The effect of priority state of working memory content on its vulnerability to interference

Kaiqi (Cathy) Zhang

Department of Cognitive Science

University of California, San Diego

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Advisory Committee

Dr. Anastasia Kiyonaga

Dr. Gedeon Deak

Dillan Cellier

Introduction

Working memory (WM) allows us to retain recent sensory information. Memories from the past can guide future actions, where we remember information that we expect to become relevant in later activities (Nobre and Stokes 2019; Baddeley 2003). We can simultaneously maintain different types of WM content for multiple goals at different times (Nobre and Stokes 2019; van Ede et al. 2019; Allen and Ueno 2018). However, since WM is limited in the amount of information it can store at once, we need to prioritize the information that is most relevant to the current goal and selectively maintain it (Oberauer and Hein 2012; Myers, Stokes, and Nobre 2017; Allen and Ueno 2018)).

When we prioritize some information over some others, it changes the neural activity patterns associated with the different WM items (Lepsien, Thornton, and Nobre 2011; Poch, Campo, and Barnes 2014; Yantis 2008; Lorenc et al. 2020). For instance, prioritized information that is in the focus of attention is easier to detect in the neural signals (Barth and Schneider 2018). These different activation patterns have led to questions about how deprioritized information is remembered when it is not activated in the focus of attention. Some theories suggest that deprioritized information is just held at a lower level of activity, while others suggest that it is stored in a fundamentally different neural code (Lorenc, Mallett, and Lewis-Peacock 2021).

One implication of how prioritized information is stored may be how susceptible it is to irrelevant distractions. In previous studies, the effect of task irrelevant distractions has been explored. Some studies have found that memory for the maintained information became noisier when it differed from the distractor, and the memory for WM content was shifted toward the distractor features (Rademaker et al. 2015). The effect of distraction is not uniform across all situations. We know that WM is sometimes harmed by distraction, but other times it is not (Rademaker et al. 2015; Lorenc, Mallett, and Lewis-Peacock 2021; Makovski and Jiang 2007). The effect also depends on distractor characteristics. For example, when the distractor is similar to maintained WM content, it is more likely to interfere with the memory than when the distractor is dissimilar (Allen et al. 2015).

We think the prioritization state of WM content may affect how vulnerable it is to interference. There has been inconsistency in literature about the effect of distractors on working memory content. Some theories suggest that prioritized information is most robust against interference because it has a stronger neural activation (Compte 2000; Lorenc, Mallett, and Lewis-Peacock 2021). Others bring up the exact opposite: when WM content is right in the center of attention, irrelevant information is most likely to interfere with it. In that case, if the information is moved out of the center into a deprioritized state, or the latent state, it might actually be protected from interference (Lewis-Peacock et al. 2012; Trübutschek et al. 2017). Therefore, we think that how susceptible the information is to interference may tell us about how information is maintained at different levels of prioritization.

We wish to investigate how the factors of prioritization state and distractor similarity interact in influencing working memory performance. We could find that some prioritization states are more susceptible to task irrelevant interference than others. If we find that deprioritized information is more subject to interference, it might mean that it is not maintained in a fundamentally different state. It may simply be less activated, and the lower level of neural activation could lead to the vulnerability against distraction. Alternatively, if the deprioritized information turns out to be most robust, it may be protected because it is moved out of the center of attention into a latent state. It would then suggest that there could be fundamentally different representational states in working memory.

Methods

Participants

Our task incorporates both prioritization and distraction with stimuli on continuous scales.The sample size for this experiment is calculated based on published literature with similar designs. We extracted the lowest effect size of .2 for distraction from effect sizes ranging from .2 to .78 (Rademaker et al. 2015; Allen and Ueno 2018; Hitch et al. 2018). With the goal of $\eta_p^2 = .2$ and $\alpha = .05$, we obtain a sample size of 26. Taking into consideration publication bias and data exclusion, we aim to recruit 30 participants.

We recruited 30 UC San Diego undergraduate as participants (4 male, 25 female, 1 nonbinary; mean age = 21.9 years, range = 18-39) through UCSD's SONA: Psychology Department Subject Pool (https://ucsd.sona-systems.com/). The study is designed to last at least 30 and no more than 60 minutes. Participants will receive course credit for their participation (0.5 credits for every 30 minutes of participation, minimum of 0.5 credits for 30 minutes of participation, and maximum of 1 credit for 60 minutes of participation). All participants were able to read and speak English, have normal or corrected-to-normal near, distance, and color vision, and normal hearing. All participants provided informed consent in accordance with the policies of UC San Diego Institutional Review Board.

