Limitations on flexible allocation of visual short-term memory resources with multiple levels of attentional prioritization.

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Abstract

Studies suggest that visual short-term memory (VSTM) is a continuous resource that can be flexibly allocated using probabilistic cues that indicate test likelihood (i.e., attentional priority to those items). Previous studies using simultaneous cues have not examined this flexible allocation beyond two distinct levels of priority. Moreover, previous studies have not examined whether there are individual differences in the ability to flexibly allocate VSTM resources, as well as whether this ability benefits from practice. The current study used a continuous report procedure to examine whether participants can use up to three levels of attentional priority to allocate VSTM resources via simultaneous probabilistic spatial cues. Three experiments were performed with differing priority levels, cues, and cue presentation times. Group level analysis demonstrated flexible allocation of VSTM resources, however, there was limited evidence that participants could use three priority levels. A temporal analysis suggested that task fatigue, rather than practice effects, may interact with item priority. A Bayesian individual-differences analysis revealed that a minority of participants were using three levels of attentional priority, demonstrating that, while possible, it is not the predominant pattern of behavior. Thus, we provided evidence that flexible allocation to three attentional-levels is possible under simultaneous cuing conditions for a minority of participants. Flexible allocation to three categories may be interpreted as a skill of high performing participants akin to high memory capacity.

Visual short-term memory (VSTM), the system used to hold visual information on-line for short periods of time, has received considerable attention (Luck & Vogel, 2013); In particular, the nature of the representational limitations has been the subject of much debate. Many previous studies examining the nature of VSTM representations have focused on how different models explain changes in performance across memory loads (e.g., van den Berg, Awh, & Ma, 2014). Although the debate surrounding the precise nature of the limits of VSTM is on-going (Fougnie et al., 2016; Schurgin et al., 2020; Zhang & Luck, 2008), there are other properties of VSTM beyond working memory (WM) capacity limits that must be accounted for by these models. For example, a key prediction of continuous-resource models is that individuals should be able to flexibly allocate resources to objects according to their goals. This prediction has been supported using simultaneously presented spatial-cues (i.e., at the same time as the memory array; Emrich et al., 2017), feature-based cues (Dube et al., 2017) as well as feature-based monetary reward (Klyszejko et al., 2014), and frequency-based priority for memory of attentional templates in single and dual-target visual search (Huynh Cong & Kerzel, 2022). In each of these studies, memory performance for individual items was proportional to the level of priority or reward. Thus, these studies suggest that the reported precision of an item in memory is best characterized by the amount of attentional prioritization, and not by the total number of objects in memory, consistent with a flexible and continuous model of VSTM resources.

The question remains, however, whether there are limits to the number of distinct attentional levels that can be implemented to effectively allocate VSTM resources. In other words, at a given time, how many levels of priority can be maintained between concurrently memorized representations. Previous studies using simultaneously presented cues have only tested two levels of attention prioritization (Emrich et al., 2017; Dube et al. 2017, Klyszejko et al., 2014; Salahub et al., 2019). By contrast, some recent studies using pre-cues (cues presented before the memory array) have shown memory accuracy and precision could be influenced by up to four levels of priority (e.g., Allen & Uneno, 2018; Yoo et al., 2018). However, cues appearing at different times relative to the memory array have different effects on attention and memory. For instance, retro-cues have been distinguished from other types of cues because they direct attention to internal representations rather than affecting encoding at perception, like a pre-cue (Griffin & Nobre, 2003; Souza & Oberauer, 2016). Similarly, simultaneous cues limit the contribution of preparatory attentional control and are therefore significantly different from pre-cues, which allow participants to plan locations to be attended before the memory array appears. Thus, it is unclear if the evidence from pre-cue studies regarding the number of priority levels would extend to flexible allocation with simultaneous cues.

In addition, while numerous studies have identified that is possible to flexibly allocate VSTM resources, these effects have primarily been examined at the group level, potentially ignoring important individual differences. The attentional control literature has established that there are large individual differences in the ability to inhibit distractors and focus on goal-relevant information (e.g., Unsworth et al., 2021). As well, WM capacity is cemented as an individual characteristic central to theories of cognition that has been correlated with other cognitive abilities such as fluid intelligence and learning (Luck & Vogel, 2013). Even further, it is likely a direct relationship between attentional control and WM capacity that determines memory performance (Emrich & Busseri, 2015), furthering the importance of an investigation into individual differences in flexible allocation ability. In the present study we report three similar experiments that allow for combined analyses on a full sample of 99 unique participants to investigate individual differences in flexible allocation ability, with experiment as a between-subject factor.

Finally, to fully investigate the limits of flexible allocation, meta-task related effects on performance should be considered (e.g., practice effects, fatigue). Practice with feedback (Adam & Vogel, 2018) may allow participants to better differentiate priority categories within the attentional set, leading to improved task-performance over time. Alternatively, performance may worsen across the task as even short periods of time can lead to fatigue, impairing response precision, especially if participants did not nap before testing (MacDonald et al., 2018). While traditional studies of learning, practice effects, and fatigue have used multi-session designs, the current study uses a novel approach comparing performance over the full length of the task. By looking at trial-by-trial changes in response precision utilizing a mixed-effect model, it is possible to isolate the effect of time-on-task between the priority conditions.

Accordingly, the aim of the current study was to examine whether it is possible for three levels of priority to guide attention during a simultaneous cueing memory task. Participants were shown two distinct cues to indicate the high- and medium-priority items, with no cue indicating low-priority items – but notably these low-priority items are not distractors and are still test candidates. In Experiment 1a and 1b the high-priority object was tested 50% of the time, a medium-priority object tested 25% (1a) or 30% (1b) of the time, and two low-priority objects with no spatial cues each tested 12.5% (1a) or 10% (1b) of the time. In Experiment 2, the difference between high- and lower priority conditions were exaggerated (70%, 20%, 5%). If it is possible for participants to allocate memory resources using three attentional-levels, we predicted response error—the inverse of precision and a proxy for resource allocation—to scale with each items' respective priority, as has been previously shown with two levels of priority (Emrich et al., 2017; Dube et al., 2017). We also examined individual differences through a Bayesian model analysis of task strategy and meta-task effects by analysing whether performance across the different cue conditions changes over the course the experiment (temporal analysis).

