

Spatial constraints on probability learning in visual working memory

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Author Note

Support was provided by NSF BCS-1632296 to A. B. L. We thank Ian Krajbich and Brandon Turner for helpful suggestions, as well as Rayan Magsi, Beau Snoad, Rebecca Freeman, Eleni Christofides, Jarom Longhurst, Agostina Rodriguez, and Di Zhou for assistance with data collection.

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Abstract

Visual working memory is limited in capacity, so it is essential to use it efficiently. Previous work has shown that statistical learning can help boost working memory efficiency by prioritizing the encoding and/or maintenance of objects most likely to be tested. In this study, we considered that the potential benefits of statistical learning could be limited by spatial constraints. Across three experiments, we found that statistical learning prioritizes working memory allocation to items based on their likelihood of being tested, but this prioritization is greatly modulated by spatial constraints. In particular, when two locations each had a high probability of being tested, we primarily observed performance benefits over low probable locations when these two locations were horizontally adjacent to one another. Vertically adjacent and diagonally arranged high probable locations produced no accuracy benefit over low probable locations and a modest response time benefit. These findings contrast with previously observed hemifield-independent effects (i.e., a “bilateral field advantage”) and reveal surprising limitations on the potential benefits of statistical learning.

Keywords: statistical learning, working memory, spatial coding, hemifield independence, bilateral field advantage

Spatial constraints on probability learning in visual working memory

Working memory, the ability to actively maintain representations of sensory information after the perceptual input is no longer available, is an essential cognitive function (Baddeley & Hitch, 1974; Luck & Vogel, 1997; Soto, Heinke, Humphreys, & Blanco, 2005). However, we are only capable of maintaining a limited amount of information at a time. Therefore, any opportunity to increase our encoding and maintenance of relevant information while rejecting irrelevant information should be highly desirable. One such opportunity is provided by our implicit learning mechanisms, which constantly monitor the environment for statistical regularities, without the need conscious intent (Stadler & Frensch, 1998).

For example, consider a radiologist who must compare a patient's old and new scans for any adverse developments. This task requires the radiologist to store information from the first image in visual working memory in order to compare it to the second image. Since capacity is limited, he/she cannot store all of the first image's contents, so the process can take many successive steps. After some training, however, the radiologist will begin to learn which parts of the scan are the most relevant and which are totally irrelevant, making the comparison process more efficient.

This scenario, in which statistical learning benefits working memory, is supported by several recent studies (Brady, Konkle, & Alvarez, 2009; Olson, Jiang & Moore, 2005; Umemoto, Scolari, Vogel, & Awh, 2010). For example, Umemoto, Scolari, et al. had participants store eight colored items for a brief delay, followed by a same/different judgment on a single test item. Without informing the participants, the experimenters tested items in one specific quadrant of the display (i.e., the high-probable quadrant) more frequently than items in the other quadrants (i.e.,

the low-probable quadrants). As the experiment progressed, the participants became more accurate on test items from the high-probable quadrant than those in the low-probable quadrants, confirming that statistical learning beneficially biased working memory encoding.

The results of Umemoto, Scolari, et al. (2010) underscore how working memory profits from statistical learning (see also Olson et al., 2005), but the extent of this benefit remains to be fully understood. In this paper, we will further examine how statistical learning modulates working memory, particularly focusing on how the modulation is subject to spatial constraints.

In pursuing these questions, we acknowledge the intellectual debt we owe to Glyn Humphreys, who, with his colleagues, made countless contributions to our current understanding of visual working memory and the representation of space. For working memory, his contributions include studies of its basic properties (Delvenne, Braithwaite, Riddoch, & Humphreys, 2002), the relationship between visual working memory and other cognitive processes/phenomena, including perception (Soto, Wriglesworth, Bahrami-Balani & Humphreys, 2010), attention (Soto et al., 2005; Soto, Hodsoll, Rotshtein & Humphreys, 2008), and visual marking (Olivers, Humphreys, Heinke, & Cooper, 2002; Watson, Humphreys & Olivers, 2003), as well as how visual working memory is characteristically impaired in neuropsychological patients (Duncan, Bundesen, Olson, et al., 2003; Riddoch, Humphreys, Blott, Hardy, & Smith, 2003). For the representation of space, or *spatial coding* (Humphreys, 1998), his work on hemispatial neglect and extinction helped to establish how distinct neural substrates control the allocation of attentional resources to the left vs. right portions of both space-based and object-based representations (Heinke & Humphreys, 2003; Riddoch & Humphreys, 1983). Additionally, his work in healthy adults has produced evidence for distinct processing resources in the left and right visual hemifields (Delvenne, Castronovo, Demeyere & Humphreys, 2009, 2011).

Informed by the work of Humphreys and others, we predicted that statistical learning would be limited in the ways that it can boost working memory performance. For example, we were interested in determining the influence of a phenomenon known as the *bilateral field advantage*. This refers to the finding, as discussed above (Delvenne, Castronovo, et al., 2009, 2011), in which objects presented between two hemifields (i.e., bilaterally) are more efficiently processed than the objects presented within a single hemifield (i.e., unilaterally; Alvarez & Cavanagh, 2005; Alvarez, Gill, & Cavanagh, 2012; Delvenne & Holt, 2012; Franconeri, Alvarez, & Cavanagh, 2013; Holt & Delvenne, 2015; Ludwig, Jeeves, Norman, & DeWitt, 1993; Störmer, Alvarez, & Cavanagh, 2014). A few studies have demonstrated this phenomenon specifically in the domain of working memory (Delvenne, 2005; Holt & Delvenne, 2014; 2015; Umemoto, Drew, Ester, & Awh, 2010). These effects are thought to be a consequence of the anatomical separation of the two hemispheres in the processing of our two visual hemifield representations (see Delvenne, 2012, for a review).

How might the bilateral field advantage limit the positive benefits of statistical learning? If we return to the paradigm of Umemoto, Scolari, et al. (2010), recall that items were tested in one display quadrant with greater frequency than in the other quadrants and that participants began to perform better for the test items in the high-probable quadrant. According to a strong version of the bilateral field advantage, known as *hemifield independence* (cf. Alvarez & Cavanagh, 2005), two totally separate pools of resources – in this case, working memory resources – are each devoted to one hemifield. Here, participants should only be able to boost their performance by prioritizing the resource pool allocated to the side containing the high-probable quadrant. While it would be advantageous to withdraw processing resources from locations in the opposite hemifield and reallocate them to the high-probable quadrant, hemifield

independence stipulates that this would not be possible. Therefore, we would predict any improved working memory performance in the high-probable quadrant to come at the expense only of the low-probable quadrant within the same hemifield. The two quadrants in the opposite hemifield should yield similar performance to one another.

Note that many studies do not report pure hemifield independence, including those of Delvenne (2005) and Umemoto, Drew, et al. (2010). Those studies showed an improvement in working memory capacity – but not a doubling of capacity (as predicted by pure hemifield independence) – when comparing between vs. within hemifield conditions. It is believed that visually crowded displays, in which multiple items within the same hemifield occupy the same receptive fields, increase the degree of hemifield independence observed (Umemoto, Drew, et al., 2010); in cases with fewer objects, results are more likely to show *semi-independent* hemifield effects. In such a scenario, we would predict perhaps some transfer of resources from the low-probable quadrants in the opposite hemifield to the high-probable quadrant; nevertheless, we would expect the largest effects of prioritization to occur within the hemifield containing the high-probable quadrant.

