The Role of Saliency for Visual Working Memory in Complex Visual Scenes

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Given its severe capacity limitations, visual working memory (VWM) can process only a tiny fraction of the complex visual world. While selection of relevant information from cluttered scenes is a main topic of research on visual attention, it has not received much research efforts in the VWM community. Based on knowledge from visual-attention research, we develop a task that mimics the complexity of real-world scenes while maintaining tight experimental control over stimulation and allowing for the application of state-of-the-art computational models and neuroscientific techniques. In two experiments, we provide solid evidence that the distribution of a limited VWM resource is parametrically influenced by *saliency* (i.e., how much an object stands out from its immediate surround). Our third experiment demonstrates that – in contrast to the real world – saliency is virtually maxed out for relevant objects in typical laboratory studies of VWM, likely yielding a pronounced underestimation of this major influence on VWM. We discuss various, not necessarily exclusive, mechanisms by which saliency might influence VWM performance, including saliency-dependent distribution of resources, encoding efficiency and faster/better filtering of unnecessary information and relate our results to the Theory of Visual Attention (TVA).

Keywords: visual short-term memory, priority map, attention, complex scenes, visual perception

In light of the constantly changing flow of information entering the eyes and being transmitted to visual cortical areas, visual working memory (VWM) is thought to provide a stable percept of the world (Aagten-Murphy & Bays, 2018; Schneider, 2013; Tsubomi, Fukuda, Watanabe, & Vogel, 2013). Due to the severe capacity limitations of this system, at each instant, people perceive only a tiny fraction of the massive amount of available information (Rensink, 2004; Simons & Levin, 1997; Simons & Rensink, 2005). Faced with this overwhelming stream of information (Tsotsos, 1990) and the short time between two eye movements, the visual system must somehow manage to focus its resources on only the most relevant aspects of the scene. Unfortunately, relevant objects are typically presented among a complex mix of other objects and variable background features (Henderson & Hollingworth, 1999; Hollingworth, 2008). So, some set of mechanisms must decide how to distribute the limited VWM resource quickly. This remains true independent of whether this means to allocate fixed slots or a flexible resource (see Cowan, 2001; Luck & Vogel, 2013; Ma, Husain, & Bays, 2014).

In contrast to these real-world affordances on VWM, the typical VWM paradigm features only a few isolated to-be-remembered objects within each scene; in the most canonical version, for example, the memory array consists of 2 to 8 colored squares on a gray background (H. R. Liesefeld, Liesefeld, & Müller, 2019; Luck & Vogel, 1997; Zhang & Luck, 2008, Fig. 1a). Participants then have to decide whether one of the squares changed color in a second dis-

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play (*change detection*) or reproduce the color of a probed object (*continuous report*). A wide variety of versions of this basic paradigm exist, but the focus on isolated objects is common to virtually all of them, even those that additionally include a few distracting objects (Allon & Luria, 2019; Jost & Mayr, 2016; A. M. Liesefeld, Liesefeld, & Zimmer, 2014; McNab & Klingberg, 2008; Vissers, van Driel, & Slagter, 2016; Vogel, McCollough, & Machizawa, 2005). While providing tight control over visual stimulation and task affordances, such memory displays clearly lack the complexity of real-world scenes humans are facing day to day. Thus, to examine information selection in complex scenes, new tasks are needed.

Questions regarding the selection of visual information are at the core of theories of visual attention: It is typically assumed that attention allocation is guided via an abstract spatial representation of the visual scene coding only for the relative importance at each location (Bisley & Mirpour, 2019; Bundesen, Habekost, & Kyllingsbæk, 2005, 2011; Fecteau & Munoz, 2006; Zelinsky & Bisley, 2015). Activation at this so-called priority map is a combination of top-down (observer inherent) and bottom-up (stimulus inherent) factors (Chelazzi, Marini, Pascucci, & Turatto, 2019; Gaspelin & Luck, 2019; H. R. Liesefeld, Liesefeld, Pollmann, & Müller, 2019; H. R. Liesefeld & Müller, 2019b; Wolfe & Horowitz, 2017). While top-down factors have attracted some VWM research (Bundesen et al., 2011; Dube, Emrich, & Al-Aidroos, 2017; Emrich, Lockhart, & Al-Aidroos, 2017; A. M. Liesefeld et al., 2014; Sauseng et al., 2009; Vogel et al., 2005), bottom-up factors have been largely ignored.