Stimuli and apparatus

The experiment was run using Pavlovia (https://pavlovia.org/) with PsychoPy3 (Peirce et al. 2019). In order to capture the direction and degree of any bias of memory content, we incorporated two stimulus spaces on continuous scales, a color space and a shape space.

For the color stimuli and color response wheel, we specified a set of 360 evenly spaced colors by adjusting the hue in the HSV model (Hue, Saturation, Value) from 1 to 360. These colors were then converted into RGB values and used to define color stimuli as built-in circle objects in PsychoPy (diameter = 0.3, all units of length in ratio to window height). We created the color wheel by organizing all 360 colors with increasing hue value, with saturation fixed at 0.85 and value fixed at 0.94.

In order to incorporate another set of stimuli with similar properties, we used the newly validated shape space developed by Li et al. (2020) where angular distance along a 2D circle is a proxy for visual similarity. We embedded 16 shapes into a gray wheel as visual anchors so participants can quickly pinpoint a small area for the shape they wish to select. The remaining shapes are organized accordingly. Both the wheels are the same size (diameter = 0.5) and displayed in positions (x,y) = (0.35,0) or (-0.35,0) in all trials.

In order for the distractors to have equal opportunities to interfere with both types of stimuli, we designed our distractors so they incorporate both color and shape features. We fill the shapes with the colors we created using ImageMagic (https://imagemagick.org/) so each distractor is a colored shape.

We created a neutral noise in order to establish baseline behaviors. We first overlapped all 360 shapes and rotated the resulting shapes 90°,180° and 270° clockwise. The three rotated shapes are overlapped again with the original to create the final outline. Then we fit a white noise pattern into the outline and blurred the edges so it does not have a clear shape that might resemble certain shape stimuli.

Due to the restriction of closed campus and social distancing during COVID-19, all participants performed the experiment on personal electronic devices. In order to ensure similar visual experiences among participants, we included reminders in the instructions on using recommended browsers and avoiding special display features such as dark mode.

Design and procedure

We adopt a within subject, two-way, eight-level, with two factors of interest: WM priority level (prioritized vs. deprioritized item tested) × Distractor condition: (Neutral, 20°, 40°, 60° distance from WM samples). We will manipulate which WM sample item (color vs. shape) is prioritized on each trial. We will manipulate the similarity between WM samples and distractor stimuli. There will be a neutral distraction condition (noise), and on each trial with a distractor, it will be equidistant in feature space from both the prioritized and deprioritized WM sample stimuli. There will therefore be distraction conditions: Neutral, ∓20°, ∓40°, ∓60°). We will also manipulate which of the two WM sample items is proposed for recall: prioritized (higher point value) or deprioritized (lower point value). WM stimuli will be drawn from two different categories (color and shape), and a factor of no interest will be which category is prioritized on each trial. Every combination of conditions will occur equally often, counterbalanced within each block, and in randomized order. In each trial, the shape and color items are equally likely to be tested, regardless of priority state.

Each trial began with the presentation of a slightly larger fixation cross for 1000 ms to alert participants to the new trial. Next, two stimuli, a color and a shape, will appear on either side of the fixation ((0.35,0) and (-0.35,0)) for 1000 ms. We switch the positions of the color and the shape randomly during the trial while maintaining an equal number of trials with each stimulus in the left or right position. Participants were instructed to remember both items for the duration of the trial. After a 500 ms delay with a fixation on the blank screen, a pair of numeric values (1 and 5) will appear at the same positions for 1500 ms. Participants will be awarded points for every item they remember correctly (error within 20°) at the end of each trial, and these values will indicate the number of points they will receive if they correctly report the item in the corresponding position. After a delay of 500 ms, the distractor (or noise) appears at the center of the screen for 250 ms, followed by another delay of 750 ms. Participants were told that the distractor is task irrelevant and were instructed to ignore it. Then either a color wheel or a shape wheel will occur on the side of the probed stimulus ((0.35,0) or (-0.35,0)). Participants have 4000 ms to recreate the color or the shape from their memory, depending on the type of wheel present.