Beyond the predictions of the bilateral field advantage, another way in which statistical learning could be influenced by spatial constraints is via a *euclidian spatial coding scheme*, in which spatial distance from the high probable location predicts performance in the low probable locations. This account is drawn from work like the classic Kosslyn mental imagery study (1973), in which subjects took longer to confirm details of a remembered image the further these details were from an initial focus point. Subsequent studies of working memory have shown that increased distance between to-be-memorized items led to poorer performance (Awh, Jonides, & Reuter-Lorenz, 1998; Bays & Husain, 2008).

All told, we sought to determine if statistical learning would be influenced by the bilateral field advantage, euclidian coding, or any other unanticipated spatial constraint. In three experiments, we asked participants to perform a working memory task in which one rotated T stimulus was presented in each quadrant. Then, after a working memory delay, the participants had to report the orientation of one of the four items. Like Umemoto, Scolari, et al. (2010), we manipulated the frequency of the probed target locations, so that participants would learn to prioritize high-probable quadrants to boost their working memory performance accordingly.

To assess working memory performance, we analyzed both accuracy and response time (RT). While the earliest models of working memory, such as Sternberg's serial scanning model (Sternberg, 1966), hinged on RT phenomena, most studies of visual working memory have focused on accuracy data. This is because the more recent studies have primarily sought estimates of memory capacity, which do not consider RT (Cowan, 2001; Pashler, 1988). That said, it has been argued that RT provides equally valuable data in evaluating the quality of memory representations (Gilchrist & Cowan, 2014; Jensen, 2006; Luce, 1986; Pearson, Raškevičius, Bays, Pertzov, & Husain, 2014; Posner, 1978).

To preview our results, we found some evidence that euclidian coding interacted with statistical learning effects in Experiment 1. In Experiments 1 and 2, we found what we believed to be support for a bilateral field advantage interacting with statistical learning. However, to our surprise, the results of Experiment 3 suggested that a *horizontal advantage*, in which working memory is better for two horizontally adjacent items than two vertically adjacent items, could explain the apparent hemifield effects. We conclude first and foremost that statistical learning is indeed bounded by spatial constraints. Further, at least in tasks like ours, a horizontal advantage may explain apparent hemifield effects.

Experiment 1

In this first experiment we asked participants to remember four items in a memory array, distributed across the four display quadrants (i.e., upper-right, upper-left, lower-left, and lower-right). After these items disappeared, we implemented a partial report procedure (Sperling, 1960; Luck & Vogel, 1997), in which a retrospective cue pointed to one location; participants had to report the orientation of the item that was initially presented in the sample array, at the cued location. For each participant, we assigned one quadrant as the “high-probable” quadrant, which we tested more frequently than any of the other three “low-probable” quadrants. There were three types of low-probable quadrants, based on their relative positions with respect to the high-probable quadrant: within-hemi-adjacent, across-hemi-adjacent, and across-hemi-diagonal (we will henceforth refer to these as within-adjacent, across-adjacent and across-diagonal, respectively).

We expected to observe the best performance for the item in the high-probable quadrant, like Umemoto, Scolari, et al. (2010). Additionally, we also expected to observe differences among the three low-probable quadrants. A bilateral field advantage would predict that, in order to boost processing of the high-probable quadrant, participants should withdraw more resources from the within-adjacent quadrant compared to the equidistant across-adjacent quadrant. According to a distance account, we should see the worst performance in the across-diagonal quadrant, which is farthest from the high-probable location.

Method

Participants

Forty individuals participated in Experiment 1 (18 females; mean age = 19.6 years). All participants reported normal or corrected-to-normal visual acuity and normal hearing. The Ohio State University IRB approved this protocol. Participants received course credit or monetary compensation (\$10/hour).

Apparatus and Stimuli

Participants were tested in a dimly lit room. Stimuli were presented on a 24" LCD monitor and generated using MATLAB (www.mathworks.com), with Psychtoolbox extensions (Brainard, 1997; Pelli, 1997). In the working memory task, placeholder displays contained four circles (diameter: 2.55°; all visual angles are calculated for a typical viewing distance of 60 cm), each of which was centered within one of the four quadrants (eccentricity: 3.61° from center), on a gray background. Memory displays contained four differently rotated white Ts, each at a unique canonical orientation (i.e., 0°, 90°, 180°, and 270°), on a gray background. The spatial placement of each orientation was shuffled randomly on each trial. Each T subtended 1.02°x1.02° and was centered in the location that had been occupied by a placeholder. Retrospective cue displays contained a white triangle (0.05°) in the center of the screen indicating the location of T to be reported (i.e., the target). Correct responses were followed by a green fixation along with a three “chirp” sequence lasting 300ms; incorrect responses were followed by a red fixation along with a low-tone buzz for 200ms and a 1 sec blank screen to discourage incorrect responses.

Design

During the training phase (epochs 1-4; 3 blocks per epoch; 36 trials per block), the cue pointed more frequently to one quadrant (50%; High-probable quadrant) than any of three other quadrants (16.7%; Low-probable quadrants, including within-adjacent, across-adjacent, and across-diagonal locations). The high-probable location was consistent for the duration of the training phase and counterbalanced across participants. During the testing phase (epochs 5-6), the cue pointed to each quadrant with equal frequency (25% per quadrant; see Figure 1A).

Procedure

Partial report working memory task.

Participants initiated each working memory trial by clicking on a small white square (.51°x.51°), which appeared in the center of screen. After the click, the placeholder display appeared for 500 ms, and then the memory display that contained four rotated Ts appeared for 200 ms. The Ts were then removed for a 700 ms retention period. Next, participants were shown the cue in the center of screen for 100 ms. Participants reported whether the cued T was orientated at 0°, 90°, 180°, or 270°, using the up, right, down, and left arrow keys, respectively, on a standard keyboard, upon response, the display was removed, and the visual and auditory feedback were provided. Participants completed 24 practice trials before advancing to the main trials (Figure 1B). They were encouraged to respond both accurately and quickly, but with a greater emphasis on the former.

Recognition test

After the working memory task, we assessed explicit awareness of the probability manipulation, first by asking participants to self-report whether they thought the target was

equally likely to appear anywhere on the display. Regardless of their answer, they were told that the target was more often located in one quadrant than the others. We then tested explicit knowledge directly by asking participants to select the quadrant that they best guessed to be the high-probable one.