As an example of the former, Emrich et al. (2017, see also Dube et al., 2017) directly manipulated the task relevance of the various to-be-remembered objects in a clever set of experiments. Within each display they indicated via small bars (*cues*) how likely each object was to be probed afterwards. Interestingly, the likelihood of being probed was a much better predictor of how well an object's feature was reported later on than the number of objects in the display (set size) that almost all (computational) models of VWM focus on. Notably, increasing the number of objects, which had produced performance decrements in so many previous studies, also decreases the probability that each individual object is probed proportionally. Thus, an individual object's priority might be *the major* determinant for how much VWM resource it receives, producing set-size effects as a by-product. However, cues like those used by Emrich et al. are unlikely to appear in real life and, in fact, it is often unclear which objects turn out to be relevant later on. Among equally relevant objects, priority-dependent allocation of VWM resource must be determined by other contributors to the priority map, *saliency* in particular.

An object is salient if (at least) one of its features stands out, like the blackness of a black sheep in a flock of white sheep. More technically, saliency is determined by local feature contrast (H. R. Liesefeld, Moran, Usher, Müller, & Zehetleitner, 2016; Nothdurft, 2000): via lateral inhibition (i.e., at the same hierarchical level of visual processing), neurons with overlapping tuning curves (i.e., coding similar features) mutually suppress each other (*iso-feature suppression*; Li, 2002); the resulting net activity is highest for features that differ maximally from their immediate surround, because the respective neuronal activity is not suppressed. All else being equal, salient objects produce peaks on the attention-guiding priority map, thus drawing attentional resources.

Now consider the typical VWM display introduced above (Fig. 1a, see also Fig. 1c and Fig. 1d): The contrast between the isolated squares' colors and the gray background renders all of them highly salient. Moreover, any variation in saliency is left to chance: colors vary in contrast to the (often arbitrarily chosen) background and objects mutually provide contrast to each other depending on their (often random) spatial arrangement. Furthermore, if eccentricity is not controlled for (as is often the case), this provides another source of variation in saliency (Carrasco, Evert, Chang, & Katz, 1995; Carrasco & Frieder, 1997). This uncontrolled variation in saliency might explain some of the apparently random variation in VWM performance across trials (Fougnie, Suchow, & Alvarez, 2012; van den Berg, Shin, Chou, George, & Ma, 2012, for a related argument, see Brady & Alvarez, 2015).

Indeed, it has been shown that saliency plays a role in VWM for icons on maps (Fine & Minnery, 2009) and objects in photographs or drawings of natural scenes (Pedale & Santangelo, 2015; Santangelo & Macaluso, 2013; Spotorno, Tatler, & Faure, 2013; Stirk & Underwood, 2007, for a review, see Santangelo, 2015; Fig. 1b). To quantify saliency, these researchers analyzed their stimuli with a computational saliency model (Itti, Koch, & Niebur, 1998). Notwithstanding the potential to gain important insights and the appeal of the ecological validity, this approach is necessarily correlative in nature (i.e., saliency is not experimentally controlled) and the validity of the employed saliency-model output is not guaranteed. The downside of such correlative approaches (see also Brady & Alvarez, 2015; Brady & Tenenbaum, 2013) is that it remains unclear in how far other aspect of the stimuli influence the results, such as the discriminability of the remembered object features or their placement in the scene (e.g., center bias, Tseng, Carmi, Cameron, Munoz, & Itti, 2009, decreasing retinal resolution towards the periphery; Curcio, Sloan, Kalina, & Hendrickson, 1990; Legras, Gaudric, & Woog, 2018; Østerberg, 1935; Park, Chung, Greenstein, Tsang, & Chang, 2013) or many further potential influences that are yet to be revealed. Also, the way these studies measured memory performance (e.g., naming as many objects as possible) strongly deviates from the typical laboratory tasks introduced above, thus prohibiting to draw from the rich set of scientific techniques developed over the

