Journal of Memory and Language 121 (2021) 104287

Contents lists available at ScienceDirect

Journal of Memory and Language

journal homepage: www.elsevier.com/locate/jml

# Working memory prioritization: Goal-driven attention, physical salience, and implicit learning

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A B S T R A C T

Items in working memory (WM) are prioritized if they are relevant to task goals, are physically salient, or have acquired importance from implicit learning. We propose that all forms of prioritization increase the likelihood of recall, but only goal-driven attention will affect the quality of those representations. In a delayed-estimation task with four colors, prioritization was manipulated via a predictive spatial cue (goal-driven attention), a non-predictive peripheral cue (physical salience), or implicit learning of a previously relevant target location. Probabilities of recalling the target ($P_{target}$) and memory precision were estimated using a Bayesian implementation of the mixture model. Strong evidence was observed that all forms of prioritization increased $P_{target}$, whereas physical salience and implicit learning had only weak or negligible effects on precision compared to goal-driven attention. We propose that generating and maintaining high-resolution memories is an effortful process that will primarily be invoked when participants voluntarily prioritize memory items.

## Introduction

Working memory (WM) has a limited capacity and is unable to store all information encountered in the environment. This limited capacity places heavy demands on prioritization including selecting which information to encode into WM and maintaining the quality of these selected representations over time. Prioritization is based on several factors such as relevance to task goals, physical salience, and implicit learning from past experience (Awh, Belopolsky, & Theeuwes, 2012). Prioritization by any of these methods results in better recall (Fang, Ravizza, & Liu, 2019; Gong & Li, 2014; Ravizza et al., 2016; Schmidt et al, 2002; Umemoto et al., 2010; see Ravizza and Conn. 2021 for a review), but it is unclear whether all modes of prioritization affect WM in the same way. The goal of the current study was to investigate how WM representations are affected by the mode of prioritization.

Here, we investigated three ways in which prioritization influences WM performance. First, information that is relevant to task goals can be prioritized in a voluntary manner through goal-driven attention. Second, physical salience (e.g., high contrast, sudden onset, loudness) can capture attention even if the information is not task relevant. Third, information that has been previously selected can influence prioritization through implicit learning despite being irrelevant to current task goals. All three ways of prioritization improve WM performance, but it is unclear whether this improvement is due to the same underlying mechanisms.

Leading models of WM generally assume that prioritization is important for maximizing a limited-capacity resource (Baddeley, 2012; Cowan, 1999), but they assume that the effects on performance are equivalent regardless of how information is prioritized. For example, several models posit that both goal-driven attention and physical salience increase the activation level of items in long-term memory (Cowan, 1988, 1999; Brown, Preece, & Hulme, 2000; Farrell & Lewandowsky, 2002). Thus, both ways of prioritizing information are thought to increase the likelihood that information is encoded. After attentional selection at encoding, these models are agnostic as to the fate of information that has been prioritized through different selection mechanisms. Information that is strongly activated, either by goal-driven attention or physical salience, is placed in the "focus of attention" (FOA) and is maintained in an active state by control processes such as attentional refreshing and articulatory rehearsal (Cowan, 1999; although see, Oberauer (2019); thus, maintenance processes are presumed to be similar regardless of how information is prioritized. Moreover, no model has addressed the effect of prioritization through an implicitly learned attentional bias. In the present study, we assessed the effect of prioritization on the likelihood that information is selected at encoding as well as whether the mode of prioritization had similar or different effects on the quality of the representation.

Prioritization could improve WM in at least two ways: 1) increasing the probability that information is selected for encoding into WM and, 2) if selected, by generating and maintaining a high-quality representation.

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https://doi.org/10.1016/j.jml.2021.104287
Received 17 February 2020; Received in revised form 20 August 2021; Accepted 30 August 2021
Available online 6 September 2021
0749-596X/

We hypothesize that the mechanisms of prioritization do not entirely overlap and that prioritization through goal-driven attention increases both the likelihood of encoding and the quality of the representation. In contrast, we suggest that physical salience and implicit learning primarily orient attention to prioritized information while having less of an effect on representational quality.

This hypothesis is consistent with observed differences in the effects of prioritization in perceptual tasks; namely, goal-driven attention enhances both the speed of orienting and the strength of the perceptual representation of attended stimuli whereas physical salience primarily affects the former (for a review, see Prinzmetal & Landau, 2008). For example, both predictive (goal-driven attention) and non-predictive (physical salience) spatial cues improved reaction time in a facial discrimination task while only predictive cues improved accuracy (Prinzmetal, McCool, & Park, 2005). Moreover, neural responses to goal-driven prioritization increased along the visual pathway whereas the effects of physical salience remained at a constant, and lower, level (Dugué et al., 2020). These observations suggest that goal-driven attention leads to longer or deeper processing of the attended stimulus than physical salience and, perhaps, implicit learning.

Rather than affecting the strength of attentional processing, physical salience and implicit learning primarily affect the speed of orienting (Riggio & Kirsner, 1997; Huang, Theeuwes, & Donk, 2020). Event-related potential studies support this hypothesis; for example, the latency of the N2pc component, an early marker of selective attention, was shorter for physically salient targets in a visual search task compared to non-salient targets, but the amplitude of the N2pc was unchanged (Bachman et al., 2020). Similarly, implicit perceptual learning resulted in shorter latencies of the N2pc when stimuli were irrelevant to a visual search task than when they were task relevant and, thus, engaged goal-driven attention (Qu, Hillyard, Ding, 2017). In contrast, targets selected through goal-driven attention showed higher N2pc amplitudes rather than latency differences compared to non-prioritized targets (Kiss, Van Velzen, & Eimer, 2007). Physically salient items are thought to be prioritized through bottom-up attention (Santangelo, 2015) which is both automatic and transient (Müller & Rabbitt, 1989) and this is reflected in shorter latencies of attentional selection rather than an increase in the strength of attentional effects.