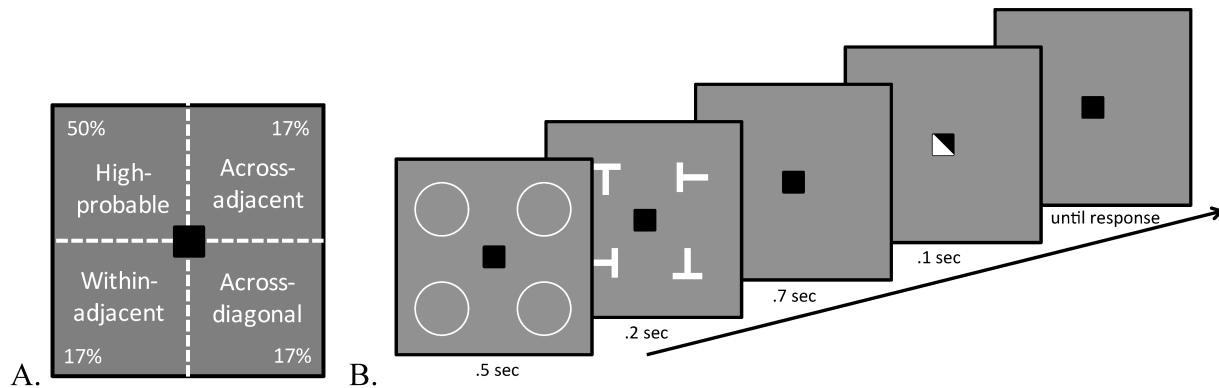


Figure 1. A. Design. The cue pointed more frequently to the High-probable quadrant (50%) than to any of other three quadrants (17% each). B. Procedure. Participants were asked to remember four randomly rotated Ts and were subsequently asked to report the orientation of the T that had been presented in the cued location.

Results and discussion

Accuracy.

Response accuracy for the four quadrant types is plotted, by epoch, in Figure 2A. An analysis of variance (ANOVA) was first carried out on the training phase data, including quadrant type (high-probability, within-adjacent, across-adjacent, and across-diagonal) and epoch (1–4) as within-subject factors. Results revealed significant main effects of both quadrant type, $F(3, 117) = 5.31, p < .005, \eta^2 = .12$, and epoch, $F(3, 117) = 20.81, p < .001, \eta^2 = .35..$ The two-way interaction between quadrant type and epoch was also significant, $F(9, 351) = 1.99, p < .05, \eta^2 = .05.$

We ran a second ANOVA on the testing phase data, again including quadrant type \times epoch (5-6). Results again showed two significant main effects, $F(3, 117) = 8.00, p < .001, \eta^2 = .17$ for quadrant type; $F(1, 39) = 6.27, p < .05, \eta^2 = .14$. No significant interaction was found, $F < 1$.

We next more closely compared the individual quadrant types. We collapsed across all epochs (see Figure 2B), and we tested each of these for statistical significance, using paired-samples t-tests with a Holm-Bonferroni correction for familywise error (Holm, 1979). Results showed greater performance for the high-probable quadrant than across-diagonal quadrant, $t(39) = 3.48, p_{adjusted} = 0.006, d = .58$. Numerically, performance was also greater for the high-probable quadrant than the within-adjacent quadrant, although this was not significant, $t(39) = 2.05, p_{adjusted} = 0.188$. Importantly, however, performance for the high-probable quadrant was not reliably different from the across-adjacent quadrant, $t(39) = .11, p_{adjusted} = 0.91$. Additionally, performance for the across-adjacent quadrant was not reliably different from the within-adjacent quadrant, $t(39) = 1.80, p_{adjusted} = 0.24$, but it was significantly greater than the across-diagonal quadrant, $t(39) = 3.25, p_{adjusted} = .01, d = .54$. The accuracy scores for the within-adjacent and across-diagonal quadrants did not reliably differ, $t(39) = 1.65, p_{adjusted} = .21$.

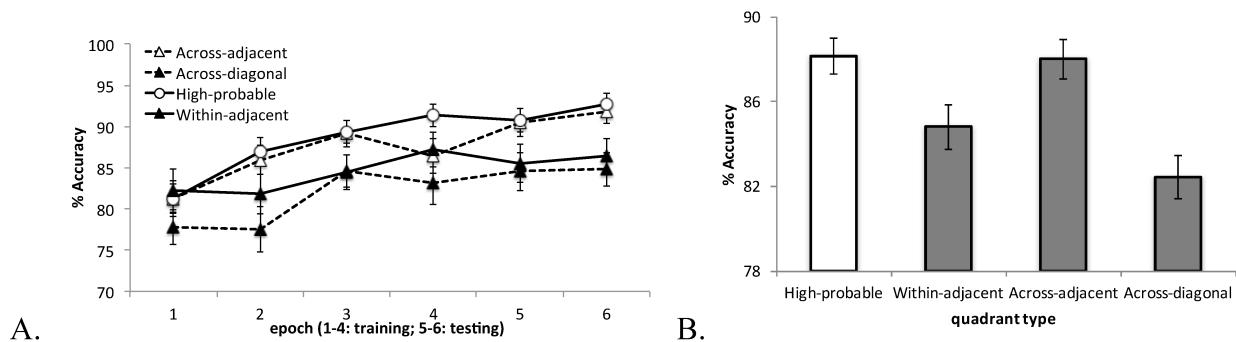


Figure 2. Accuracy in Experiment 1. A. Experiment 1's visual working memory performance as a function of the target's quadrant and epoch. B. Overall performance after collapsing all epochs. Error bars show ± 1 within-subjects standard error of the mean.

Response Time (RT).

Correct responses were analyzed after removing trials with RTs slower than 3-standard deviations above the mean and faster than 250 ms, which eliminated 1.5% of trials. Mean RTs for the remaining trials are plotted in Figure 3.

As in the accuracy data, an analysis of Quadrant Type \times Epoch (1-4) ANOVA revealed main effects of both quadrant type and epoch, $F(3, 117) = 10.70, p < .001, \eta p^2 = .22$ and $F(3, 117) = 36.08, p < .001, \eta p^2 = .48$, respectively. Also, the two-way interaction between quadrant type and epoch was marginally significant, $F(9, 351) = 1.84, p = .066, \eta p^2 = .04$. During testing (5-6 epoch), A Quadrant Type \times Epoch (5-6) ANOVA showed a significant main effect of quadrant type, $F(3, 117) = 7.89, p < .001, \eta p^2 = .17$, but not for epoch, $F < 1$. No significant interaction was found, $F < 1$. These results essentially mirror our accuracy analysis (see Figure 3A).

We next took a closer look at quadrants, again collapsing across all epochs (see Figure 3B). An ANOVA across the four quadrant types was significant, $F(3, 117) = 8.68, p < .001, \eta p^2 = .18$. Pairwise t-tests showed that RTs to the target in high-probable quadrant was faster than that in the within-adjacent, across-adjacent, and across-diagonal quadrants, $t(39) = 3.48, p_{adjusted} = 0.005, d = .59, t(39) = 3.01, p_{adjusted} = 0.02, d = .50, t(39) = 3.80, p_{adjusted} < .001, d = .62$, respectively. Importantly, RT in the across-adjacent quadrant was marginally faster than that in within-adjacent quadrant, $t(39) = 2.01, p_{adjusted} = .10, d = .41$, as well as that in the across-diagonal quadrant, $t(39) = 2.40, p_{adjusted} = .066, d = .44$. RTs in within-adjacent and across-diagonal quadrants did not differ, $t(39) = .57, p_{adjusted} = .565$. Numerically, these results mirrored

the accuracy data, with the one exception being better performance in the high probable than across-adjacent condition. Moreover, the differences among conditions were generally statistically more reliable in RT than they were in accuracy.