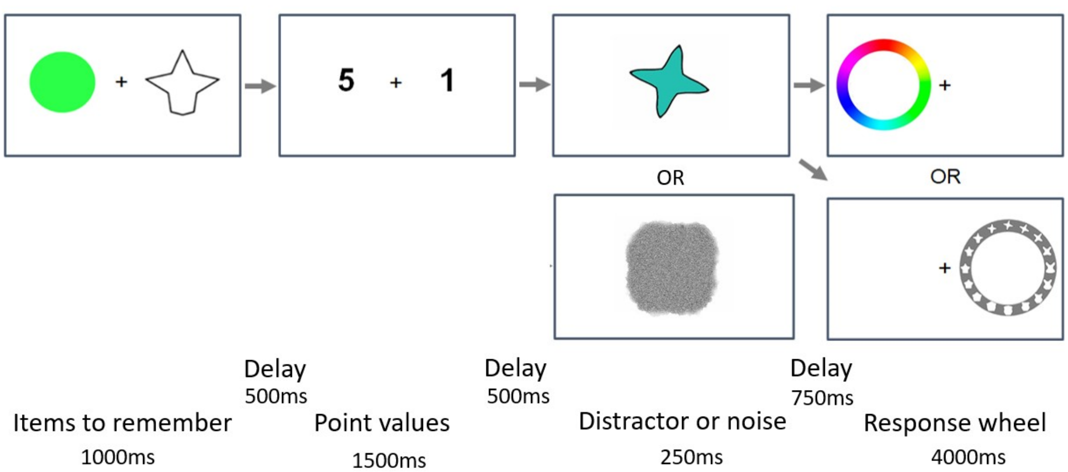


Figure 1. A single trial task flow. ITI = 1000ms.

Each participant will go through demonstrations of responding with the color wheel and the shape wheel at the beginning of the experiment. They will also participate in rounds of practice trials until their average response error is within 30° before starting the official task.

Exclusion criteria

Participants will be excluded if they omit more than ⅓ responses or if they exhibit an average overall error that is greater than 60°. None of the participants met either of these and therefore none were excluded.

Result

Overall, the average absolute response error was 15.27° across all conditions. This is comparable with similar studies (Lorenc et al. 2021; Rademaker et al. 2015), and therefore participants were able to follow instructions and complete the task well.

Stimulus type

We first examine the effect of stimulus type on both absolute response error and response time using a 2 (stimulus type: color vs. shape) × 2 (prioritization state: prioritized vs. deprioritized) × 4 (distractor distance: noise vs. 20° vs. 40° vs. 60°) repeated measures ANOVA. Each participant's average error and RT were calculated for each combination of the conditions. We found significant effects of stimulus type on error, $F(1,29) = .26$, $p < .001$, $\eta_p^2 = .33$, as well as RT, $F(1,29) = 100.79$, $p < .001$, $\eta_p^2 = .78$. Since the shape space is a completely novel space compared to the color space, such an effect is understandable. However, since there are no significant effects for interactions between stimulus type and other factors (prioritization state or distractor distance) for error or RT (all p > .05), the remaining analyses will collapse across these categories.

Response errors

We calculated the average absolute error for each combination of conditions for each participant. To look at the basic effect of the priority state, we first compare two baseline conditions without distractors. Even though when the tested item is deprioritized, the error is numerically higher than when the tested item is deprioritized, this effect is not significant. What we are interested in seeing is the effect when a distraction is present compared to not.