We propose that this fast and automatic orientation to physically salient and implicitly learned items increases the probability that the attended item is encoded. Consistent with this idea, physically salient items that captured attention were marked by indicators that they were encoded first; namely, they were recalled first in a free-recall task (Ravizza, Uivlugt & Hazeltine, 2016). Similarly, we propose that items prioritized through implicit learning will also result in the automatic orienting of attention to those items in line with ideas that implicit learning creates an "attentional habit" (Jiang et al. (2015)).

The faster but more transient effects of physical salience and implicit learning may not have as profound an effect on WM performance as goal-driven prioritization, however. We hypothesize, that representational quality is less affected from prioritization through physical salience or implicit learning. The transient effects of automatic attention selection will likely dissipate and, thus, not provide for further preferential processing of the selected stimulus. Moreover, the process of prioritizing information during maintenance takes effort and does not occur automatically. Attentional refreshing and subvocal rehearsal are both strategies that are used to maintain information in WM and both are undertaken voluntarily (Hasher and Zacks (1979); see Camos et al., 2018, for a review). There is no reason to rehearse or refresh physically salient or implicitly learned information that is irrelevant to task goals. Instead, the focus of attention (FOA) should alternate between items during retention, such that the quality of the representation of physically salient or implicitly learned information degrades in the same way as all other representations in WM.

In contrast, goal-driven attention is thought to improve recall because of a greater probability of selection at encoding and greater refreshing of the representation during maintenance (Gazzaley & Nobre, 2012). At encoding, goal-driven attention will increase the likelihood that information will be encoded first, making it more likely to enter WM (Ravizza, Uivlugt & Hazeltine, 2016). Moreover, these items may be more deeply processed at encoding as suggested from the results of perceptual tasks and, thus, the quality of the representation may benefit. Goal-driven attention is also hypothesized to produce further benefits by prioritizing information during maintenance (Awh, Vogel & Oh, 2006). During maintenance, the quality of the representation in WM remains high for goal-relevant information because this information is more likely to occupy the FOA in order to be rehearsed or refreshed. We propose that information prioritized because of its relevance to task goals is more likely to occupy the FOA and/or stay in the FOA longer during retention. Consequently, attended items are processed longer or more deeply at both encoding and/or maintenance resulting in a high-quality representation.

A few studies have compared the effects of prioritization on WM performance, typically comparing prioritization via goal-driven attention and physical salience (Schmidt, Vogel, Woodman, & Luck, 2002; Ravizza, Uivlugt & Hazeltine, 2016). These studies, however, were unable to isolate whether the observed advantage for prioritized information was due to increased selection at encoding and/or the resolution of the memory representation. This is because the dependent variable in these studies was accuracy, a measure which reflects both factors. To test our hypotheses, we used a delayed estimation task (Wilken & Ma, 2004) for color that allows for estimates of the probability that an item enters and is recalled from WM ($P_{target}$) and the precision of the memory representation (κ). We propose that all three methods will increase $P_{target}$, however, precision should be much less affected from physical salience or implicit learning.

In all prioritization conditions, we tested WM for four colors, each presented in a different quadrant. Goal-driven attention was directed using a central, spatial cue that predicted the location of the color that was most likely to be probed. In contrast, a peripheral and non-predictive cue appeared in one of the four quadrants in order to capture attention via a salient onset at that location. Implicit learning was manipulated by asking participants to first perform a visual search task in which the target was more likely to occur in one quadrant. They then performed the same WM task as described above except that no pre-cue appeared. If participants have learned to prioritize one quadrant, items that appear at that location should be better recalled. Our analyses will focus on the difference in performance for prioritized and non-prioritized information depending on how information was prioritized.

## Experiment 1

### *Methods*

The data, supplemental materials, and scripts are available here: https://osf.io/eqvam/.

*Design and Participants*. We used a between-subjects design because carryover effects have been found in how participants use the cue (Prinzmetal et al., 2015); namely, participants are more likely to treat a non-predictive cue as predictive. Moreover, implicit learning of the cued location might also carry over to the other conditions or be wiped out based on selection history in previous conditions.

Though our primary analysis used Bayesian data analysis methods, sample size was determined with a classical power analysis. To do so, an effect size (d = .68) was estimated from the main effect of cue validity for predictive and non-predictive cues in our previous WM study (Ravizza, Uivlugt & Hazeltine, 2016). With this effect size, we estimated that a minimum of 19 participants per group would provide a power of .8 to detect validity effects at an alpha of .05. Given that an implicit attentional bias in the WM task likely relies upon learning during the search task, we doubled the number of participants suggested by this power analysis and aimed to recruit 38 per group. All participants provided informed consent and had normal or corrected-to-normal vision. Thirty-four (average age = 18.82; 4 M/30F), 31 (average age = 19.29; 13 M/18F), 55 undergraduates (average age = 19.5; 12 M/43F) received course credit for their participation in the goal-driven, physical salience, and implicit learning conditions, respectively. We excluded three participants in the implicit learning condition because they performed > 3 SDs below the mean accuracy (93.8%; SD = 11%) on the search task, detecting only 50–60% of targets. Data from three additional participants in this condition were lost due to technical failures. Thus, 49 participants remained in the final sample in the implicit learning condition.

*Stimuli*. Four colored disks, each subtending .9° of visual angle, were generated using Matlab (MathWorks, Natick, MA) and MGL (http://gru.stanford.edu/mgl) and presented simultaneously at an equal distance (2.8°) from a central fixation cross at the corners of an imaginary square. To ensure colors were rendered with equal luminance, the monitors were calibrated using an I1 Pro spectrophotometer (Xrite, Grand Rapids, MI) with gamma correction. Color coordinates in CIE L*a*b* color space were converted to monitor RGB values with a white point measured as the display's white background. We generated a color wheel consisting of 180 evenly-spaced hues from a circle in CIE L*a*b color space (radius = 79, luminance = 74, a = 25, b = 38). The four colors for each trial were chosen at random with the constraint that they were separated by at least 25° on the color wheel.