Methods

Participants

Participants were recruited from Brock University using an online research pool or through posters around campus (Experiment 1a), and from the University of Guelph using an online research pool (Experiment 1b and 2). Each experiment had independent samples. All participants reported normal or corrected to normal vision and were tested for normal color vision. All procedures were approved by either Brock University's Research Ethics Board or the University of Guelph's Research Ethics Board. In accordance with the REB approved procedures, informed consent was obtained from all participants.

Participants Experiment 1a

Participants were 20 students from Brock University (7 males, 13 females) with a mean age of 20.38 (range 17-29). Participants were given the option to listen to non-lyrical music during the task on their own devices. Four participants chose to listen to music. Participants were offered a choice of research credit for courses or paid at a rate of $10/hour of participation.

Participants Experiment 1b

Participants were forty-one students from the University of Guelph (16 males, 25 females) with mean age 20.22 (range 18-26) participated for research credit. One participant was excluded before statistical analysis for having overall raw SD score > 90 SD in two conditions, suggesting they were guessing randomly most of the time.

Participants Experiment 2

Thirty-nine students from the University of Guelph (11 males, 28 females) with mean age 21.43 (range 18-27) participated for research credit. Two participants did not complete all the trials, missing 10 and 23 trials each. Missing 1% and 2.3% of all trials did not affect the priority level of the conditions; thus, they remained in the sample.

General Procedure

All experiments were variations of delayed-estimation memory tasks with four to-be-remembered objects, two distinct spatial cues indicating high and medium probability to be the test item (exact probability differed by experiment, hereafter termed the probe-likelihood), and one tested location, see Figure 1. All experiments were presented using PsychoPy (Peirce, 2008). All responses were made using the mouse by clicking on the color that best matched their memory. Response location was recorded and the circular distance between the reported color and the target color was calculated as the error. All participants completed a session of practice trials before the experimental session and were given the opportunity to ask questions or clarify the instructions.

For Experiment 1a, stimuli were presented on a 20" LCD display approximately 57 cm away. Stimuli were colored squares of 1° of visual angle with a constant distance from central fixation. Color stimuli were randomly selected from 360 unique colors from a continuous color wheel made using CIE L*a*b* color space with coordinates of a = -6 and b = 14 with a radius of 49, calibrated to the monitor and sampled with a minimum sampling distance of 30°.

For Experiments 1b and 2 stimuli were viewed on a 1280 x 1024 CRT monitor using a 75 Hz refresh rate, with viewing distance fixed at 57 cm using a head and chin rest. Stimuli were colored squares of 1.2° of visual angle with a constant distance from central fixation. Stimuli locations were chosen from a determined set of eight possible locations. Color stimuli were randomly selected from 360 unique colors from a continuous color wheel made using CIE L*a*b* color space with coordinates of a = -6 and b = 14 with a radius of 49, calibrated to the monitor and sampled with a minimum distance of 50°.

Procedure and Stimuli Experiments 1a and 1b

The experiments were conducted at two institutions simultaneously without planned collaboration, thus some differences between experiments were not theoretically motivated by the current findings. In experiment 1a, four colored squares were equally spaced around a central fixation with two spatial cues, one black and one white cue (meaning counterbalanced), on a grey background; while in 1b, four colored squares were presented around a central fixation at variable locations with a thick (high priority) and thin (low priority) spatial cue. The timing of experiments 1a and 1b were similar but not exact, see Figure 1 for the timing of each presentation. In experiment 1a the three levels of priority were 50%, 25%, and 12.5%; in experiment 1b the levels of priority were 50%, 30%, and 10%. Each experiment included 400 total trials of intermixed conditions.

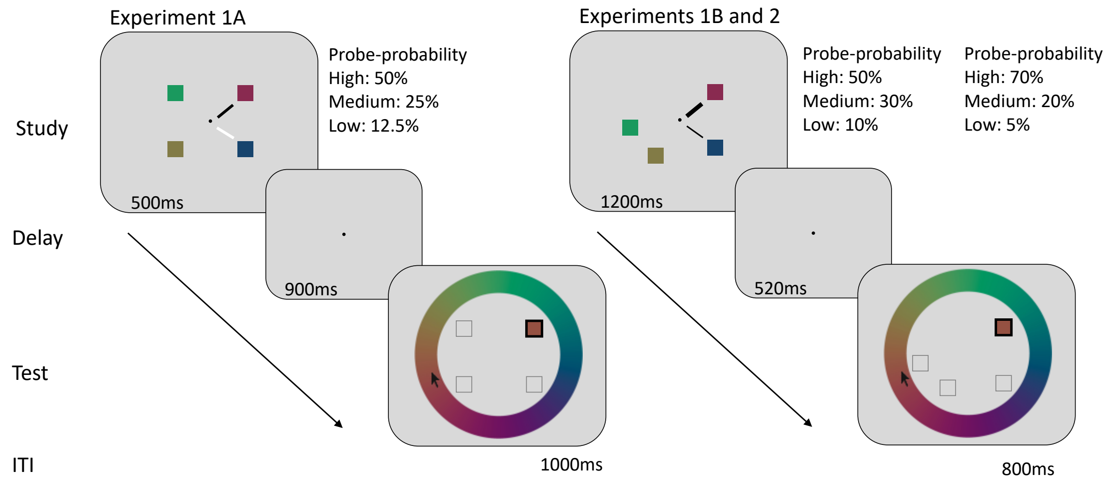
Participants in experiment 1a completed the Media Multi-tasking Inventory (Ophir et al., 2009) during the experimental session but the data is not pertinent to the current research question. Participants also performed a standard color change detection task with set sizes 2, 4, and 6, but the data was not analyzed.