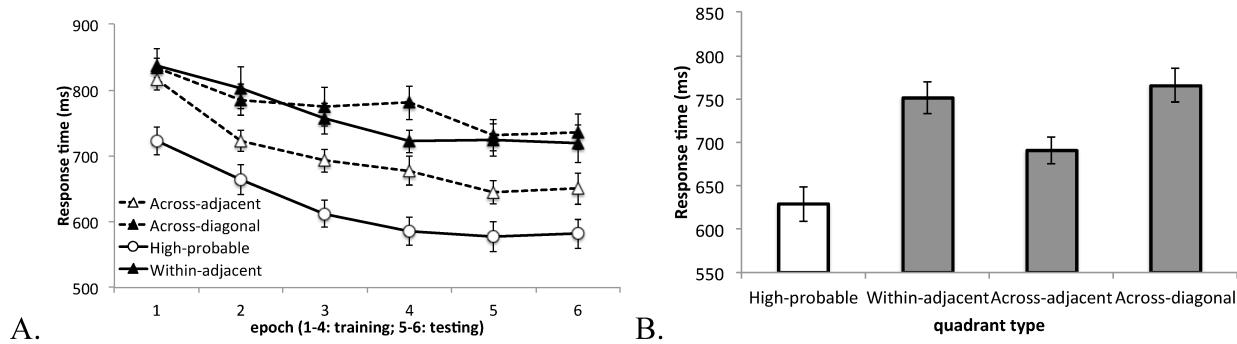


Figure 3. RT in Experiment 1. A. Experiment 1's visual working memory RT as a function of the target's quadrant and epoch. B. Overall RT after collapsing all epochs. Error bars show ± 1 within-subjects standard error of the mean.

Recognition.

Twenty-seven of the 40 participants reported that the target was not evenly distributed across four quadrants. Also, they successfully chose the most probable quadrant across four quadrants (high-probable quadrant: 87.5%, across-adjacent quadrant: 2.5%, within-adjacent quadrant: 7.5%, diagonal quadrant: 2.5%; chance: 25%), $\chi^2(3, N = 40) = 83.6, p < .001$. This shows that participants were, to some extent, explicitly aware of the statistical learning manipulation. Interestingly, however, they did not choose across-adjacent quadrant more often than within-adjacent quadrant (2.5% vs. 7.5%). While this could reflect floor effects across the low-probability quadrants, this shows that the numerically better performance in the across-adjacent quadrant, in both accuracy and RT, did not correspond to any belief that it was cued more frequently than the other low-probability quadrants.

Discussion

This experiment returned several findings. First, the statistical learning manipulation was effective, leading to greater working memory performance at the high-probable quadrant compared to the other quadrants, replicating previous work (Brady et al., 2009; Olson et al., 2005; Umemoto, Scolari, et al., 2010). Second, the prioritization of the high-probable quadrant produced clear distance effects, in which the worst accuracy and slowest RTs emerged from the across-diagonal quadrant. Nevertheless, the results were somewhat statistically weak, as the high probable quadrant was not reliably more accurate than the within-adjacent quadrant.

Was there a hemifield effect? Pure hemifield independence would have predicted prioritization of working memory resources only within a single hemifield. However, the across-adjacent and across-diagonal conditions produced differential performance measures, in both accuracy and RT. Support also fell short for semi-independence (i.e., a bilateral field advantage); while performance in the across-adjacent quadrant was numerically superior to the within-adjacent quadrant in both accuracy and RT, neither of these effects were statistically reliable.

Experiment 2

One limitation of Experiment 1 was that we may not have placed great enough demands on prioritizing working memory resources. That is, we only incentivized the prioritization of one quadrant, and if participants had spare capacity beyond that, we had little control over how they might have used it. In Experiment 2, we created two high probable quadrants for each participant. Our intent in having participants prioritize two quadrants was to create a greater disparity in both accuracy and RT for high-probable vs. low-probable quadrants.

Given that we already acquired evidence for a distance effect, our present goal was to now specifically seek evidence for hemifield effects. To do this, we assigned each participant to either the Between-hemifield or Within-hemifield group. The former group had one high-probable quadrant in one hemifield and the other in the adjacent quadrant in the other hemifield; the latter group had both high probable quadrants in the same hemifield (see Figure 4).

By a pure hemifield independence account, working memory resources cannot be transferred from one hemifield to another. In the case of the within-hemifield group, the high probable quadrants cannot be boosted by borrowing resources from the two low-probable quadrants in the other hemifield. Therefore, a pure hemifield independence account predicts no difference in performance between the high and low probable quadrants for this group. A semi-independent bilateral field advantage would allow some sharing across hemifields and would thus allow for some performance benefits in the high-probable vs. low-probable quadrants for the within-hemifield group. Both the pure hemifield independence and semi-independent bilateral field advantage accounts predict the same thing for the across-hemifield group: specifically, there should be greater performance in the high-probable than low-probable quadrants, since resources can be shifted within hemifields. Finally, when comparing the two groups, all versions of the bilateral field advantage – i.e., both pure hemifield independence and semi-independence – predict that the working memory improvement in the high-probable vs. low-probable quadrants should be greater for the across-hemifield group than for the within-hemifield group.

Method

The method was identical to Experiment 1, except where noted below.

Participants

Forty-eight individuals participated in Experiment 2; 24 participants were randomly assigned to each group (Between-hemifield group: 11 females, mean age = 18.8 years; Within-hemifield group: 13 female, mean age = 18.9).

Design

Instead of having one high-probable quadrant, there were two high-probable quadrants (each being cued 33.3% of trials) and two low-probable quadrants (each cued 16.7% of trials; see Figure 5). The two high-probable quadrants were always adjacent to one another. For the between-hemifield group, one high-probable quadrant was placed in each hemifield; we counterbalanced across participants whether these were both in the upper or lower portion of the display. For the within-hemifield group, the two high-probable quadrants were both placed in the same hemifield; we counterbalanced across participants whether these were both on the left or right side of the display.

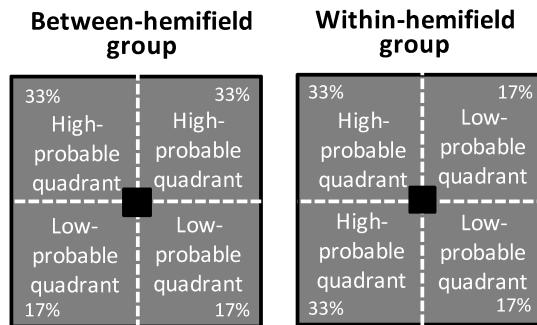


Figure 4. Design of Experiment 2. There were two high-probable quadrants (each cued 33% of trials) and two low-probable quadrants (each cued 17% of trials). High probable quadrants were either placed in different hemifields (Between-hemifield group) or in the same hemifield (Within-hemifield group).

Procedure

The procedures for the Working Memory task and Recognition Test were the same as in Experiment 1.

Results and discussion

Accuracy.

Response accuracy during training for the quadrant types and groups are plotted, by epoch, in Figure 5A. A group as between-subject factor \times quadrant type (high-probable quadrants and low-probable quadrants) \times epoch (1-4) ANOVA revealed significant main effects of both quadrant type, and epoch, $F(1, 46) = 10.13, p < .005, \eta p^2 = .18$; $F(3, 138) = 12.75, p < .001, \eta p^2 = .22$, respectively. Importantly, we found a significant interaction between group and quadrant type, $F(1, 46) = 8.08, p < .01, \eta p^2 = .15$. Other effects were not significant (smallest $p = .12$).