*Procedure*. Goal-driven attention to a location was isolated by manipulating the probability that an item at a cued location will have to be recalled (Schmidt, Vogel, Woodman, & Luck, 2002; Ravizza, Uivlugt & Hazeltine, 2016). A predictive (50% valid), central cue was presented consisting of a black fixation cross, subtending .4° of visual angle, with the lines of one quadrant, chosen randomly, turning white and thickening to indicate the position most likely to be probed (Fig. 1, left). Colors at the three uncued locations were equally likely to be probed (16.7%). Participants were informed that the cue would often predict the location of the probed item so that attention could be deployed in a strategic, goal-driven manner.

To assess the effects of physical salience, a non-predictive (25% valid), peripheral cue in the form of a white, circular frame appeared at the location of one of the colors, subtending 2° of visual angle (Fig. 1, center). The prioritized quadrant was chosen at random on each trial. The cue did not predict the probed location and participants were told to ignore it. Thus, any benefit to the cued item can be attributed to automatic orienting to the cued location.

The predictive and non-predictive cues appeared for 50 ms followed by a 100-ms interval before the test array of four colored disks which appeared for 300 ms (Fig. 1); this short cue-to-target interval prevents inhibition of return in the physical salience condition but is long enough to allow for attentional selection in the goal-driven condition (Klein (2000)). The cue was absent in the implicit learning condition and the color in each quadrant was equally likely to be probed at recall.

After a delay of 1 s, memory for the array was tested by presenting a probe at the location corresponding to one of the items. Participants were asked to click on a color wheel in order to indicate the color of the disk at the probed location. The color wheel rotated across trials so that participants could not anticipate where colors would appear at recall. This ensured that they had to remember the color itself rather than a location on the color wheel. A practice block of 5 trials was given before the main task. Participants then performed 12 blocks of 48 trials each for a total of 576 trials per participant.

Before performing the color WM task, participants in the implicit learning condition searched for a rotated T among Ls (Fig. 1, right), in which the target was presented more often in one quadrant than the other three (50% vs 16.7%). The prioritized quadrant was counterbalanced across participants. Stimuli were presented in white font on a black background. Twelve stimuli were presented at random locations in the display with a minimum spacing of 1.6°. Three stimuli were presented in each quadrant and subtended 1.6°. The display stayed on the

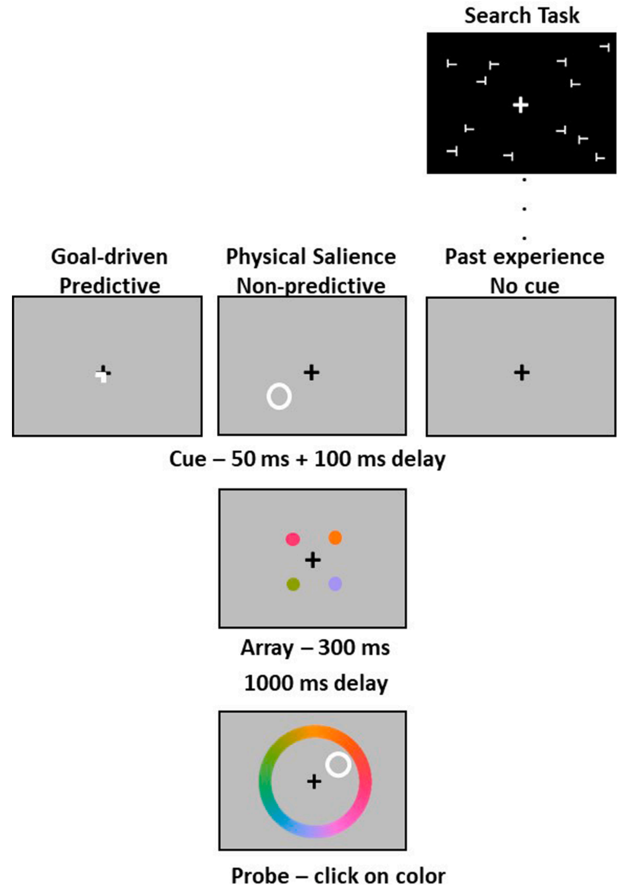


**Fig. 1.** Experimental procedure. Participants performed a working memory task with 4 colors. Colors were preceded by a central, predictive cue (left; goal-driven condition), a peripheral, non-predictive cue (center; physical salience condition), or no-cue (right; past experience condition). In the latter condition, participants performed a search task in which the target appeared more frequently in one quadrant. At recall, participants clicked on a color wheel to indicate the color at the probed location after a 1-second delay.

screen until participants used the mouse to click on the target. There was a jittered .6 – 1 s ITI between trials. Participants were not informed about the greater target prevalence based on location so that learning would be implicit; however, awareness was assessed at the end of the WM task. Seven blocks of the search task (36 trials per block) were performed after a practice block of 4 trials.

*Data Analyses*. Deviations between the original and reported color were calculated for each trial. These errors were then fit using a hierarchical Bayesian framework (Oberauer et al., 2017) applied to the three-component Swap Model (Bays, Catalao, & Husain, 2009) (see Supplementary data for model fits). This model (Bays, Catalao, & Husain, 2009) assumes errors come from a mixture of a uniform distribution, reflecting a guess response when an item is not in memory and a Gaussian (von Mises) distribution reflecting mnemonic imprecision when an item is in memory. In addition, this model estimates a measure of swap rate, the rate at which participants misreported the color of a different item than the one that was probed. We estimated the swap rate in order to get a purer measure of whether the target was in WM. For example, reporting a color from a different location than the one probed might appear as a random (guess) response but, instead, the error was due to misremembering the location of the color. Given our hypothesis that prioritization increases the likelihood that items enter WM, it is critical to get as pure a measure as possible of this variable.