Procedure and Stimulus Experiment 2

The presentation was the same as Experiment 1b with the following exceptions: the high-priority cued item was tested on 70% of trials, the medium priority cued item was tested on 20% of trials, and the two uncued items were tested on the remaining 10% of trials (5% each). Participants completed a total of 1,000 trials with conditions intermixed. See figure 1.

Figure 1

Example trials from each experiment



Note. All experiments were delay estimation tasks consisting of a study phase, delay, and untimed test phase. In experiment 1a spatial cues were differentiated by color (black and white), in experiments 1b and 2, line thickness differentiated the high- and medium-priority cues. In all experiments the meanings of the cues were counterbalanced

General Analysis

Responses were measured as the circular distance between the target and reported color value in degrees (i.e., circular error). The standard deviation of circular error was used as a measure of (im)precision; in the current analysis, summary statistics such as standard deviation of the circular error have been demonstrated to be the most reliable measure for testing differences between conditions (Ma, 2018). Participants were excluded for poor performance measured as having overall raw SD score > 90 SD in at least two conditions, which suggested they were guessing randomly most of the time. Tests between conditions were performed using Bayesian repeated-measures ANOVA to quantify evidence for the null-hypothesis (Bayes Factor, BF_{01}) or the alternative hypothesis (BF_{10}). A Bayes factor larger than 3 is considered moderate evidence in the given direction, and a Bayes factor larger than 10 is considered strong evidence in the given direction (Wetzels et al., 2011). Bayesian repeated-measures ANOVA and

Bayesian pairwise t-tests were conducted using JASP (JASP Team, 2018) using default priors.

Follow-up analysis methods for Bayesian individual difference model comparison and temporal patterns on precision are discussed below.

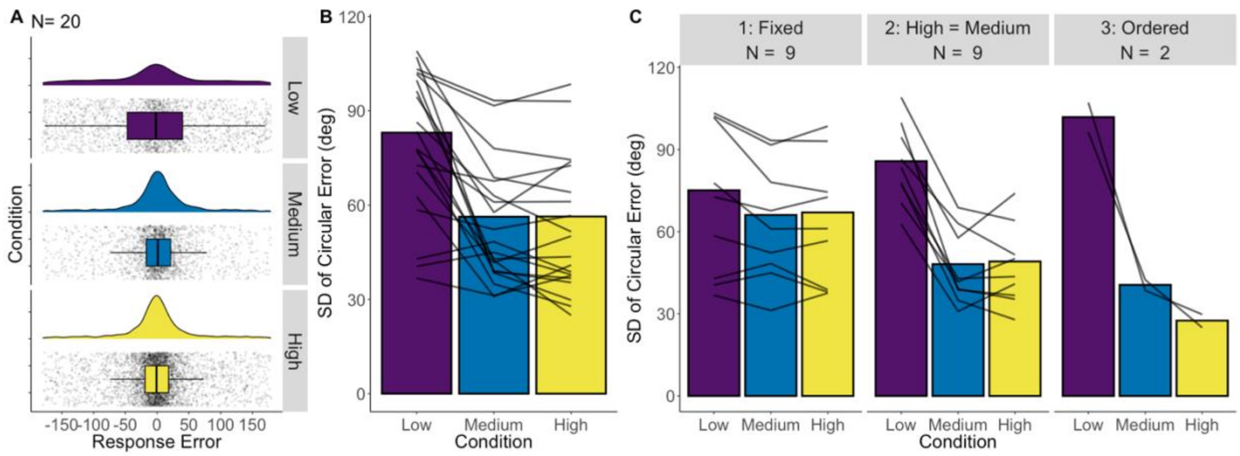
Results

Experiments 1a and 1b

The purpose of each experiment was to examine whether more than two attentional-levels can guide attention by having two explicit attentional cues to high and medium priority items, while the uncued items were not to be ignored and were still test candidates. In experiments 1a and 1b, one-way ANOVAs on cue condition (high vs. medium vs. low) revealed significant main effects (both BF_{10}'s > 1000), showing participants differentially prioritized items given the cue information. Planned comparisons showed strong evidence that uncued, low-priority items (1a SD = 80.03; 1b SD = 74.40) were reported with worse precision than medium-priority items (1a SD = 52.80 ; BF_{10} = 303.87; 1b SD = 48.27; BF_{10} > 1000)) and high-priority items (1a SD = 53.02 and 1b SD = 42.97; both BF_{10}'s > 1000), demonstrating that participants were able to prioritize cued items over uncued items. Although experiments 1a and 1b were run concurrently with similar designs, experiment 1b had a longer study time which may have made it easier for participants to use the cues. However, there was no difference found between the medium and high priority items: in experiment 1a there was substantial evidence of no difference between the medium- and high-priority items BF_{01} = 4.276; while in experiment 1b there was no evidence to support either a difference or no difference between the conditions (BF_{10} = 1.246, in a one-tailed test). No difference in response precision suggests there was no difference in the allocation of attention between the two higher priority conditions. See figures 2A-B and 3A-B.