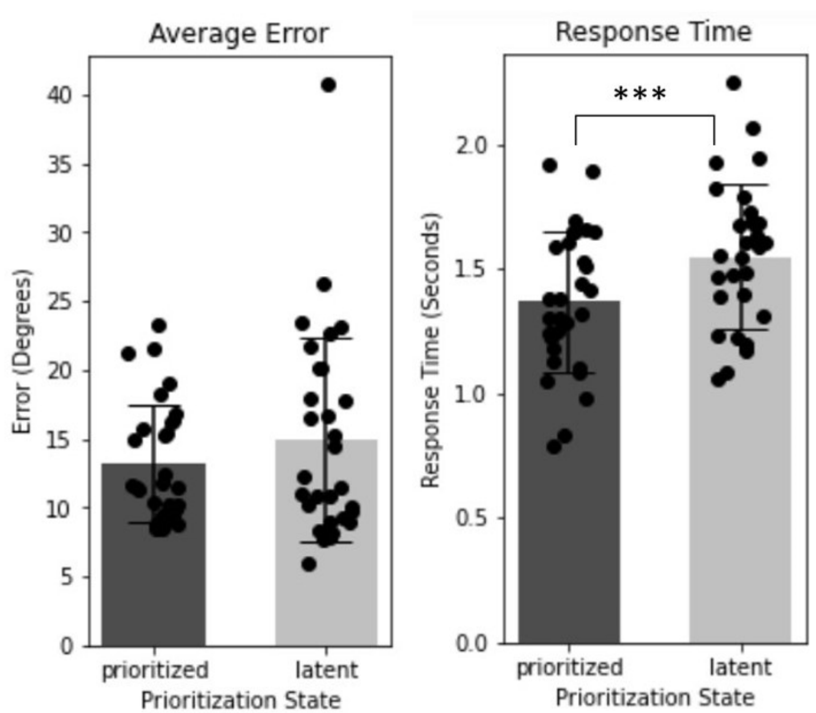


Figure 2. Basic effects of priority states. Average error (degrees) and average response time (seconds) for baseline conditions without distractors.

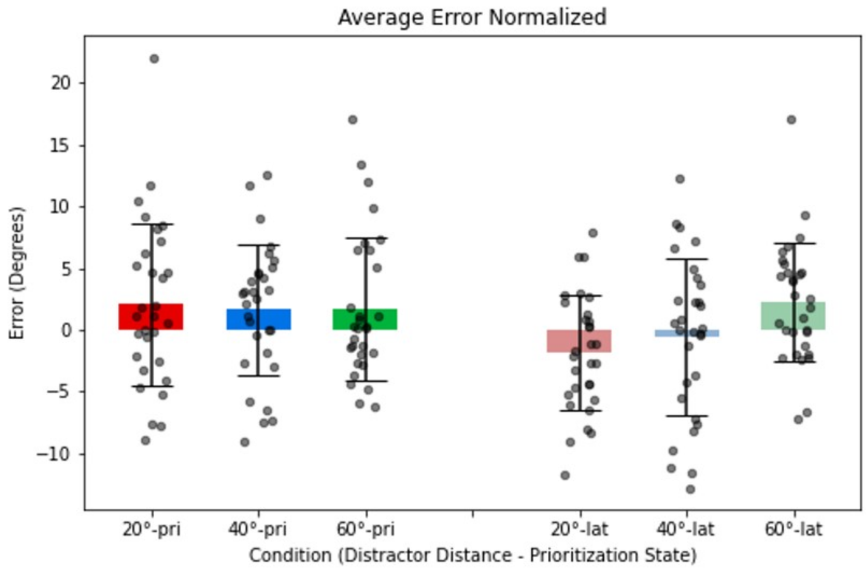
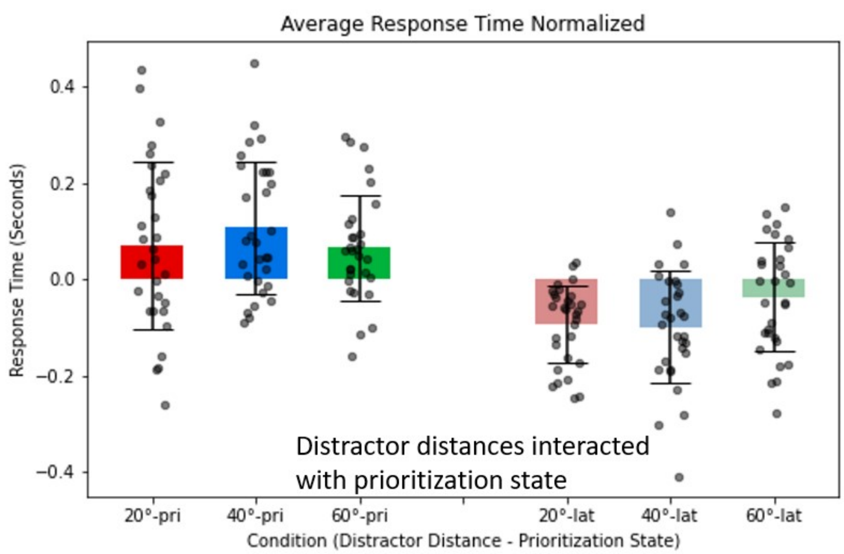


Figure 3. Average error normalized (degree) against corresponding baseline conditions. Significant



interaction between distractor distances and prioritization states.

Figure 4. Response time normalized (seconds) against corresponding baseline conditions. Significant interaction between distractor distances and prioritization states.