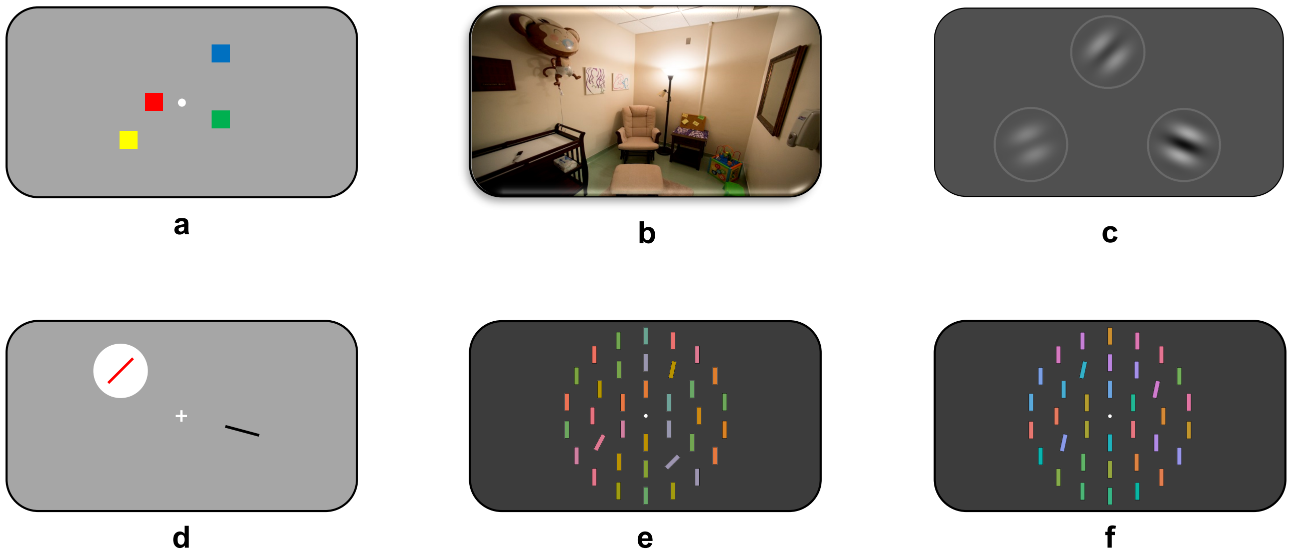

Figure 1. *Various Types of Memory Displays Employed in VWM Tasks*
Note. (a) The most canonical VWM memory display; (b-e) Memory displays used in various previous studies that examined the influence of saliency on VWM performance; (e-f) our displays. (a) Countless studies have examined VWM for isolated colored squares; (b) A real scene similar to those used in the VWM study by Pedale and Santangelo (2015); (c) Klink, Jeurissen, Theeuwes, Denys, and Roelfsema (2017) used Gabor gratings and manipulated saliency via the gratings' contrasts; (d) Bays, Gorgoraptis, Wee, Marshall, and Husain (2011) flashed a bright cue at the end of the encoding period to increase the a selected object's saliency; (e-f) Our displays mimic the complexity of real-world scenes while maintaining a high level of experimental control and allowing a continuous manipulation of saliency (via the relevant objects' tilts); (e) Displays contained three target bars of different saliency in Exp. 1 and the *mixed* condition of Exp. 2 and (f) three target bars of the same saliency in the *same* condition of Experiment 2.