Figure 2

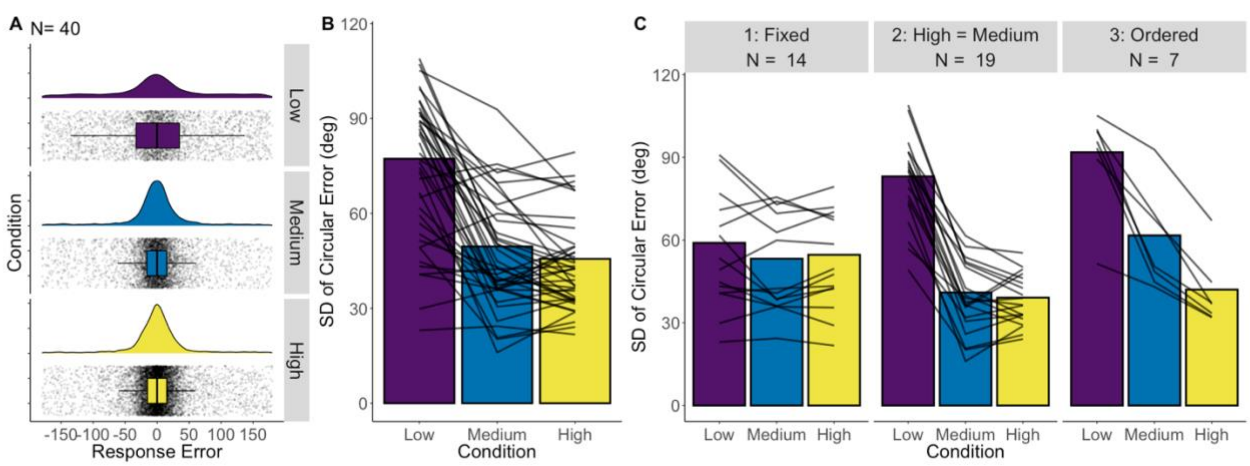
Results from Experiment 1a



Note: **A.** Distribution of error in degrees by priority conditions. Boxplots overlaid on all data points. Based on Raincloud-plots (Allen et al., 2021). **B.** Graph of the standard deviation of circular error by condition. **C.** Graph of circular error by condition grouped by the best fitting strategy according to the follow-up Bayesian model comparison.

Figure 3

Results from Experiment 1b



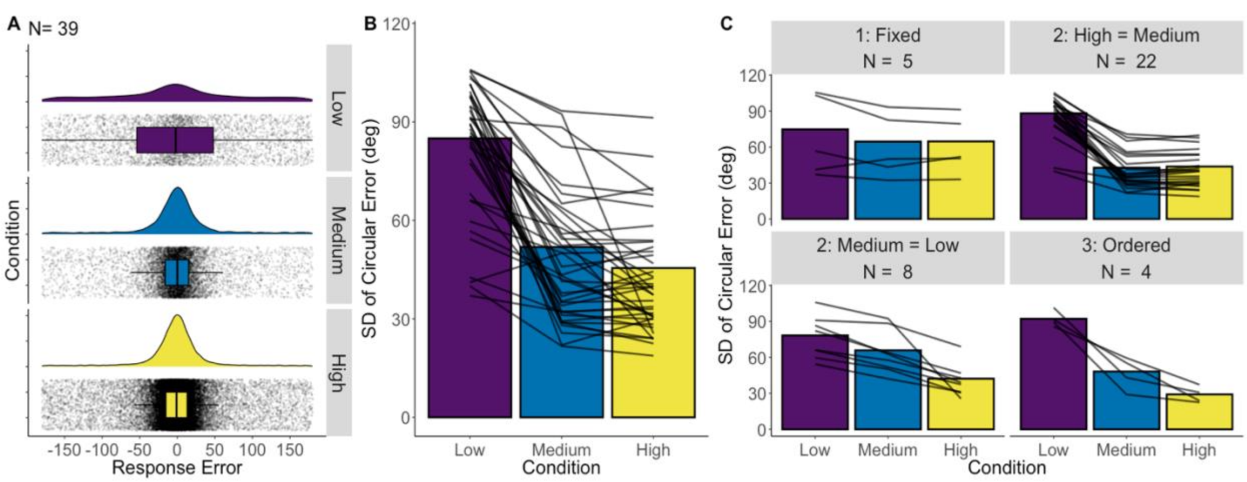
Note: **A.** Distribution of error in degrees by priority conditions. Boxplots overlaid on all data points. **B.** Graph of the standard deviation of circular error by condition. **C.** Graph of circular error by condition grouped by the best fitting strategy according to the follow-up Bayesian model comparison.

Experiment 2

In experiments 1a and 1b, there was no evidence the high- and medium-priority conditions were differentiated. This may have been because there was not a large enough difference in the probe-likelihood to incentivize this strategy. Thus, in experiment 2, the difference between the high and medium conditions was increased (70%, 20%, 5%). As before, there was strong evidence for the effect of cue condition ($BF_{10} > 1000$), showing participants differentially prioritized items. Planned comparisons showed strong evidence that the low-priority items (SD = 82.66) were reported with worse precision than medium-priority items (SD = 48.24, $BF_{10} > 1000$) and high-priority items (SD = 42.34, $BF_{10} > 1000$), demonstrating that participants were able to prioritize cued items over uncued items. In contrast from the previous two experiments, there was moderate evidence of a difference between the medium- and high-priority items ($BF_{10} = 3.627$). See figure 4A-B. Although only moderate in strength this provides evidence that three priority levels could be used to guide attention and memory resources when

Figure 4

Results from Experiment 2



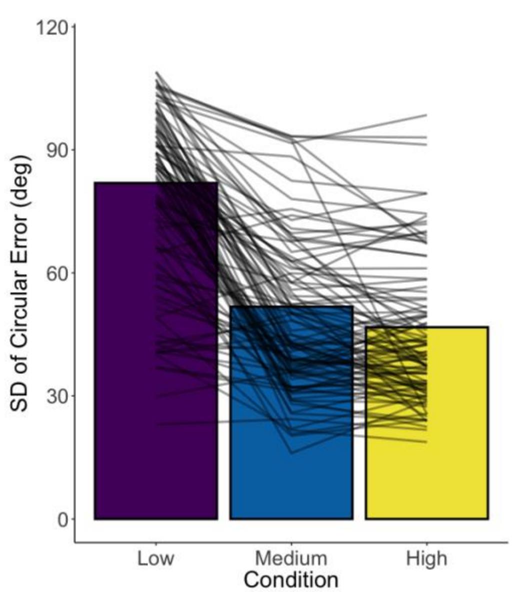
Note: A. Distribution of error in degrees by priority conditions. Boxplots overlaid on all data points. **B.** Graph of the standard deviation of circular error by condition. **C.** Graph of circular error by condition grouped by the best fitting strategy according to the follow-up Bayesian model comparison.

the priority levels are substantially different in a simultaneous cuing task.