The hierarchical Bayesian mixture model outputs three parameters: the probability that the response comes from any item in the memory set

(*Pm*), precision (κ), and the probability that the response is a feature of the target (*Pt*) (see Supplemental Figs. 1–3 for model fits). From these estimates, we derived the probability that the response reflects the color of the probed item, or $P_{target}$, and the probability that colors were swapped, $P_{swap}$, as follows:

$$P_{target} = Pm^{*}\ Pt$$

$$P_{swap} = \mathrm{Pm}^{*}(1 - \mathrm{Pt})$$

Given that Pm includes both the probability of a swap and the probability of recalling the target, analyses focused on the latter estimates in order to isolate these two sources of error. Guess rates (1-Pm) are available as Supplementary Table 1 at https://osf.io/eqvam/.

Our focus on the $P_{target}$ as an indicator of whether items were encoded into and recalled from WM does not imply that encoding is binary. Some WM models assume that all items are encoded with greater or lesser precision and that participants never "guess" (Bays and Husain, 2008; van den Berg et al., 2012; Wilken & Ma, 2004). We and others (Myers et al., 2014; Gunseli et al., 2015; Weber, et al., 2016; Pertzov, Manohar, Husain, 2017) assume, however, that items may enter WM with such low precision that the response is no better than a guess (Donkin et al., 2013). Moreover, there is a tight correspondence between guess rate and participants' self-reports of guessing (Adams, Vogel, & Awh, 2017). Thus, estimating the $P_{target}$ provides a way to assess the likelihood that items have been encoded with enough precision that their recall is better than a guess.

We have predicted that precision will show little effect from physical salience or implicit learning. Bayesian statistical analyses are, thus, the most appropriate to use as we can assess evidence both for and against the null hypothesis. For the WM analyses, we report the mean posterior value and the 95% Highest Density Interval (HDI) in brackets next to the mean to describe the posterior distribution over the parameters in each of the prioritization conditions. Values within the HDI are more credible (i.e., have higher probability density) than values outside the HDI, and the values within the HDI have a total posterior probability of 95%. To assess the effect of prioritization on the estimates, we report the difference between prioritized and non-prioritized trials in terms of the parameter value and the corresponding HDI. We also report Bayes Factors (BF) to evaluate the strength of evidence for the null hypotheses with BFs less than 1 reflecting support for the null hypotheses. BF were estimated via the Savage-Dickey approximation method (Wagenmakers, Lodewyckx, Kuriyal, & Grasman, 2010).

To test our hypothesis, we modeled two separate interaction effects for each parameter. Each interaction compared prioritization effects (i.e., prioritized target – nonprioritized target) from voluntary (goal-driven attention) and automatic (physical salience or implicit learning) attention. We predict an interaction effect in precision in both analyses in which precision effects are greater as a result of goal-driven attention than either physical salience or implicit learning. In contrast, only main effects of prioritization are predicted for $P_{target}$. While we had no strong hypotheses for $P_{swap}$, we surmise that deeper processing from goal-driven attention may produce a stronger binding between color and location and, thus, reduce $P_{swap}$ compared to physical salience and implicit learning.

## Results and discussion

*Search Task.* Before the WM task, participants performed a search task in which the target was more likely to appear in one quadrant. Search accuracy was high (infrequent: 95.6%; frequent: 96.2%) and did not reliably differ between targets at the frequent and infrequent locations, $t(48) = 1.80$, $p = .078$. Target location affected RT, however (Fig. 2). A 2 (frequent/infrequent) × 7(block) repeated-measures ANOVA produced main effects of location, $F(1,48) = 20.79$, $p < .001$, $\eta_p^2 = .30$, and block, $F(6,288) = 32.36$, $p < .001$, $\eta_p^2 = .40$. Targets at the more frequent quadrant were detected faster than those at the infrequent locations and participants showed learning over time (Fig. 2). The lack of a reliable interaction effect indicated that speed increased similarly at both frequent and infrequent locations, $F(6,288) = 2.00$, $p = .066$, $\eta_p^2 = .04$.

Using the post-experiment survey data, we coded participants as aware of the location contingency if they answered that they noticed the target occurred more frequently in one location and they correctly identified the frequent quadrant. About 23% (n = 11/49) of participants stated they were aware of the frequent target location and correctly identified it. Upon running the analyses described above using awareness as a between-subjects factor, we observed that none of the interactions with awareness were significant (all *ps* > .15; see Supplemental Fig. 4).

We found variability in learning with some participants showing

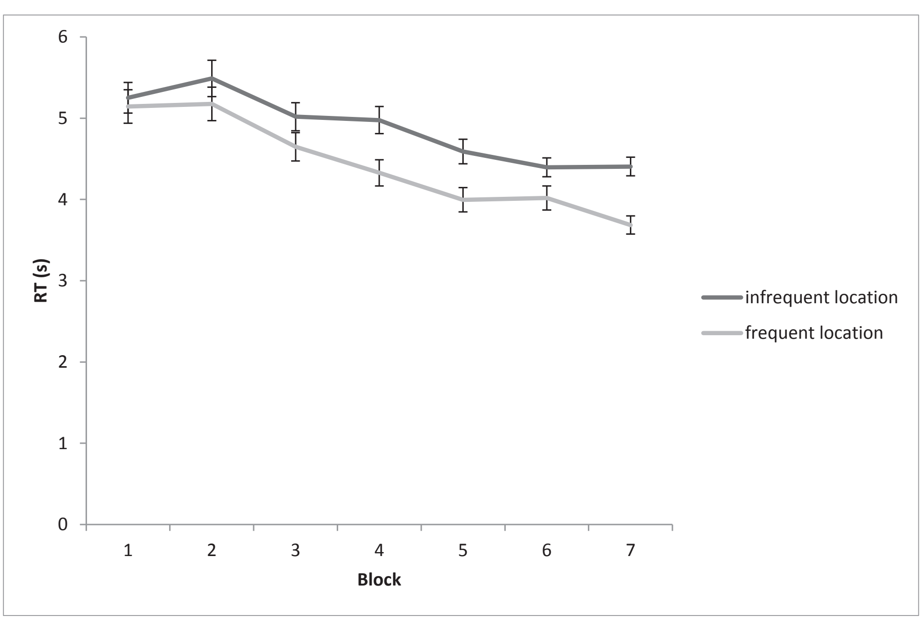


**Fig. 2.** Search task results from Experiment 1. Reaction time in the search task for targets presented in the frequent (light gray) and infrequent (dark gray) locations across blocks. Error bars indicate standard errors of the mean. Only participants in the implicit learning (no cue) condition performed this task.

