Supplementary materials for

Interactions between visual working memory representations

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1. Overview of supplement

There are many analytic approaches available for quantifying performance in visual working memory tasks using delayed estimation. The main paper uses an approach that is simple and requires minimal assumptions. Here, we provide the raw probability distributions and the results of analyses using a more sophisticated mathematical model to quantify performance. The model was based on the mixture model of Bays, Catalao, and Husain (2009). This model conceives of visual working memory as a set of normally distributed representations on a circular space, each with a mean value that can be shifted systematically away from the true orientation of the sample stimulus. It also assumes that the observer may occasionally confuse the first and second items on a given trial and report the wrong one ("swap errors"). Because the set size was low (two items) and constant, and the analyses focused on the mean value of the distribution rather than its shape, there are no meaningful differences between this model and other common models of visual working memory in the context of the present experiment.

The model can be expressed as this equation:

$$p(\hat{\theta}) = P_{\mathrm{T}} * \Phi(\hat{\theta}, \theta_{\mathrm{T}} + \mu, \kappa) + P_{\mathrm{NT}} * \Phi(\hat{\theta}, \theta_{\mathrm{NT}}, \kappa) + (1 - P_{\mathrm{T}} - P_{\mathrm{NT}}) * \frac{1}{2\pi}.$$

In this model, $p(\hat{\theta})$ represents the estimated probability of making a response at a particular orientation. There are four free parameters in the model. $P_{\rm T}$ represents proportion of responses based on the cued target. $P_{\rm NT}$ represents proportion of trials with swap errors, on which the observer erroneously reports the uncued target (*nontarget responses*). The observer may also fail to report either the cued target or the uncued target (with a probability of $1 - P_{\rm T} - P_{\rm NT}$) and instead make a completely random guess. Kappa (κ) is the concentration parameter of a circular normal (von Mises) distribution (Φ), which represents the precision of the report. Mu (μ) is the central tendency of the von Mises distribution (Φ) for target-based responses, which represents systematic shifts of the representation away from the true value. Mu (μ) is negative if the response to the cued target is in the direction of the uncued target (attraction) and positive if the response is away from the uncued target (repulsion). The Mu (μ) parameter is analogous to the mean response error that was the focus of the main analyses. Maximum likelihood estimates of each parameter were obtained using a non-linear optimization algorithm (Nelder & Mead, 1965), separately for each participant and the orientation difference. To ensure that global maxima were found, the optimization was repeated with multiple different initial parameter values.

First Target/ First Report First Target/ Second Report Second Target/ First Report Second Target/ Second Report 0.05 Away from the other ite Away from the other ite ard other ite vard other item Away from the other it Away from the other iten 0.02 0.03 0.04 Probability Near 0.01 0.00 -150 -100 -150 -100 -150 -100 -50 0 100 150 100 150 100 150 -150 -100 -50 100 150 50 -50 0 50 -50 0 50 0 50 First Target/ First Report First Target/ Second Report Second Target/ First Report Second Target/ Second Report 0.05 Away from the other item Away from the other item Away from the other item Away from the other iter the other he other item e other item he other item 0.02 0.03 0.04 Probability Far 0.01 0.0 -150 -100 -50 0 50 100 150 Response Error (°) -150 -100 -50 0 50 100 150 Response Error (°) -150 -100 -50 0 50 100 150 Response Error (°) -150 -100 -50 0 50 100 Response Error (°) 150

2. Probability distributions of response errors in Experiment 1

Fig. S1 Probability distributions of response errors (collapsed across participants) from Experiment 1 for each combination of presentation and report order for trials in which the difference in orientation between the two targets was either *near* (22.5°, 45°, and 67.5°, top row) or *far* (112.5°, 135°, and 157.5°, bottom row). The *vertical red line* in each panel indicates the actual orientation of the target item being reported, and the *broken black lines* indicate the possible positions of the other target. On *near trials*, there were clearly more responses on the opposite side of orientation space from the other target (*blue region*; repulsion bias). On *far* trials, there were clearly more responses on the same side as the other target (*orange region*; attraction bias). It is also clear that participants made occasional responses at the orientation of the wrong target (the orientations indicated by the *vertical black lines*).



Fig. S2 a Mean mu (μ) estimates as a function of the orientation difference for the first and second target (collapsed across report order) and **b** for the first and second report (collapsed across presentation order). Positive values indicate bias away from the uncued target (repulsion) and negative values indicates bias toward the uncued target (attraction). **c** Mean mu estimates for the *near* and the *far* conditions for each combination of the presentation and the report order, collapsed into near and far conditions. *Error bars* show the within-subjects standard error of the mean (Morey, 2008). * p < .05, FDR corrected

4. Kappa, P_{NT} , and Guess estimates from a mixture model with swap errors in Experiment 1



Fig. S3 a Mean Kappa, **b** mean P_{NT} , and **c** mean Guess estimates for each combination of presentation and report order, collapsed into the *near* and the *far* conditions. There were no significant differences in Kappa between the *near* and *far* conditions. There were more swap errors (i.e., a greater mean P_{NT}) in the *near* condition than in the *far* condition. There tended to be more guess responses in the *far* condition than in the *near* condition, but guess rates were very low and the differences among conditions were not significant. *Error bars* show the within-subjects standard error of the mean. * p < .05, FDR corrected



5. Probability distribution of response errors in Experiment 2

Fig. S4 Probability distributions of response errors in Experiment 2, organized as in Fig. S1



Fig. S5 Mean mu (μ) estimates in Experiment 2, organized as in Fig. S2

7. Kappa, P_{NT} , and Guess estimates from a mixture model with swap errors in Experiment 2



Fig. S6 a Mean Kappa, b mean P_{NT} , and c mean Guess estimates in Experiment 2, organized as in Fig. S3



8. Probability distribution of response errors in Experiment 3

Fig. S7 Probability distributions of response errors in Experiment 3, organized as in Fig. S1





Fig. S8 Mean mu (μ) estimates in Experiment 3, organized as in Fig. S2

10. Kappa, P_{NT} , and Guess estimates from a mixture model with swap errors in Experiment 3



Fig. S9 a Mean Kappa, b mean P_{NT} , and c mean Guess estimates in Experiment 3, organized as in Fig. S3

11. Statistical analyses of Kappa estimates

We conducted statistical analyses to test whether the precision of a representation (quantified as the kappa value from the mixture model) was influenced by the attentional cues in Experiment 2 and 3. Because the cued item was always tested first and the uncued item was always tested second, a direct comparison of the cued and uncued items would be confounded by report order. We therefore compared the kappa estimates for the cued and uncued items in Experiments 2 and 3 with the kappa estimates from the first- and second-reported items in Experiment 1. Specifically, we conducted two separate two-way ANOVAs with a within-subject factor of

report order/cuing (Report 1: cued vs. Report 2: uncued) and a between-subject factor of experiment (Experiment 1 vs. 2 and Experiment 1 vs. 3). In the ANOVA with Experiment 1 versus 2, the two-way interaction was significant, F(1, 30) = 11.18, p = .002, $\eta_p^2 = 0.27$, indicating that precued items were maintained in memory with higher precision compared with unprecued items (precued: 51.73 vs. unprecued: 29. 66). In the ANOVA with Experiment 1 versus 3, the two-way interaction was not significant (F < 1), suggesting that postcue did not increase the precision of the representation.

References

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