Combined Experiment Data Analyses

Due to the conceptual and methodological similarity of the experiments, the results of all three experiments were put into a Bayesian repeated-measure ANOVA with cue condition and experiment as predictor variables. Consistent with the prediction that cue priority would correlate with response precision, the best fitting model was one with only cue condition as a predictor (BF_{10} > 1000). All levels of priority are significantly different from each other in the combined sample: low (SD = 78.79) vs medium (SD = 49.17) (BF_{10} > 1000); low vs high (SD = 44.74) (BF_{10} > 1000); medium vs high (BF_{10} = 5.842). See figure 5. This analysis provides evidence that three levels of priority may be maintained to guide attention and memory, but with the caveat that it is a smaller effect size than we had expected based on results from studies with two levels of priority.

Figure 5
Standard deviation of circular error from combined data by priority condition



Note: N = 99. All levels of priority are significantly different from each other in the combined sample: low vs medium (BF_{10} > 1000); low vs high (BF_{10} > 1000); medium vs high (BF_{10} = 5.842)

Temporal Analysis

Although the effect is small, the results of the three studies combined provide evidence that it is possible to maintain three levels of attentional priority. One possible explanation for the modest effect may be that performance on the task changes over time through practice effects or fatigue. We may expect an effect of fatigue showing time on task leads to reduced accuracy and it may interact with item priority showing accuracy to become more similar over time (converging performance). Alternatively, if time on task interacts with priority conditions to increase the difference in performance (diverging performance) it may indicate learning to effectively use the cues.

Method.

To examine whether performance changed over time, we examined response error using mixed-effect models with fixed effects for the test variables of trial and condition, and random intercepts for each participant. Trial number was centered and scaled such that estimates indicate change per 100 trials (over the 400 trials of experiments 1a and 1b, and the 1000 trials of experiment 2). Condition was treated as a categorical variable for all three experiments. Mixed-effect models were constructed in R using lmer from the lme4 package (Bates et al., 2015), and ANOVA (type 2) from the car package (Fox & Weisberg, 2019) was used to test significance of fixed-effects and interactions. Where the interaction was not significant, a model constructed without the interaction was used to estimate and test first-order terms.

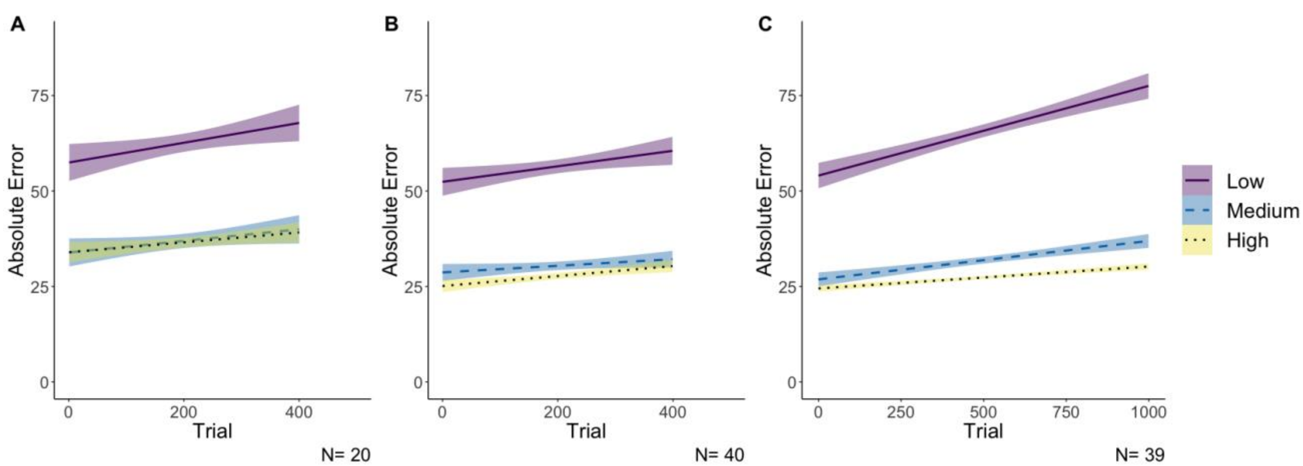
Results.

For experiments 1a and 1b, this analysis showed there were significant main effects of condition, (1a: $C^2(2) = 547.07$, $p < .001$; $C^2 (2) = 1397.28$, $p < .0001$), and trial, (1a: $C^2(1) = 16.06$, $p < .001$; 1b: $C^2(1) = 21.06$, $p < .0001$), but no interaction, (1a: $C^2 (2) = 1.69$, $p = .429$; 1b: $C^2 (2) = 1.76$, $p = .413$). Meaning that over 100 trials, participants in 1a increased their absolute error by 1.67° (*se* = 0.42), and participants on average were 6.68° less accurate at the end of the task relative to the start, $t = 4.01$, $p < .001$. See figure 6A. Similarly, participants in experiment 1b increased their absolute error by 1.24° per 100 trials (*se* = 0.27), meaning participants on average were 4.96° less accurate at the end of the task relative to the start, $t = 4.59$, $p < .001$. See figure 6B.

For experiment 2, again there were significant main effects of condition, C^2 (2) = 3613.96, p < .001, and trial C^2 (1) = 167.62, $p < .001$. Across all conditions, absolute error increased by 1.33° per 100 trials (*se* = 0.09), $t = 15.07$, $p < .001$, meaning participants on average were 13.3° less accurate by the end of the 1000 trials. However, there was also a significant interaction, C^2 (2) = 69.17, $p < .001$. The accuracy difference between medium- and high-priority conditions (4.54° at trial 500) was estimated to increase at a rate of 0.47° (*se* = 0.17) for every 100 trials, $t = 2.83$, $p < .001$. The accuracy difference between low- and high-priority conditions (38.43° at trial 500) was estimated to increase at a rate of 1.80° (*se* = 0.22) for every 100 trials, *t*

Figure 6

Absolute error for each priority condition by trial number (time)



Note: 95% confidence intervals included. **A**. Experiment 1a; priority conditions 50%, 25%, and 12.5% probe-likelihood. **B**. Experiment 1b; priority conditions 50%, 30%, and 10% probe-likelihood. **C**. Experiment 2; priority conditions 70%, 20%, and 5% probe-likelihood.