We found similar results in the testing phase (epochs 5-6). A Group (between-subject) \times Quadrant type (within-subject) \times Epoch (within-subject) ANOVA showed a significant main effect of quadrant type, $F(1, 46) = 12.94, p = .001, \eta p^2 = .22$. Again, importantly, quadrant type and group significantly interacted, $F(1, 46) = 6.06, p < .05, \eta p^2 = .12$. Other effects were not significant (smallest $p = .18$).

In both training and test, the main effects of quadrant type confirm robust statistical learning, but this was qualified by the group \times quadrant interactions, which showed that the expression of learning was contingent on the hemifield placement of the high-probable quadrants. To get a closer look at the quadrant effect within each group, we next collapsed across all epochs (see Figure 5B), and computed pairwise t-tests. Results confirmed a significant quadrant effect for the between-hemifield group, $t(23) = 3.81, p = .001, d = .98$, but no difference

for the within-hemifield group, $t(23) = .25, p > .8$. These results are consistent with the interpretation that when both high-probable quadrants are within hemifield, the performance cannot be improved, since additional capacity cannot be borrowed from the other hemifield; yet, when each hemifield has one high-probable quadrant, the capacity within each hemifield can be prioritized toward the high-probable quadrant. These results are in line with the bilateral field advantage account.

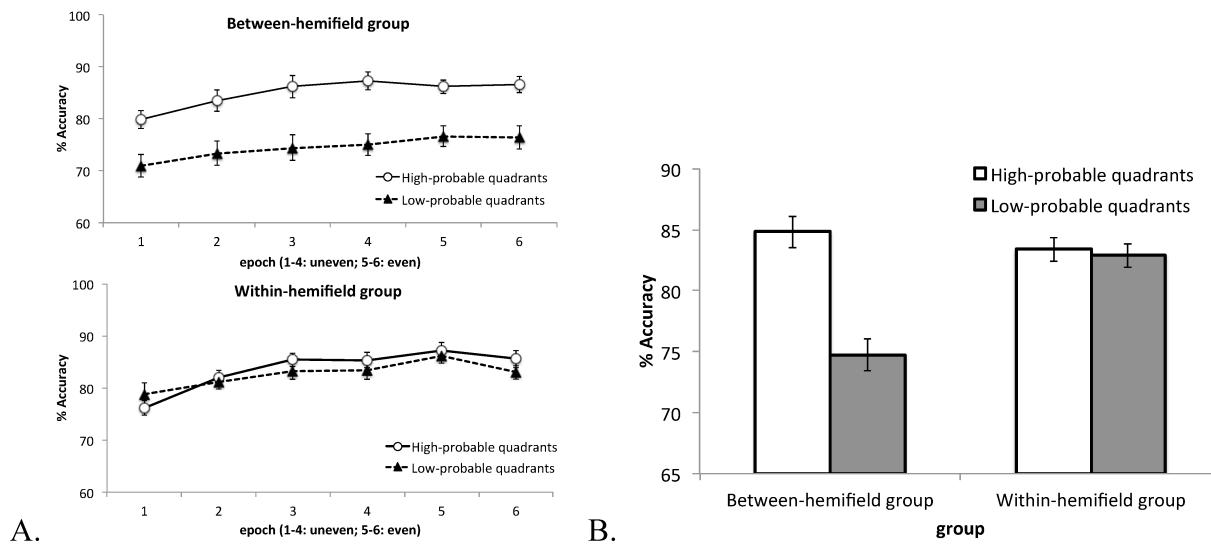


Figure 5. Accuracy in Experiment 2. A. Experiment 2's visual working memory performance as a function of the target's quadrant and epoch in two groups (top: Between-hemifield group; bottom: Within-hemifield group). B. Overall performance after collapsing all epochs. Error bars show ± 1 within-subjects standard error of the mean.

RT.

Trimming removed 1.4% of trials. Mean RTs for the two quadrant types across epoch are shown in Figure 6A. For the training phase data (epochs 1-4), the Group x Quadrant Type \times Epoch ANOVA revealed main effects of quadrant type and epoch, $F(1, 46) = 7.71, p < .01, \eta^2 = .14$; $F(3, 138) = 22.28, p < .001, \eta^2 = .33$. Other effects were not significant (smallest $p = .25$). Unlike the accuracy data, we did not find a significant interaction between group and quadrant type, $F(1, 46) = 1.16, p > .2$.

Testing phase results (epochs 5-6) were similar to those of training. The Group x Quadrant Type \times Epoch ANOVA revealed a main effect of quadrant type, $F(1, 46) = 6.61, p < .02, \eta p^2 = .13$, and marginally significant main effect of epoch, $F(1, 46) = 2.98, p = .091, \eta p^2 = .06$. Also, the quadrant type \times epoch interaction was significant, $F(1, 46) = 6.26, p < .02, \eta p^2 = .12$. This resulted from a larger effect of quadrant in epoch 6 than epoch 5, although we do not have any clear prediction for the effect to increase over time, especially since the probability manipulation was removed. At the very least, we can say that the learning effect did not subside during test. Again, there was no significant interaction between group and quadrant type, $F(1, 46) = 1.04, p > .3$. Further, the main effect of group was significant, $F(1, 46) = 4.14, p < .05$, with faster RTs in the within-hemifield group. Other effects were not significant (smallest $p = .31$).

We next collapsed across all epochs and looked more closely at the effect of quadrant within each group (see Figure 6B). For the between-hemifield group, RTs to the high probable quadrants were marginally faster than to the low-probable quadrants, $t(23) = 2.00, p = .059, d = .43$. Interestingly, unlike in the accuracy data, the within-hemifield group also showed a marginally significant quadrant effect, $t(23) = 1.89, p = .071, d = .39$. The similar effect size across the two groups explains why we failed to see any significant interactions between group and quadrant type. We note that, when both groups were combined in the initial analysis above, the quadrant effect was significant, whereas it was only marginal in each group when analyzed separately. We assume this was due to the reduction in statistical power – due to smaller respective sample sizes – for each of these tests.