To see if memory is more or less accurate with the presence of a distractor compared to without, we normalized the data with respect to the baseline performance in the same prioritization state (Figure 2). A 2 (prioritization state) × 3 (distractor distance) repeated measures ANOVA on normalized error revealed main effects of distractor distances, $F(2,29) = 3.72$, $p = .035$, $\eta_p^2 = .20$, and the interaction, $F(2,29) = 4.79$, $p = .012$, $\eta_p^2 = .25$, but not on prioritization state, $F(1,29) = 2.90$, $p = .099$, $\eta_p^2 = .09$. We followed up with repeated measures one-way ANOVAs on the effect of distractor distances on items in prioritized and deprioritized state. We found a significant effect of distractor distance on the response error for deprioritized items, $F(2,29) = 9.65$, $p < .001$, $\eta^2 = .40$, but not for prioritized ones, $F(2,29) = 0.08$, $p = .92$, $\eta^2 = .01$. In the prioritized conditions, although the errors exhibit an increasing trend with the presence of distractors, none of the errors were significantly different from the baseline. In the deprioritized conditions, the effect of distractors was sensitive to distractor similarity: when the distractor is 20° away, error decreased significantly; when the distractor is 60° away, error increased significantly compared to baseline. With different levels of similarity, distractors could have completely opposite effects.

Response time

Average response time for each combination of conditions was calculated for each participant. We can first see the basic effect of priority state by comparing the two baseline conditions. When no distractor is present, the response time for prioritized items is significantly shorter than deprioritized items (Figure 2). This agrees with the idea that the prioritized item is more actively maintained and therefore more accessible.

Similarly, normalized RT was calculated with respect to baseline conditions (Figure 4). 2 (prioritization state) × 3 (distractor distance) repeated measures ANOVA on normalized RT revealed main effects of prioritization, $F(1,29) = 25.09$, $p <.001$, $\eta_p^2 = .46$, and the interaction, $F(2,29) = 4.68$, $p =.013$, $\eta_p^2 = .24$, but not on distractor distances, $F(2,29) = 1.51$, $p =.23$, $\eta_p^2 = .09$. In one-way ANOVAs that decompose this interaction, the effect of distractor distance on RT is evident for deprioritized items, F(2,29) = 6.96, p = .004, $\eta^2 = .32$, but not for prioritized ones, F(2,29) = 1.54, p =.22, $\eta^2 = .10$. In the deprioritized conditions, the effect of distractors is sensitive to distractor similarities. For distractors 20° and 40° away, response time decreased significantly compared to baseline. This effect is not significant for distractors 60° away.

Discussion

Looking at effects of priority state, we conclude that when no distractor is present, participants are able to recall prioritized items faster than deprioritized items. There is also a trend in increased memory accuracy although the difference is not significant. This is consistent with the findings that prioritization can be a memory boost (Myers, Stokes, and Nobre 2017; Oberauer and Hein 2012).

Incorporating results when a distractor is present, we see that distractors have different effects on prioritized vs deprioritized content.

For the prioritized content that is already in the focus of attention, distractors tend to make it less accurate and less accessible. It takes longer for participants to identify and pull out the information from working memory. The effect of a distractor on deprioritized content really depends on distractor similarity: The presence of a similar distractor may have boosted the deprioritized content and made it more accessible than it would have been without a distractor. This might be because a similar distractor is refreshing the memory for information in latent state. If no distractor is present, the information would have remained in latent maintenance, and there would not exist a benefit of refreshment. If the distractor is pretty distinct, however, not only the distractor does not help memory, it actually harms it. There is significantly higher error when the distractor is 60°, suggesting that memory became less accurate in the face of the distractor. With different effects between priority states and within the same state, we conclude that the effect of interference depends on the interaction between the two factors.

Conclusion

In this study, we find intriguing results that could reconcile competing claims in the literature. We find that the level of priority determines the susceptibility of WM content against interference. It is not always the case the task irrelevant distraction harms working memory. With the right combination of conditions, when the distractor is similar with information being maintained, it could also boost memory for deprioritized items.

We see that how we prioritize information will determine how our memory reacts to distractions from the environment. Working memory is functionally flexible, and this enables us to manage different goals and switch between multiple tasks in daily lives. We rely on working memory to complete complex cognitive tasks, and understanding its related mechanism could help paint a bigger picture of human memory processes.

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