= 8.13, $p < .001$. The pattern of the interaction suggests that fatigue effects were more pronounced in the lower priority conditions than the highest priority condition. See figure 6C.

Bayesian Individual Differences Analysis

Individual differences in flexible allocation ability may be responsible for the current results: It may be that some participants are using three attentional templates, while others are not, thus obscuring the expected differentiation of response precision at the group level in experiments 1a and 1b particularly. If participants are able to use three distinct levels of attentional prioritization, it is expected that behaviour would be organized into three separable response bins based on increasing error with decreasing priority; we consider this to be *ordered* response type. However, three alternative attentional template strategies are considered: *fixed*, meaning error across the three levels of priority was equal (i.e., did not use cue information); *high = medium*, meaning the high- and medium-priority conditions were equal but had less error than the low priority; or *medium = low*, meaning the medium- and low-priority conditions were equal but had greater error than the high-priority condition; see Table 1 for summary.

Method.

To investigate different patterns of behavior exhibited by participants, Bayesian model selection was run following the methods of Dowd et al. (2015): testing the best model fit between four specified models (described above, summarized in Table 1) for each participant. All models were fit to the SD error parameter. As described by Dowd et al. (2015), the best fitting model for each participant was determined using deviance information criterion (DIC), a relative measure of model fit calculated using the MemToolbox (Suchow et al., 2013). This analysis was completed using MATLAB R2017a.

Table 1
Description of model parameters

Model name	*Response error (SD)*	*Corresponding number of attentional-levels*
Fixed	High = Medium = Low	One
High = Medium	High = Medium > Low	Two
Medium = Low	High > Medium = Low	Two
Ordered	High > Medium > Low	Three

Results.

Each participant's data was first fit to all 4 models reflecting possible patterns of response behavior, and the best fit model was chosen: *fixed, ordered, high = medium, and medium = low*. Of the 99 participants in the three experiments only 13 show evidence of using 3 attentional-levels by best fitting an *Ordered* model; 2, 7, and 4 people in each experiment, respectively. In contrast, 59 participants showed evidence of two attentional-levels; these were 9, 19, and 22 participants best fit by a *high = medium* model in each experiment, respectively, as well as 8 participants in experiment 2 best fit by the alternative *low = medium* model. Finally, 28 participants were best fit by a *fixed* model, suggesting they used only one attentional-level. In other words, these participants were not using the cues at all. In summary, the majority of participants only maintained two or fewer attentional-levels, independent of experiment. However, these results also indicate that using three attentional-levels is not impossible, but not the most common pattern of behavior observed. See figures 2C, 3C, and 4C showing the breakdown of best fit model in each experiment.

Discussion

Using probabilistic cueing paradigms, research has demonstrated that VSTM can be conceived as a continuous resource that is flexibly allocated according to the attentional priority of an item (Dube et al., 2017; Emrich et al., 2017; Huyhn Cong & Kerzel, 2022; Klyszejko et al., 2014). When items are indicated as more likely to be tested, they are prioritized in memory resulting in more precise memory reports. The current studies examined whether three levels of priority could guide attentional allocation through attentional-levels. Consistent with previous studies, the data support evidence that memory resources can be flexibly allocated: Across all three experiments, there was increased precision for the high-priority cued items compared to the low-priority uncued items. Despite that, across all three experiments there was only moderate evidence that three levels of priority were readily used to guide attention when simultaneously cued. In general, we observed that performance was equivalent for the high- and medium-priority items suggesting that participants did not distinguish between these two conditions. However, when all the experiments were combined, there was moderate evidence that the three priority levels were used to guide attention. This may suggest that each of the studies were under-powered on their own, and that the effect was smaller than anticipated based on the strength of the correlation between priority and precision when only two attentional-levels are needed.

The observation that only a small percentage of participants seemed to prioritize VSTM contents with three levels of priority using a simultaneous cue is surprising in light of work by Allen and Ueno (2018) and Yoo et al. (2018), both showing that three priority levels were effectively engaged when information was given by a pre-cue. In the study by Yoo et al. (2018), participants were pre-cued using colored wedges with proportional radial size to indicate the relative priority of each quadrant, with cuing probabilities of 60%, 30%, 10%, and 0%. Their results showed three distinct levels of response error which matched the behavioral relevance of the item. Specifically, experiment 4 in Allen and Ueno (2018) used distinct levels of reward, assigning each position on the display an ordinal reward level by a pre-cue, and found correspondingly graded accuracy. Thus, it may be that preparatory orienting from pre-cues is necessary for three or more levels of priority while simultaneous cues allow for only two levels of priority to readily guide attention even when viewing time is extended to 1200 ms, as in experiments 1b and 2. Indeed it has been long found that preparedness for the stimulus, or some part of a stimulus set, greatly improves accuracy of memory report compared to simultaneous and retro-active instruction (Sperling, 1960; DiPuma et al., 2023). Considering this, it is plausible that mechanisms of memory encoding are primed or off-loaded when given a pre-cue versus a simultaneous cue.