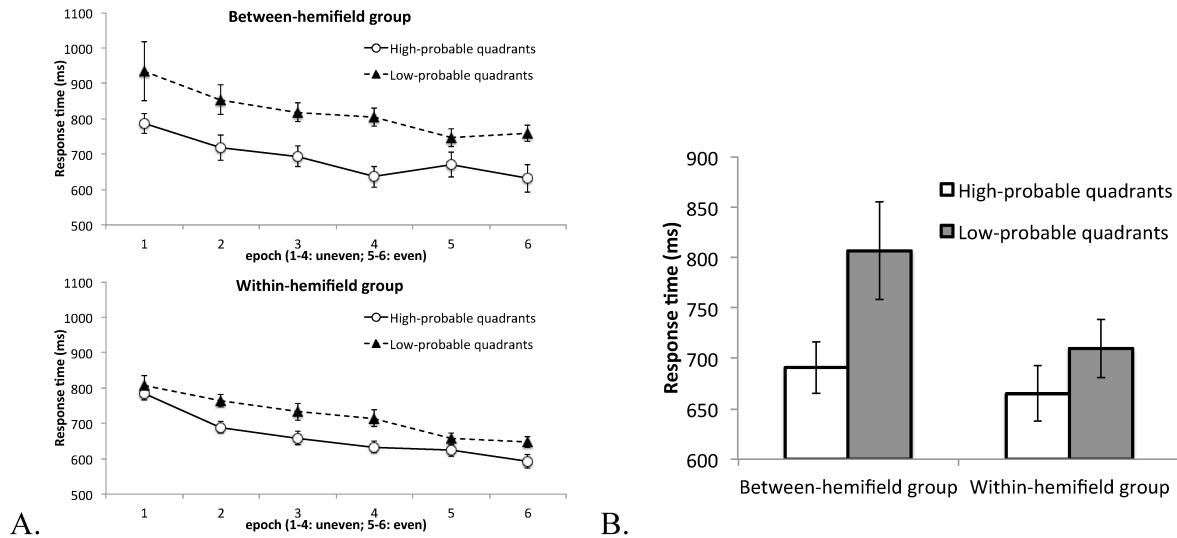


Figure 6. RT in Experiment 2. A. Experiment 2's visual working memory RT as a function of the target's quadrant and epoch in the two groups. B. Overall RT after collapsing all epochs. Error bars show ± 1 within-subjects standard error of the mean.

Recognition.

For the between-hemifield group, nine participants among 24 participants reported that the target was not evenly distributed across four quadrants. Also, participants chose one of the high-probable quadrants at an above-chance rate (87.5%; chance: 50%), $X^2(1, N = 24) = 13.5, p < .001$. For the within-hemifield group, 12 participants among 24 participants reported the target was not evenly distributed across four quadrants. Also, 66.7% of participants chose one of the high-probable quadrants, albeit not significantly so, $X^2(1, N = 24) = 2.67, p = 0.10$. These results suggest that the two groups differed in their explicit knowledge of the statistical regularities; however, a direct comparison between the two groups' choices showed no significant difference, $X^2(3, N = 48) = 2.95, p = 0.22$. Thus it is not clear whether the between-hemifield group, which demonstrated a greater behavioral statistical learning effect, was more prone to become explicitly aware of the manipulation.

Discussion

Overall, this experiment returned several findings of note. First, the quadrant by group interaction in accuracy suggested the existence of at least some degree of independent working memory resources across the two hemifields. At the very least, we have identified a clear spatial constraint in how statistical learning can benefit working memory. Based on the accuracy data alone, in which there was no advantage for high-probable over low-probable quadrants in the within-hemifield group, we might conclude pure hemifield independence. However, the statistically similar RT effects of quadrant in the two groups – with no group x quadrant type interaction – contradicts the pure hemifield account and instead favors semi-independence.

One additional intriguing pattern we observed was a tendency toward greater overall performance in the within-hemifield group than the between-hemifield group. For the within-hemifield group, this was manifested, numerically, as a selective decrease in accuracy as well as RT slowing in the low-probable condition. However, the overall performance difference between groups was not robust, as we only saw a significant main effect of group in the test phase RT. Nevertheless, the pattern is counterintuitive; why should the one group that is able to exploit the probability manipulation – the between-hemifield group – perform worse overall? We can speculate that participants could have exploited the probability information not to improve overall behavior but instead to focus and reduce overall resource expenditure. Note that our ANOVAs, in computing the main effect of group, collapsed across quadrants in such a way that gave equal weight to the means for low and high probable conditions; yet, participants actually saw twice as many high probable targets than low probable ones. That is, net accuracy and RT across the full experiment was not equal to the average of low and high probable target means; rather, these performance measures were dominated by the high-probable trials.

Therefore, the true performance difference across groups was smaller than what the main effects of group – which were already largely non-significant – imply.

Experiment 3

In this third experiment, we pursue one additional, critical issue, in which we question whether our results reflect a *horizontal advantage* instead of a true hemifield effect. Consider that, in Experiment 2, the two high probable quadrants were horizontally adjacent in the between-hemifield group, while they were vertically adjacent in the within-hemifield group. Rather than showing a bilateral advantage, perhaps the participants were better at encoding and/or maintaining horizontally vs. vertically adjacent objects. Similarly, in Experiment 1, the numerical advantage of the across-adjacent over the within-adjacent quadrant could also be explained by a horizontal advantage.

Previous researchers exploring hemifield effects have taken steps to address this concern, typically by shifting the displays such that all objects were then presented in the same hemifield, whether vertically or horizontally aligned (e.g., Alvarez & Cavanagh, 2005; Delvenne, Kaddour & Castronovo, 2011; Holt & Devlenne, 2014). These studies all found no differences for vertical vs. horizontal conditions, concluding that the observed bilateral advantages in their main experiments were due to separating objects across the visual hemifield.

In this experiment, we attempted a conceptually similar approach, although instead of shifting our displays to the left or right – and introducing variation to the objects' eccentricities – we used the same displays as in Experiment 2 but chose diagonal high-probable quadrants. That is, each participant had either upper-left and lower-right or lower-left and upper-right pairings assigned as their high probable quadrants. Thus, the two high-probable quadrants were always in

different hemifields but were not horizontally aligned. By the bilateral field advantage account, we should expect greater performance in the high-probable than low probable quadrants, as seen in the between-hemifield group of Experiment 2. By the horizontal advantage account, we should expect no difference in performance for the high-probable vs. low-probable quadrants, as seen in the within-hemifield group of Experiment 2.

Method

The method was identical to Experiment 2, except where noted below.

Participants

Twenty-four individuals from The University of California, Davis, participated in Experiment 3 (18 females; mean age = 19.7 years). All participants reported normal or corrected-to-normal visual acuity and normal hearing. The University of California, Davis IRB approved this protocol. Participants received course credit.

Apparatus and Stimuli

Participants were tested in a dimly lit room. Stimuli were presented on a 24" LCD monitor.

Design

Instead of having two high-probable quadrants adjacent to one another, they were positioned diagonally (e.g., upper-right and lower-left). We counterbalanced across participants whether these were upper-right and lower-left quadrants, or upper-left and lower-right quadrants.

Procedure

The procedures for the Working Memory task and Recognition Test were the same as in Experiments 1 and 2.

Results and discussion

Accuracy.

Response accuracy for the quadrant types and groups are plotted, by epoch, in Figure 7A. A Quadrant type (high-probable quadrants and low-probable quadrants) x Epoch (1-4) ANOVA revealed a significant main effect of epoch, $F(3, 69) = 4.77, p < .005, \eta p^2 = .17$, but neither a significant main effect of quadrant nor an interaction between quadrant and epoch, $F(1, 23) = 2.64, p > .1, F < 1$, respectively.

In the testing phase (epochs 5-6), a Quadrant type x Epoch ANOVA showed neither main effect of quadrant type nor epoch, $F(1, 23) = 1.82, p > .1, F < .1$, but a significant interaction between two factors, $F(1, 23) = 5.70, p < .05, \eta p^2 = .20$. This interaction represents a very slight crossover effect between epochs 5 and 6. Given the overall lack of a reliable quadrant effect, there is no clear interpretation of this interaction, and we expect it could have been a Type I error.

We next collapsed across all epochs (see Figure 7B), and a pairwise t-test confirmed no overall quadrant effect, $t(23) = 1.25, p > .2$.

