Priority and set size were still significant predictors in this model. Number of entries also did not mediate the effect of either priority, p = .30, or the effect of set size on learning accuracy, p = .30.

Finally, these two eye tracking measures were added to the learning response time model separately. An increasing number of entries increased response time, t = 3.66, p = < .001, but consistency did not affect learning response time, t = 1.85, p = .07. The measures of attention based on the eye tracking data therefore had an impact on learning even if they did not explain effects on test accuracy.

Discussion

Our results support the idea that prioritization facilitates learning of associations as it reduces response time and increases accuracy compared to non-prioritized stimuli in the learning phase. In addition, the negative impact of prioritization on long-term memory was replicated. Therefore, the results are mostly consistent with those of found by Williamson and Moss (2022). The results are consistent with participants used attentional refreshing or a similar mechanism to prevent decay of working memory representations for stimuli, including shifting attention to these ROIs more often. This attention could in turn lead to higher accuracy and faster response time for prioritized items during the learning phase.

However, examining the effect of attention shifts and consistency on learning generally found that increased shifts and increased consistency decreased learning accuracy and increased response time. The directions of these effects are inconsistent with the idea that these attention shifts are aiding learning. One potential limitation of these analyses is that the direction of causation is uncertain because attention shifts were not a manipulated variable. It may be that participants increased attention on items that they were struggling to learn the associations for.

It also appears that the increased shifts of attention did not alter the average duration of attention to prioritized stimuli as shown by the lack of difference in the consistency measure between prioritized and non-prioritized stimuli. Working memory load as manipulated by set size did have a strong impact on the attention shifting and consistency measures. A smaller number of stimuli enables participants to spend higher processing time on each item instead of switching between items frequently to refresh their mental representations. Nonetheless, this consistency was not a significant mediator of prioritization on test accuracy.

Neither of the two potential explanations for the reduced accuracy of prioritized items at a delayed test was strongly supported. For the skill acquisition hypothesis, there should be fewer attention shifts to prioritized stimuli if they are proceduralized faster than non-prioritized stimuli. The opposite was found. The attention consistency hypothesis predicted the increase in shifts to stimuli, but the predicted decrease in the average fixation duration per attention shift (i.e., the consistency measure) was not found. Neither the number of entries nor the consistency measure were associated with test performance and neither mediated the effect of priority at test. One unexpected finding that could have limited the ability to detect this effect was the low performance at test.

Test performance, especially for lower set sizes, was near chance levels, and it was much lower than the 60-80% accuracy seen in the study by Williamson and Moss (2022). Therefore, one limitation of our experiment was the observed floor effect in the testing phase. This difference in results may be due to the increase in the number of blocks that were presented to participants. Increasing the number of blocks to 20 from the original study's 15 blocks did increase the number of items substantially. Another possibility is that participants learned associations in relation to the position of the image or its position relative to other images. This spatial layout was not preserved at test. This floor effect may have limited variability in test performance and impacted the ability to detect a mediating effect.

There were other differences in results from this prior study. Williamson and Moss (2022) found an interaction between priority and set size on both learning and test accuracy. They found that learning accuracy was only impacted by prioritization at set size 6 and that the negative effect of prioritization at test did not occur for set size 6. These differences are possibly due to the differences in design. They changed the number of prioritized items from 1 to 3 as set size increased form 3 to 4 to 6, but in the our study the number of prioritized items were kept constant at two prioritized items. Therefore, their interactions may have been driven by the number of prioritized items rather than changes in set size.

Another potential limitation of the current study is that it is not possible to know how successful the task design was at making attention shifts overt and measurable with eye tracking. There were significant relationships observed between the eye tracking measures and learning performance, but it is possible that many attention shifts were still occurring covertly.

While set size decreased learning accuracy, it also counterintuitively led to increases in testing accuracy as shown in Figure 4. This result is consistent with that found by Collins (2018), who discusses how a model of association learning based on reinforcement learning and working memory can explain this kind of result. In that model, performance during learning reflects learning associations and holding them in working memory and the gradual learning of associations via reinforcement learning. However, associations correctly held in working memory during the learning phase reduce the reward prediction error that drives reinforcement learning. Therefore, when the contents of working memory are no longer available at a delayed test, then only items correctly learned via reinforcement learning can be responded to accurately. If the prioritization manipulation makes an item more likely to be held in working memory, then this model could explain the negative prioritization effect at test. This model does not incorporate a role for episodic memory, which limits its ability to explain why testing manipulations such as whether stimuli are blocked or presented in random order impacts testing accuracy (Newlin & Moss, 2020). It is therefore difficult to explain the large difference in testing accuracy between the study by Williamson and Moss (2022) and our study using this model.

During the testing phase, participants possibly benefited from bigger set sizes given that they were more available mnemonics which helped to recall patterns of associations more efficiently and methodically. The elaborative theory supports this idea and emphasizes the importance of mnemonics in learning associations. This theory maintains that patterns with more mnemonics are learned and recalled better compared to the learned patterns with limited elaborations (Bradshaw & Anderson, 1982).

Future planned work modifies our testing phase to preserve the spatial location of items at test to boost test accuracy. Alternatively, using fewer blocks which results in a shorter experiment time and fewer stimuli to be recalled may help test accuracy. Future studies can also increase the number of prioritized items to examine how consistency changes when prioritized items increase.

In conclusion, our results indicate that prioritization facilitates the learning of associations but replicates a negative effect of prioritization at a delayed surprise test. Currently, none of the hypothetical mechanisms explored in this study account for the pattern of results observed, but we have identified some potential fruitful future research that may provide some insight into how these memory systems and attention interact.

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