better learning for the frequent location and others showing better learning for infrequent locations. This variability may affect whether an attentional bias is observed in the WM task. To account for this, the learning effect in the search task was quantified by subtracting RT in the final two blocks from RT in the first two blocks for both frequent and infrequent conditions. We then subtracted the learning effect for infrequent items from the frequent items to get a measure of the differential learning based on location. This measure was then entered as a predictor of each of the three parameters in the model estimating the effects of implicit learning. The degree of learning during search, however, did not improve the fit of the model (DIC = 4.9905e + 04 vs. 4.9839e + 04) nor were any of the coefficients on the search term credibly different from 0. Thus, we opted for the model that did not account for learning of the target location.

*$P_{target}$.* As expected, all three modes of prioritization increased the probability that an item was encoded and recalled from WM (see Fig. 3 and Table 1). There was decisive evidence that prioritization improved $P_{target}$ as the result of goal-driven attention, $P_{target\text{-}diff}$ = .48 [.27-.71], $BF_{10} > 100$ and physical salience $P_{target\text{-}diff}$ = .13 [.06-.20], $BF_{10} > 100$. There was also substantial support that implicit learning increased the probability of encoding and recalling the target from WM, $P_{target\text{-}diff}$ = .03 [.01-.05], $BF_{10}$ = 5.98.

There was a decisive interaction effect when comparing prioritization differences from goal-driven attention and physical salience, $P_{target\text{-}interaction}$ = .17 [.06-.29], $BF_{10} > 100$. As can be observed from Fig. 3, this interaction effect was driven by a difference for non-prioritized information; namely, there was strong evidence that non-prioritized information was more likely to enter and be recalled from WM in the physical salience condition than the goal-driven attention condition, $P_{target\text{-}non\text{-}prioritized}$ = .31 [.07 - .57], $BF_{10}$ = 32.03. There was little evidence for a difference between the goal-driven attention and physical salience condition in the probability of recall of the prioritized item, $P_{target\text{-}prioritized}$ = -.04 [-.13 - .05], $BF_{10}$ = .66. Thus, non-prioritized items were much more likely to be forgotten in the goal-driven attention condition, whereas prioritized items were encoded and recalled to a similar extent for goal-driven and salience-based prioritization.

The interaction between the goal-driven attention and implicit learning conditions was also decisive, $P_{target\text{-}interaction}$ = .23 [.12-.34], $BF_{10} > 100$. This was due both to a greater likelihood of recalling the non-prioritized targets, $P_{target\text{-}nonprioritized}$ = -.32 [-.55 - -.09], $BF_{10}$ = 12.42, and a lower likelihood of recalling prioritized targets, $P_{target\text{-}prioritized}$ = .13 [.06 - .21], $BF_{10}$ = 12.01, in the implicit learning condition compared to the goal-driven attention condition. Thus, implicit learning was a strong determinant of whether a target entered and could be recalled from WM, but the effect was weaker compared to goal-driven attention.

κ (memory precision). Goal-driven attention, $\kappa_{diff}$ = 3.6 [2.7–4.6], $BF_{10} > 100$, and physical salience, $\kappa_{diff}$ = 1.6 [.8–2.4], $BF_{10} > 100$, had decisive effects on the precision of prioritized and non-prioritized representations (see Fig. 2 and Table 1). We observed substantial evidence for the predicted interaction effect between goal-driven and physical salience conditions, $\kappa_{interaction}$ = 1.0 [.4–1.6], $BF_{10}$ = 7.69. There was more evidence that the interaction was driven by greater precision of prioritized items, $\kappa_{prioritized}$ = -1.9 [-4.3. - .57], $BF_{10}$ = 1.8, than non-prioritized items, $\kappa_{non\text{-}prioritized}$ = .13 [-1.8–2.0], $BF_{10}$ = .42.

There was only anecdotal support for an effect of implicit learning on precision, $\kappa_{diff}$ = .7 [.1–1.3], $BF_{10}$ = 1.41. The decisive support for an interaction effect between goal-driven attention and implicit learning, $\kappa_{interaction}$ = 1.5 [.9–2.0], $BF_{10} > 100$, indicates only anecdotal evidence for a difference in the precision of non-prioritized items between the goal-driven attention and implicit learning conditions, $\kappa_{non\text{-}prioritized}$ = .62 [-.75–2.0], $BF_{10}$ = 1.00 whereas there was decisive support that the precision of prioritized items was greater in the goal-driven attention condition compared to the implicit learning condition $\kappa_{prioritized}$ = 3.59 [1.8 – 5.4], $BF_{10}$ > .100.

*$P_{swap}$.* Swap errors of prioritized items were reduced compared to non-prioritized items by both goal-driven attention $P_{swap\text{-}diff}$ = .31 [.10-.53], $BF_{10} > 100$ and physical salience, $P_{swap\text{-}diff}$ = .11 [.04-.18], $BF_{10} >$ 100, and there was only anecdotal evidence for an interaction effect, $P_{swap\text{-}interaction}$ = .10 [-.01 - .22], $BF_{10}$ = 1.12. This may be due to ceiling effects for prioritized items.

Implicit learning had no effect on the swap rate $P_{swap\text{-}diff}$ = 0.00 [-.02 - .02], $BF_{10}$ = .09. The decisive interaction effect, $P_{swap\text{-}interaction}$ = .15 [-.05-.27], $BF_{10} > 100$, indicated that goal-driven attention had a much stronger effect on the swap rate than implicit learning.