Although the most common strategy was not a strong match to our prediction, participants may have used a strategy that they believed would optimize their performance for the lowest effort; However, what “optimized performance” means to each participant may have differed from our expectation -- for instance *minimizing error* instead of *maximizing precision* through the use of cues (van den Berg & Ma, 2018). Because we did not reward participants for better precision on high-priority trials, it is reasonable that participants chose to minimize error overall by more evenly distributing resources among the memory items. This could have been done by grouping multiple priority conditions or even equating all items as in the *fixed* response error strategy. Yoo et al. (2018) found that participants were inclined to use a *Minimize Error* strategy even when they would have received a greater reward by maximizing precision on high-priority trials. In our experiments, performance may not have reflected the three different priority conditions because participants were not trying to perform better on high-priority trials than on medium-priority trials, instead trying to perform “well enough” on the majority of trials. For example, the interaction in the temporal analysis in experiment 2 could be interpreted as participants attempting to minimize error by protecting high-priority items at the cost of low-priority items. It should be noted that in experiment 2 the tested item was either a high- or medium-priority item on 90% of trials, meaning participants would only have the feeling of catastrophic memory errors on 10% of trials if they ignored the low-priority items.

Temporal Analysis

It is possible that participants were using all three priority levels but inefficiently or inconsistently. For instance, participants may have learned to use the cues over time, or they may have stopped using them as time-on-task continued. To test these alternatives, we investigated response error over the duration of the task using a mixed-effect model with random effects of participant and fixed effects of condition and time (trial number). In each experiment performance decreased over the duration of the task such that the SD of response error was between 4.96° and 13.3° greater by the end of the task. Only in experiment 2 was there an interaction between priority condition and trial number suggesting that participants treat the cues differently over time. Specifically, the performance decrease was more prominent in the low- and medium-priority conditions than in the high-priority condition. While it may be that participants learned to use three different cues over time, it could also be that the relatively higher probe-likelihood for the high-priority items in experiment 2 incentivized participants to protected them from the effects of fatigue (rate of increasing error).

We argue the findings from the temporal analysis support flexible allocation theories. One conceptualization of the impact of fatigue may be that fatigue decreases the total amount of memory resources available as the task goes on. In a flexible and continuous framework, we suggest that participants will allocate fewer resources to low-priority items to better maintain performance of higher priority items rather than equally diminishing performance on all items (which could be non-flexible continuous resource allocation). If resources were neither continuous nor flexible, and instead were all-or-none per item, an increase in fatigue would result in a sharp drop off in performance as participants lost discrete resources to allocate to lower priority items, i.e., effectively lowering maximum WM capacity. In contrast, subjects were not only able to maintain the allocation of resources over time, but the differences also became exaggerated as resources became depleted due to fatigue. Thus, while the current task was not specifically designed for this investigation or with hypothesis in mind; future studies could purposefully investigate differential resilience of memory performance under flexible task demands.

Individual Differences Analysis

We also examined the possibility that not all participants were able (or attempted) to employ three attentional-levels by investigating individual differences in the patterns of response errors across conditions. Bayesian model selection was used to determine which of four models designed to reflect potential patterns of responses was the best fit for each participant. Overall, most participants (59 of 99) were best fit by one of the models reflecting two attentional-levels. By contrast, 13 participants across all experiments were best fit by the ordered response model reflecting the use of three attentional cues. Interestingly, these participants were not predominantly from experiment 2 as may be expected from the initial analyses, which had the strongest evidence of three priority levels. Four participants from experiment 2 were best fit by this model, suggesting that the moderate evidence in the group analysis may instead reflect an averaging of the other response patterns (e.g., *low = medium, medium = high*). Thus, while making the priority levels dramatically different did influence how participants used the cues, it may not have had the intended effect of motivating a three attentional-level strategy throughout the task and may instead have motivated alternative strategies that utilize two attentional-levels. Regardless, while we did find evidence that it is possible for some participants to use three attentional-levels defined by priority, it was not the primary response pattern observed in any of the three experiments.

While most participants used cue information when allocating memory resources, some participants appeared to ignore the cues altogether, as evidenced by a fixed pattern of response error. It can be noted that fixed response errors were apparent in two forms: all low error responses (high precision) or all high error responses (poor precision). Thus, it seems some participants did not use the priority cues because they felt they were unnecessary to maximize their performance, whereas other participants did not use the priority cues because they lacked the intention or ability to maximize their performance. This phenomenon may be explained by the recent work from Irons and Leber (2020) which suggest that attentional control strategy is an individual difference that can be predicted by how effortful the person finds the optimal strategy. Indeed, when considering the observed increases in response error over time, it might be assumed that the optimal strategy was quite effortful. Response error tended to increase over the duration of the task, particularly for low-priority items, suggesting it may be more effortful to maintain low-priority items; perhaps this pattern extends to maintaining multiple attentional-levels. Thus, although we instructed participants to use all three levels of priority, there are reasonable strategic approaches to the task that only require two-levels of prioritization, which may reflect individual differences in abilities or strategies.

Limitations

Although Ma (2018) argued that raw error is the best measure when comparing across manipulations, it is possible that it does not capture all aspects of VSTM performance. Indeed, models have been devised to capture several theoretical aspects of memory performance, including binding errors (Bays et al., 2009; Swan & Wyble, 2014), categorical responses (Bae et al., 2015; Hardman et al., 2017), resource rationality (van den Berg & Ma, 2018) and perceptual similarity (Schurgin et al., 2020). While our analysis may not model all nuances of resource allocation, most or all of those theorized aspects of responses are captured by the measure of raw error. Although the model that best characterizes memory performance may change over time, the model that best accounts for behavior clearly needs to capture both the flexible control of resources (Dube et al., 2017; Emrich et al., 2017; Huynh Cong & Kerzel, 2022; Klyszejko et al., 2014), as well as the limitations therein. Moreover, the results of the present study suggest that individual differences are an important driver in performance that need to be considered to accurately understand both what is possible and what is readily done by participants during VSTM tasks.

Conclusion

Together, these results add to the body of literature demonstrating that VSTM resources can be flexibly allocated via attention manipulations and further that multiple attentional-levels can guide attention and thus the distribution of memory resources. Specifically, it was found that that although resources can be flexibly allocated, it is not readily done with more than two attentional-levels when simultaneously cued unlike in pre-cue studies. Our results also reveal individual differences in approach or cognitive flexibility in response to multiple cue conditions. Thus, a full understanding of VSTM may require the examination of individual differences in flexible allocation of VSTM resources.