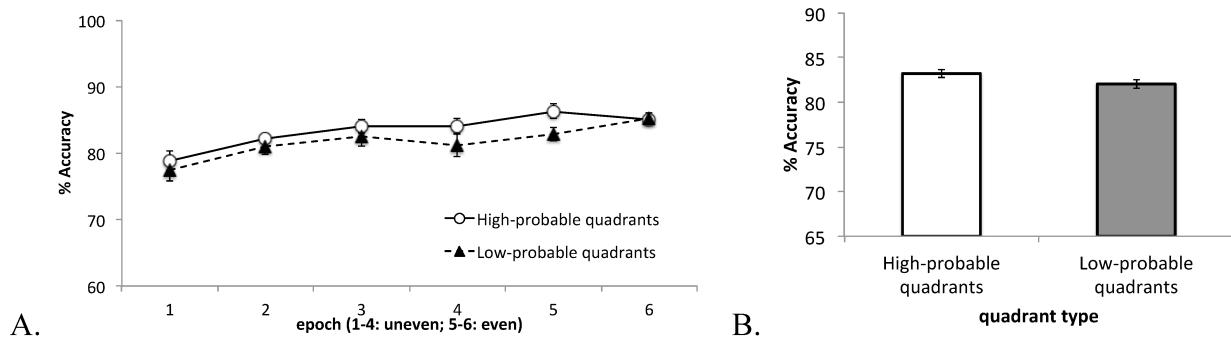


Figure 7. Accuracy in Experiment 3. A. Experiment 3's visual working memory performance as a function of the target's quadrant and epoch. B. Overall performance after collapsing all epochs. Error bars show ± 1 within-subjects standard error of the mean.

RT.

Trimming removed 2.0% of trials. Mean RTs for the two quadrant types across epoch are shown in Figure 8A. For the training phase data (epochs 1-4), similar with Experiment 2, the Quadrant Type \times Epoch ANOVA revealed main effects of quadrant type and epoch, $F(1, 23) = 9.93, p < .005, \eta p^2 = .30$; $F(3, 69) = 30.28, p < .001, \eta p^2 = .57$, but no significant interaction between quadrant type and epoch, $F < 1$.

In the testing phase (epochs 5-6), the Quadrant Type \times Epoch ANOVA revealed a marginally significant main effect of quadrant type, $F(1, 46) = 4.08, p = .055, \eta p^2 = .15$, but no main effect of epoch, or interaction, $Fs < 1$.

We next collapsed across all epochs and looked at the overall effect of quadrant, in similar fashion to the within- and between-hemifield groups of Experiment 2 (see Figure 8B). The high probable quadrants showed a marginally faster RT than the low-probable quadrants, $t(23) = 2.05, p = .052, d = .44$.

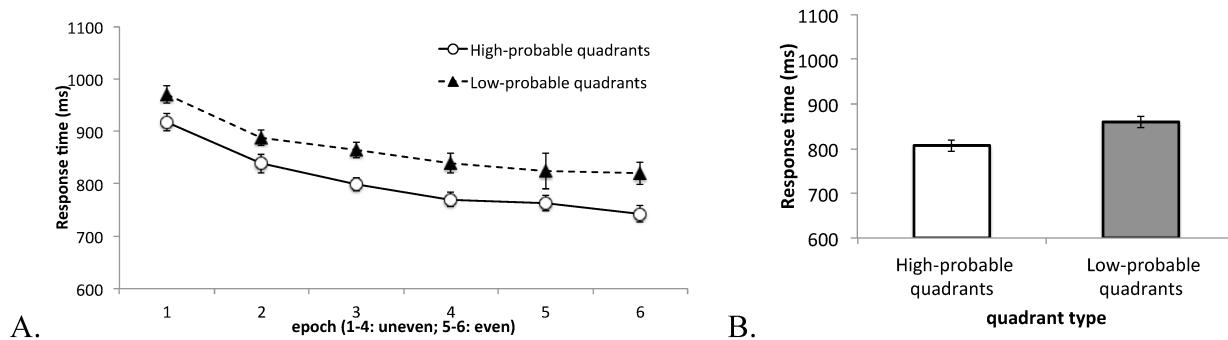


Figure 8. RT in Experiment 3. A. Experiment 3's visual working memory RT as a function of the target's quadrant and epoch. B. Overall RT after collapsing all epochs. Error bars show ± 1 within-subjects standard error of the mean.

Cross-experiment comparisons

The evidence for a bilateral field advantage seems much weaker in this experiment than it did in the between-hemifield group of Experiment 2. In fact, the Experiment 3 data look quite similar to that of the within-hemifield group of Experiment 2. Next, we statistically compare the Experiment 2 and Experiment 3 results.

For accuracy, a Group (three groups; between-subject) \times Quadrant type (two quadrants; within-subject) ANOVA revealed a significant main effect of quadrant type, $F(1, 69) = 11.85, p = .001, \eta^2 = .15$, and a significant interaction, $F(2, 69) = 7.38, p = .001, \eta^2 = .18$, but no group effect, $F < 1$. To follow up the quadrant-type interaction, we conducted two separate cross-experiment ANOVAs: 1) diagonal group (Experiment 3) vs. between-hemifield group (Experiment 2) and 2) diagonal group (Experiment 3) vs. within-hemifield group (Experiment 2). Recall that we previously compared the within- and between-hemifield groups in our analysis of Experiment 2. For the diagonal vs. the between-hemifield group, we found a significant main effect of quadrant type, $F(1, 46) = 16.06, p < .001, \eta^2 = .26$, and importantly, we found a significant interaction, $F(1, 46) = 10.05, p < .005, \eta^2 = .18$. There was no group difference, $F <$

1. In contrast, we did not find any significant effects from the ANOVA on the diagonal vs. within-hemifield group, $Fs < 1$.

In RTs, there was a significant main effect of quadrant type, $F(1, 69) = 9.82, p < .005$, $\eta p^2 = .13$, and a significant main effect of group, $F(2, 69) = 5.60, p < .01, \eta p^2 = .14$, but the two factors did not interact significantly, $F < 1$. This result reflects the similar effect sizes of quadrant in all three groups.

Taken together, these results confirm that the diagonal positioning of the high-probable locations in Experiment 3 produced results closely matching those of the within-hemifield group of Experiment 2. This suggests that a horizontal advantage largely explained the strong quadrant effect of the between-hemifield group in Experiment 2.

Recognition.

Thirteen participants among 24 participants reported that the target was not evenly distributed across four quadrants. Also, participants chose one of the high-probable quadrants at an above-chance rate (83.3%; chance: 50%), $X^2(1, N = 24) = 10.7, p = .001$. This robust explicit knowledge contrasts with the relatively weak behavioral advantages for quadrant shown during the main task. This suggests a dissociation between the ability to exploit incidentally acquired statistical information and to acquire explicit knowledge of such information.

General discussion

We are able to maintain internal representations of only few items at the same time, even when the items are very simple, such as colors or shapes. Therefore, other cognitive functions

such as statistical learning help to increase our performance by focusing on the items most likely to be task relevant. As has been previously shown, we found that statistical learning can robustly guide working memory prioritization (Brady, et al., 2009; Olson, et al., 2005; Umemoto, Scolari, et al., 2010). However, we found here that such learning was subject to spatial constraints.