*Summary.* The results of Experiment 1 were generally supportive of our hypotheses that learning through experience primarily affects the probability that information is encoded and recalled rather than the quality of the representation, whereas goal-driven attention affects both processes. We predicted, however, that an effect on precision would only be observed in the goal-driven attention condition and this was not the case. Decisive evidence was obtained for physical salience improving both the probability of encoding and recall and precision. The effect in precision for salient locations might be a byproduct of the advantage it has at encoding. Colors at the salient location may be drawn into the FOA first and, given the short delay of 1 s, there may not be enough time to bring other locations into the FOA. With more time, the salience advantage may dissipate given that it is not beneficial to keep the salient item in the FOA. In Experiment 2, we test this hypothesis by doubling the delay period and observing whether there is a reliable effect of salience

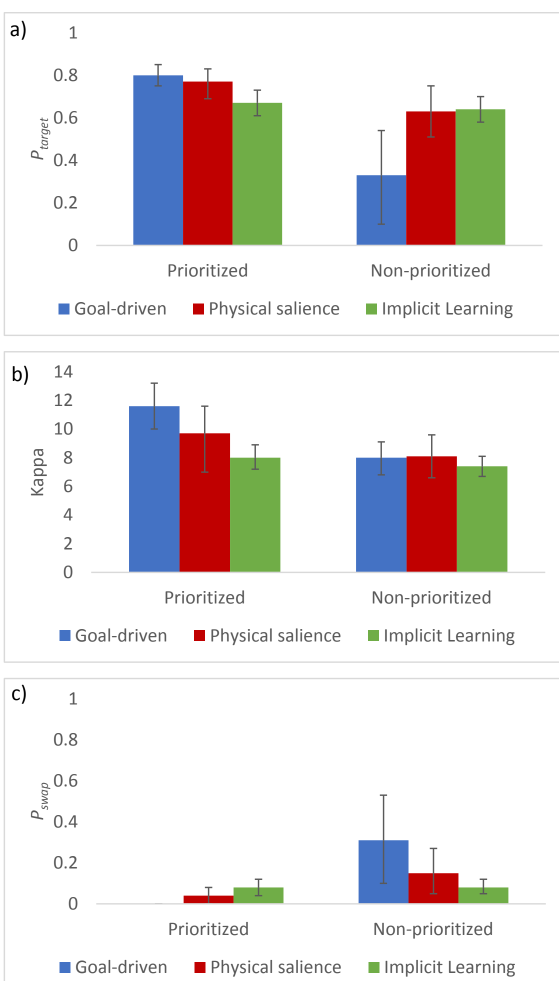


**Fig. 3.** Experiment 1 results. Parameter estimates of a) $P_{target}$, b) kappa, and c) $P_{swap}$ as a function of goal-driven attention (blue), physical salience (red), and implicit learning (green). Error bars indicate 95% HDI. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

**Table 1**
Parameter estimates for $P_{target}$, κ, and $P_{swap}$ in prioritized and non-prioritized trials.

| | $P_{target}$ | | κ | | $P_{swap}$ | |
|---|---|---|---|---|---|---|
| | Prioritized | Non-prioritized | Prioritized | Non-prioritized | Prioritized | Non-prioritized |
| Goal-driven | .80[.75-.85] | .33[.10–54] | 11.6[10.0–13.2] | 8.0[6.8–9.1] | 0[0.0–0.0] | .31[.10-.53] |
| Physical salience | .77[.69-.83] | .63[.51-.75] | 9.7[7.0–11.6] | 8.1[6.6–9.6] | .04[0-.08] | .15[.05-.27] |
| Implicit Learning | .67[.61-.73] | .64[.58-.70] | 8.0[7.2–8.9] | 7.4[6.7–8.1] | .08[.04-.12] | .08[.05-.12] |

on precision.

## Experiment 2

In Experiment 2, we investigate whether lengthening the delay will abolish the salience effect on precision. In contrast, we predict that a significant effect should remain for prioritization through goal-driven attention.

*Participants*. Thirty-nine undergraduates (4 M/35F) with an average age of 18.74 years and 35 undergraduates (12 M/23F) with an average age of 19.71 received course credit for their participation in physical salience and goal-driven conditions, respectively. All participants provided informed consent and had normal or corrected-to-normal vision. Two participants were excluded in the salience condition for technical failures that resulted in the loss of their data. A participant in the goal-driven condition was excluded for failing to follow instructions and aborting 1/6 of their trials without choosing a color. This left 37 and 34 participants in the salience and goal-driven condition, respectively.

*Stimuli*. The stimuli were identical to Experiment 1.

*Procedure and Analyses*. The procedure and analyses were the same as Experiment 1 except the delay was extended from 1 s to 2 s.

## Results and discussion

$P_{target}$. Both forms of prioritization improved the probability of recalling the target from WM (Fig. 4a). There was decisive evidence that prioritization improved $P_{target}$ as the result of goal-driven attention, $P_{target\text{-}diff}$ = .22 [.11-.37], $BF_{10} > 100$ and substantial evidence for an effect of physical salience $P_{target\text{-}diff}$ = .04 [.01-.07], $BF_{10} = 9.85$. There was decisive evidence for an interaction, $P_{target\text{-}interaction}$ = .17 [.06-.29], $BF_{10} > 100$, but only anecdotal evidence that the larger effect of goal-driven attention was due to greater probability of recall for cued colors $P_{target\text{-}prioritized}$ = -.08 [-.17 - .01], $BF_{10} = 2.08$ or lower probability of recall for uncued colors, $P_{target\text{-}nonprioritized}$ = .10 [-.06 - .28], $BF_{10}$ = 1.74.

κ (memory precision). As we predicted, there was more evidence for the null hypothesis that physical salience had no effect on precision, $\kappa_{diff}$ = .40 [-.33–1.13], $BF_{10} = .28$, when the delay was lengthened (Fig. 4b). In contrast, substantial evidence was observed that precision was better for stimuli prioritized through goal-driven attention, $\kappa_{diff}$ = 1.04 [.30–1.80], $BF_{10} = 7.13$, even with a longer delay. Unlike Experiment 1, there was no evidence for an interaction, $\kappa_{interaction}$ = -.64 [-1.7 - .40], $BF_{10}$ = .09, however, we note that the cuing effect was reduced in Experiment 2 in both conditions and the ability to detect this effect may be reduced.