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Open Practices Statement:

None of the experiments were preregistered. The data analyzed here is not publicly available because the REB procedure did not include explicit consent to publish the data in a repository, however data are available by reasonable request. The materials and code are available at https://osf.io/jpxz3/.

Declarations

Funding

This project was funded by a Natural Sciences and Engineering Research Council (NSERC) Discovery Grant awarded to SME [435945], NSERC Discover Grant awarded to NA [RGPIN-2018-04689], and supported by NSERC Postgraduate Scholarship Doctoral Program awarded to HAL, and a NSERC Canada Graduate Scholarship awarded to BD.

Conflicts of interest

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Ethics Approval

All experimental procedures were approved by the Research Ethics Board at either Brock University (12-267) or the University of Guelph (####).

Consent to Participate.

In accordance with the REB approved procedures, freely given and informed consent was obtained from all participants.

Consent for Publication

Participants were informed that the results of the study could be published in an academic journal at the time of consent. No identifying information is published.

Availability of data, code, and materials

Materials and code will be made available at https://osf.io/jpxz3/. The data cannot be publicly available in a data repository but may be available upon reasonable request.

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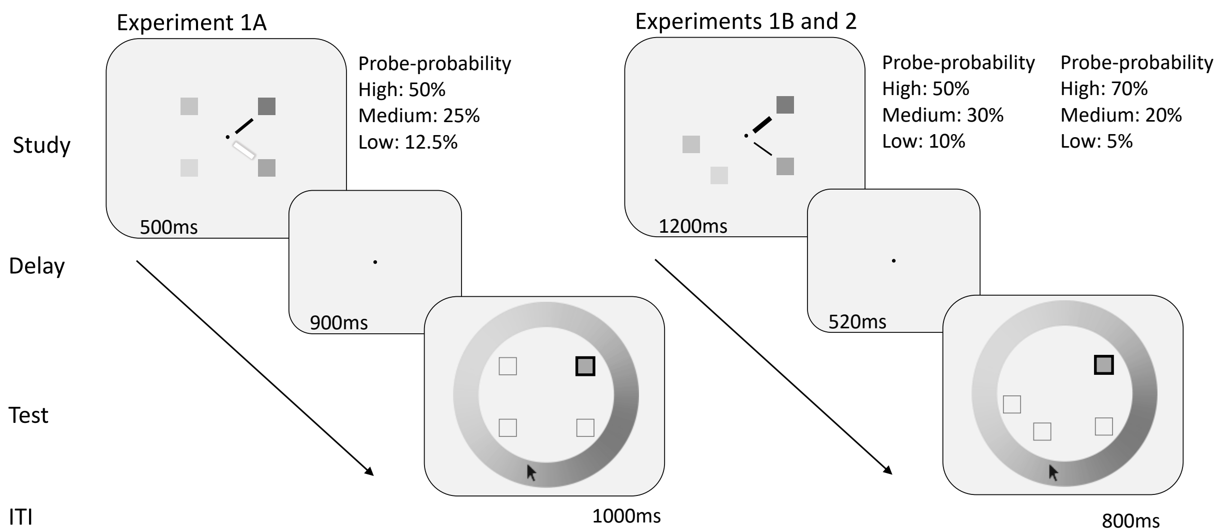
Appendix: Modified for greyscale versions of select figures.

Figure 1

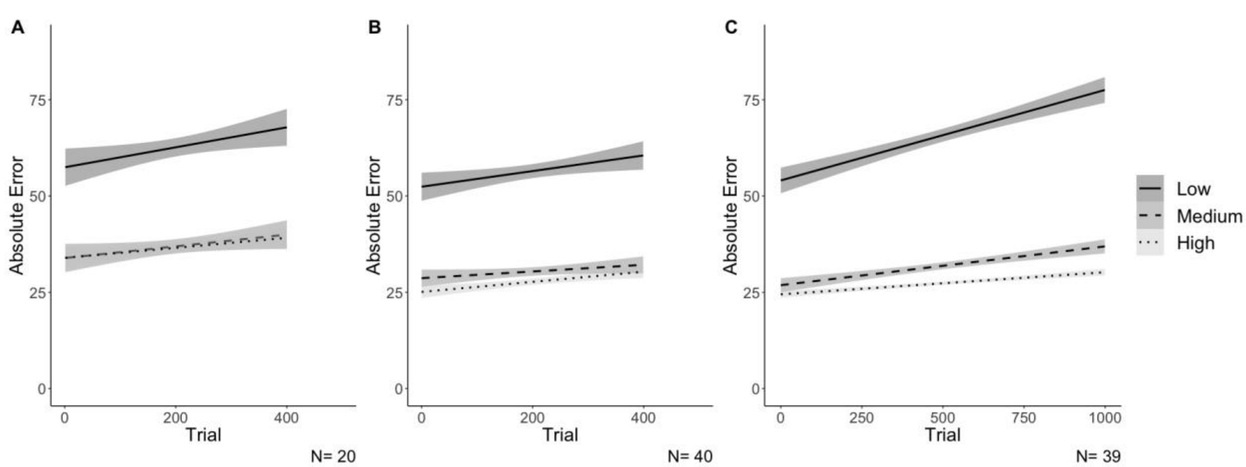
Example trials from each experiment



Note. All experiments were delay estimation tasks consisting of a study phase, delay, and untimed test phase. In Experiment 1a spatial cues were differentiated by color (black and white), in Experiments 1b and 2, line thickness differentiated the high- and medium-priority cues. In all experiments the meanings of the cues were counterbalanced

Figure 6

Absolute error for each priority condition by trial number (time)



Note: 95% confidence intervals included. **A**. Experiment 1a; priority conditions 50%, 25%, and 12.5% probe-likelihood. **B**. Experiment 1b; priority conditions 50%, 30%, and 10% probe-likelihood. **C**. Experiment 2; priority conditions 70%, 20%, and 5% probe-likelihood.