We initially hypothesized that we would find a bilateral field advantage – expressed as either total hemifield independence or semi-independence. Indeed, the results of Experiment 1 were consistent with a bilateral field advantage, although not robustly so. Stronger apparent evidence came from Experiment 2. When we placed two high-probable quadrants in one hemifield and two low-probable quadrants in the other hemifield (i.e., for the within-hemifield group), we found no accuracy advantage for the high-probable quadrants. It would have been advantageous for participants to transfer spare memory capacity from low-probable locations in one hemifield to high probable locations in the other. This is especially the case given that capacity is limited and performance is not at ceiling. Yet, when it was possible to transfer such resources within hemifields, our participants did not hesitate to do so: in the between-hemifield group, in which one high-probable quadrant was placed within each hemifield, we found robust statistical learning effects on accuracy. The significant RT benefit for high-probable vs. low-probable quadrants in the within-hemifield group contradicted a pure hemifield independence account, which predicted no performance difference between the two hemifields. Overall, our support for the bilateral field advantage was consistent with many other studies, including several with working memory that had not used a statistical learning manipulation (Delvenne, 2005; Holt & Delvenne, 2014; 2015; Umemoto, Drew et al, 2010).

Nevertheless, the results of Experiment 3 force a total reinterpretation of our data. In this last experiment, the bilateral field advantage disappeared when we placed one high probable

location in each hemifield -- but in diagonal positions, so that they were not horizontally adjacent to one another. We did observe a small RT benefit in the high probable condition here, but this benefit was no greater than that seen in the within-hemifield group of Experiment 2 (which could not have arisen from a bilateral field advantage).

We can only speculate as to why we saw a horizontal advantage but no bilateral field advantage in this study, especially given the previous demonstrations of the latter in working memory tasks that did not use a statistical learning manipulation. One key difference between our study and the previous ones, brought on by the nature of our statistical learning manipulation, is that our high-probable locations remained the same on every trial. Therefore, participants had extended practice in repeatedly prioritizing these display locations. In contrast, the studies by Delvenne and colleagues (Delvenne, 2005; Holt & Delvenne, 2014; 2015) and by Umemoto, Drew, et al. (2010) required trial-by-trial shifting of the locations to be stored in memory. It is possible that the repeated nature of our task reduced resource demands and overcame the hemifield constraints observed by others, leaving only a horizontal advantage.

Horizontal advantages have often been reported in the broader literature on attention and perception, including studies on texture segregation (Ben-Shahar, Scholl & Zucker, 2007), object-based attention (Marino & Scholl, 2005), the Simon effect (Nicoletti & Umiltà, 1984), saccadic eye movements (Goldring & Fischer, 1997), and peripheral letter recognition (MacKeben, 1999), among other phenomena. Such horizontal effects have been attributed to the typically broader expanse of behaviorally relevant information along the horizontal meridian than the vertical one, and, in Western cultures, to lifelong experience in reading horizontally (Abed, 1991). That said, many studies reporting horizontal effects presented stimuli spanning the left and right visual hemifields, so it is not always clear whether such effects represent

bilateral or horizontal advantages (see, e.g., Greenberg et al., 2014). Overall, our current results could potentially share common mechanisms underlying other horizontal advantages reported in the literature.

The present results speak to the value of collecting and analyzing RT data in working memory tasks, something that was practiced in the earliest studies in this research area (Sternberg, 1966), but has since been done only occasionally (Gilchrist & Cowan, 2014; Hyun, Woodman, Vogel, Hollingworth & Luck, 2009; Jensen, 2006; Luce, 1986; Pearson, et al., 2014; Posner, 1978). In all three experiments, we found at least one significant effect of statistical learning in RT that was not present in accuracy. This included the quadrant effect for the within-hemifield group in Experiment 2 and the diagonal group in Experiment 3. We cannot be sure why we saw these dissociations between our two dependent measures. It is possible that RT is simply a more sensitive measure of performance. Another possibility is that the RT effect could have carried some distinct information relating to the time it took participants to successfully retrieve and reach a decision on the correct object representation from working memory. A third possibility is that the observed slowing in the low-probability quadrants could have been due to an expectancy violation; that is, participants on each trial anticipated a cue pointing toward a high probable location and may have experienced some degree of surprise when low probable locations were cued. Such an expectancy violation could have led to a response slowing that was unrelated to target processing. Further work, using computational modeling (e.g., Pearson et al., 2014), could help tease apart these various possibilities.

One potential concern with these experiments is that we did not track eye position to verify fixation. It is possible that participants moved their eyes to the high probable locations, which could potentially have brought performance benefits in both accuracy and RT. However,

it is unlikely that eye movements could account for our data in a parsimonious way. First, the memory displays were presented only briefly (200 ms), and were followed soon after by the retro-cue, which was at the display center. Because of the small size of this cue, it would have been difficult to discriminate outside of the fovea, so participants would have needed to make multiple eye movements in rapid succession during each trial. Moreover, moving the eyes during working memory retention has been shown to impair performance, especially when spatial information must be preserved (Golomb & Kanwisher, 2012; Lawrence, Myerson, Oonk & Abrams, 2001). These points notwithstanding, let us assume participants did move their eyes. In Experiment 2, the most strategic position would be at the midpoint between the two high-probable locations. Here, we would expect both accuracy and RT benefits for these locations, compared to the low probable locations. However, we saw this pattern only for the between-hemifield group, not for the within-hemifield group. In Experiment 3, the midpoint of the two high-probable locations was at fixation, so participants had no incentive to move their eyes. Thus, an eye movement account does not provide a parsimonious explanation for the spatial constraints on performance that we observed.

Another question we can ask is which stage(s) of visual working memory is/are influenced by either statistical learning and/or the horizontal advantage? Here, we can only speculate, as our manipulations were not designed to assess separate processing stages, such as encoding vs. storage. If we look to previous work, Umemoto, Scolari, et al. (2010) suggested that statistical learning acted upon the stage of memory encoding. For the horizontal advantage, we of course do not have previous studies to consider. However, researchers examining the bilateral field advantage have suggested that it acts upon both encoding and storage stages (Umemoto, Drew, et al., 2010; Holt & Delvenne, 2014, 2015; Alvarez & Cavanagh, 2005). For

example, Umemoto, Drew, et al. (2010) compared simultaneous vs. sequential presentation of the to-be-remembered objects and found a similar advantage for unilateral vs. bilateral presentation. This showed that the bilateral advantage was not working to ease the demands of encoding multiple vs. single objects at a time, thus suggesting that the advantage was manifested during storage. In additional work, Holt and Delvenne (2014; 2015) produced evidence that the bilateral field advantage affects both encoding and storage stages. Ultimately, we cannot be sure which stages of processing the joint influence of statistical learning and the horizontal advantage acted upon; future studies, using more suitable experimental design, will be needed.

A further question we can ask of our data was the importance of explicit knowledge of the statistical learning manipulation. We found that many participants had indeed become aware of the high probable quadrants. Interestingly, while this awareness was consistent across the experimental manipulations, the quadrant effects during the memory tasks were not. Therefore, awareness could not explain the overall pattern of data we observed; nevertheless, it would be useful to use a more subtle statistical manipulation in future experiments to better compare explicit vs. implicit knowledge states.

In summary, our experiments confirmed the effects of statistical learning on working memory performance, albeit subject to spatial constraints. These findings demonstrate interesting limitations on how learning can benefit visual working memory.

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