$P_{swap}$. Decisive evidence was observed that goal-driven attention lowered the probability of swapping the location of the target and another stimulus, $P_{swap\text{-}diff}$ = -.13 [-.30-.02], $BF_{10} > 100$ (Fig. 4c). There was more support for the null hypothesis in the case of the effects of physical salience, $P_{swap\text{-}diff}$ = .004 [-.02-.02], $BF_{10} = .11$, however. There was substantial evidence for an interaction effect, $P_{swap\text{-}interaction}$ = .13 [.01 - .27], $BF_{10}$ = 4.14. This interaction was driven by a difference in $P_{swap}$ in cued trials, $P_{swap\text{-}prioritized}$ = .08 [.03 - .13], $BF_{10} < 100$, whereas swap rate in the non-prioritized trials were equivalent, $P_{swap\text{-}nonprioritized}$ = -.05 [-.21 - .08], $BF_{10}$=.76.

*Summary*. Despite the longer delay, prioritization effects were still observed on the probability of encoding and recalling the target for both physical salience and goal-driven attention. The improvement in precision from physical salience in Experiment 1 was not observed when the delay was lengthened, although it remained present as a result of goal-driven attention. This result lends credence to our hypothesis that the effects of physical salience on precision are transient and, when given enough time, dissipate because there is no reason to keep physically salient stimuli in the FOA.

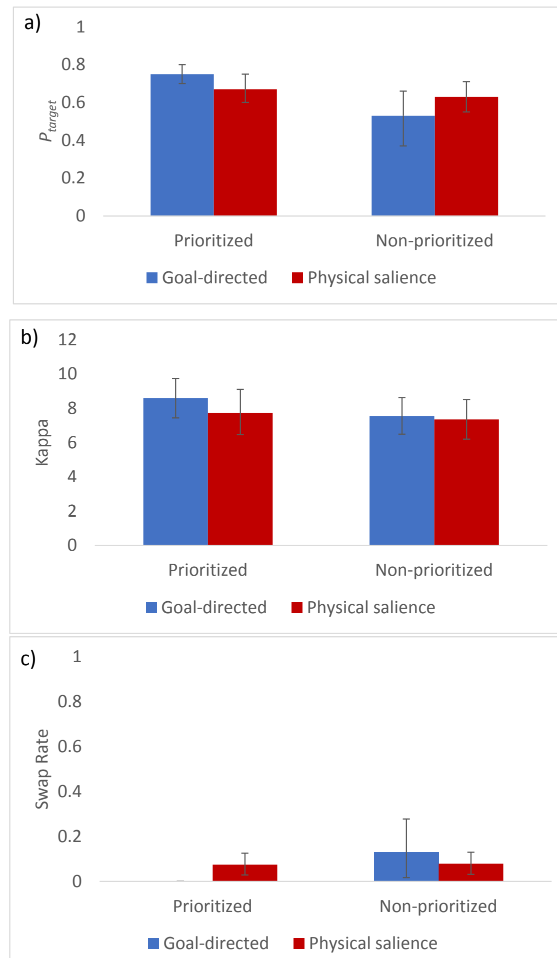


**Fig. 4.** Experiment 2 results. Parameter estimates of a) $P_{target}$, b) kappa, and c) $P_{swap}$ as a function of goal-driven attention (blue) and physical salience (red). Error bars indicate 95% HDI. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

## General discussion

In this study, WM performance was enhanced in different ways depending on how information was prioritized. We proposed that prioritization through goal-driven attention increases the likelihood that items enter WM and then helps generate and maintain a high-quality representation until recall. Accordingly, we found that goal-driven attention increased both the likelihood of recall and the precision of the prioritized item. We also proposed that physical salience and implicit learning should benefit WM primarily by increasing the probability of encoding and recall with a negligible effect on precision. The data strongly support this hypothesis for the effects of prioritization through implicit learning; that is, there was more evidence to support that implicit learning improved the probability of recall rather than affecting precision. In contrast, physical salience had an effect both on the probability of recall and the precision of the representation in Experiment 1. This advantage in precision, however, was weaker compared to goal-driven attention and dissipated with a longer delay suggesting that it was a transient effect due to enhanced selection at encoding.

*The effects of prioritization on memory encoding*

Prioritization increased the likelihood that items entered and were recalled from WM regardless of the manner in which priority was set. This supports our idea that all ways of setting priority involve an initial orienting to the prioritized location that facilitates the encoding of the item (Bays & Husain, 2008; Prinzmetal, Ha, & Khani, 2010; Umemoto et al., 2010). Implicit learning, however, had a more modest effect on recall than goal-driven attention, which may be due to variability in learning the prioritized location in the search task. While adding search time to the model did not account for variance in WM performance, other factors such as individual differences in the time for implicit learning to be extinguished might contribute to lower prioritization effects.

The primary difference, however, between goal-driven attention and the more automatic forms of prioritization was in the probability of recalling non-prioritized targets. Goal-driven attention resulted in a lower likelihood that non-prioritized items would be encoded and recalled from WM but did not confer an equivalent advantage for prioritized items compared to the advantage from physical salience. This result is similar to others showing better performance for non-prioritized items when priority is determined by physical salience rather than goal-driven attention (Ravizza, Uivlugt & Hazeltine, 2016; Schmidt et al., 2002). It is possible that participants overused the predictive cue as a strategy to reduce WM load by ignoring the other colors in order to do well on most trials. Alternatively, or additionally, it may be that the strong effect on precision from goal-driven attention necessitates longer or deeper processing that, in turn, might take away resources from encoding non-prioritized items.

*The effects of prioritization on memory precision*

Neither physical salience nor implicit learning increased precision for prioritized items as strongly as goal-driven attention. This finding is consistent with perceptual and neural studies finding an advantage to the speed of orienting to prioritized information regardless of how it is prioritized while additional effects, reflective of deeper processing, are only observed for goal-driven attention (Bachman et al., 2020; Dugué et al., 2020; Prinzmetal, McCool, & Park, 2005). In addition to deeper or longer processing at encoding, physical salience and implicit learning may also confer less advantage on the precision of prioritized items because of the effortful nature of maintaining WM representations; that is, when items are not relevant to the goal of the task, more effort to maintain those items over others in WM is not expended. Regardless of the reason, these data suggest that differences in the quality of the representation rather than the likelihood of encoding and recall are primarily responsible for the weaker prioritization effects observed in WM accuracy from physical salience (Schmidt, Vogel, Woodman, & Luck, 2002; Berryhill et al., 2012; Ravizza, Uivlugt & Hazeltine, 2016) and implicit learning (Jiang et al. (2015)) compared to goal-driven attention.

In this study, physical salience did not maintain precision to the same degree as goal-driven attention, despite their equivalent effects on the likelihood of encoding and recalling the target. The result is consistent with another study showing that parametric changes of physical salience modulated the probability that an item was in memory but not estimates of precision (Constant & Liesefeld, 2021). We found a transient effect of salience on precision when time to recall is short, which may be due to bottom-up attention involuntarily placing the cued item in the FOA. With a relatively short delay, such as the one used in Experiment 1, the FOA may not have time to alternate to representations at the other locations. Indeed, no effect of physical salience on precision was observed for a longer delay in Experiment 2.

There was only anecdotal evidence for an effect of implicit learning on precision even when the memory delay was short. This difference between the effects of salience and implicit learning on precision may be due to a physical cue indicating which quadrant is prioritized. This cue captured attention in an exogenous manner whereas the effects of implicit learning require directing internal attention. Weaker effects in the implicit learning condition are consistent with studies finding greater effects on performance from external attention than internal attention (Fang, Ravizza, & Liu, 2019; Myers et al., 2015).

*The effects of prioritization on memory swap*

Swap rate also differed based on how information was prioritized. Both goal-driven attention and physical salience lowered swap errors to an equivalent degree in Experiment 1, although no effect was observed for physical salience in Experiment 2. Note, however, that swap errors were so low for prioritized items that it is difficult to interpret whether or not goal-driven attention might have a larger effect on reducing swap errors than physical salience. Implicit learning, however, had no effect on the swap rate which, again, might be due to the lack of a physically present location cue. Such a location cue might induce greater binding of the color to the location in the goal-driven and physical salience conditions.

*Relation to other studies*

This is the first study to investigate how implicit learning of statistical regularities improves WM performance by directly estimating the probability of target encoding and precision. Our results are consistent with a previous study in which participants detected changes in a memory array that were either large (e.g., rectangle → circle) or small (e.g., oval1 → oval2) (Umemoto, Scolari, Vogel, & Awh, 2010). The results of that study showed that implicit learning improved the detection of large changes of the memory array, but that there was no benefit in the detection of small changes. These results are consistent with our findings as the detection of big changes was thought to reflect the existence of the object in WM whereas small changes indicated quality of the representation (Umemoto, Scolari, Vogel, & Awh, 2010).

While there are a handful of studies investigating the effects of implicit learning of statistical regularizes on WM (Olson, Jiang, & Moore, 2005; Umemoto, Scolari, Vogel, & Awh, 2010; Won & Leber, 2017), ours is one of the few to investigate the transfer of prioritization to an unrelated WM task. Indeed, one study failed to find transfer from implicit learning in a search task to a memory task (Addleman, Tao, Remington, & Jiang, 2018). Addleman, et al. (2018) suggest that that transfer only occurs when two tasks require attention to be moved in the same habitual way. It may be that our search and WM tasks were similar enough to promote transfer. For example, targets in the search task were more likely to be in one quadrant and participants had to move their attention from one quadrant to another if the target was not in the frequent location. Similarly, participants were asked to encode the colors in all four quadrants of our WM task and, so, must move attention from one quadrant to another in an attempt to memorize the array. In the study in which there was no transfer (Addleman, Tao, Remington, & Jiang, 2018), search targets were superimposed on background scenes in each quadrant and the memory for these scenes was later probed. The memory array was displayed throughout a block of several search trials so that participants were not necessarily moving attention between scenes. As suggested by Addleman, et al. (2018), it may be that the key determinant of transfer is the similarity in attentional habits between tasks.

Previous investigations of prioritization in WM have targeted filtering, with some information allowed into WM while other information excluded in an all-or-none fashion (Dube, Emrich, & Al-Aidroos, 2017). Consider a situation, however, in which you are introduced to a new group of co-workers and are told beforehand that you will be working closely with one of them. In this case, you should prioritize the future co-worker's name above the others while trying to remember the others' names as well as you possibly can. A strength of this study is that it focuses on situations in which all information must be remembered, but some information is more important. This allowed us to study the process of setting priority independently from processes used to ignore or remove information from WM.

## Conclusions

In sum, our predictions about how different modes of prioritizing information affect WM were generally supported. Physical salience, implicit learning, and goal-driven attention all improved the likelihood of an item entering and being recalled from WM, but the latter was the best method of ensuring a high-quality representation. While goal-driven attention and physical salience have been extensively studied, the current study is the first to test predictions derived from a mechanistic framework of how WM performance depends upon the manner of prioritization. Moreover, this study expands upon previous results by investigating for the first time how prioritization due to implicit learning of statistical regularities affects WM performance. Our results suggest that implicit learning is more similar to prioritization through physical salience than goal-driven attention. Overall, our results contribute to a more mechanistic understanding of the interaction between attentional selection and working memory.

## CRediT authorship contribution statement

**Susan M. Ravizza:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization, Supervision, Project administration. **Timothy J. Pleskac:** Methodology, Software, Formal analysis, Data curation, Writing – review & editing. **Taosheng Liu:** Conceptualization, Methodology, Software, Resources, Writing– review & editing.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgments

We would like to thank Travis Ambrosio, Katelyn Hacker, Sarah Liddy, Sophia Ripley, and Leah Singman for their help in data collection. T.L. is supported by a grant from the National Science Foundation (2019995).

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jml.2021.104287.

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