last two decades for standard VWM tasks (for an overview see H. R. Liesefeld & Müller, 2019a), including advanced computational models of VWM performance (e.g., Bays, 2014; Brady & Tenenbaum, 2013; Donkin, Nosofsky, Gold, & Shiffrin, 2015; Hardman, Vergauwe, & Ricker, 2017; H. R. Liesefeld, Liesefeld, Pollmann, & Müller, 2019; Oberauer & Lin, 2017; Rouder et al., 2008; van den Berg, Awh, & Ma, 2014; Zhang & Luck, 2008) and neuroimaging markers of VWM maintenance (Christophel, Klink, Spitzer, Roelfsema, & Haynes, 2017; Harrison & Tong, 2009; Sauseng et al., 2009; Serences, Ester, Vogel, & Awh, 2009; Vogel & Machizawa, 2004). Furthermore, in "real-world" scenes there is often no straight-forward way to determine "set size" and the number of objects typically by far exceeds VWM capacity in realistic scenes (Bundesen et al., 2005; Cowan, 2001; H. R. Liesefeld, Liesefeld, Pollmann, & Müller, 2019; Luck & Vogel, 2013; Morey, 2011; Pashler, 1988; Rouder, Morey, Morey, & Cowan, 2011; Schneider, 2013).

Other studies have directly manipulated saliency in more controlled VWM tasks. Klink et al. (2017), for example, had participants remember the orientation of Gabor gratings and manipulated saliency by changing the contrast (Fig. 1c; see also Knops, Piazza, Sengupta, Eger, & Melcher, 2014; Melcher & Piazza, 2011). One downside of this procedure might be that not only saliency, but also the discriminability of the to-be-remembered orientation depends on Gabor contrast. In fact, in psychophysical studies, Gabor contrast is typically used to scale discrimination difficulty (e.g., Alvarez & Cavanagh, 2008). Furthermore, even medium-contrast Gabors (i.e., for which the discrimination of orientations does not become prohibitively difficult) are still isolated objects clearly standing out from the uniform background so that these stimuli would allow sampling only the upper range of saliencies. Others have used an uninformative bright flash (cue) to transiently increase the saliency at a certain location (e.g., Bays et al., 2011; Ravizza, Uitvlugt, & Hazeltine, 2016; Schmidt, Vogel, Woodman, & Luck, 2002, Fig. 1d). In contrast to what we are aiming at here, it is the cue that is salient and not the to-be-remembered object itself. In addition to the concern of sampling only the upper range of saliencies, inducing saliency via an independent event might dramatically change the (temporal) dynamics of resource allocation in comparison to a manipulation of the object's saliency itself and it might be difficult to independently and gradually manipulate the saliency of various objects in this way; furthermore, the cue might interfere with processing the cued object, thus undoing some of the attentional advantage (Merikle, 1976; Tabi, Husain, & Manohar, 2019).

To examine how saliency attracts VWM resource in a bottom-up manner with the same level of experimental control as in typical laboratory studies while still mimicking the complexity of real-world scenes, we devised a new VWM task based on knowledge from the visual-attention literature. As demonstrated below, this task allows to directly, gradually, and independently manipulate each object's saliency across a wide range, while keeping the discriminability of the to-be-remembered feature and each object's behavioral relevance untouched, and enables the use of modern (neuro-)cognitive models and methods.

Our construction of the memory displays is based on our previous experience with visual search. In particular, H. R. Liesefeld et al. (2016) devised visual-search displays that allowed a gradual manipulation of the search target's saliency (see also Nothdurft, 2000; Rangelov, Müller, & Zehetleitner, 2017; van Zoest & Donk, 2006) and showed that search becomes faster as a continuous function of target saliency even beyond the point where targets "popped out" (i.e., where search speed was uninfluenced by the number of to-be-searched objects), spanning average (target-present) search times from 400 ms up to 1400 ms. This was achieved by placing a tilted target bar in a dense array of vertical non-target bars. By adapting the tilt of the target bar (and therefore the contrast between target and non-targets), target saliency could be controlled to any desired precision. H. R. Liesefeld, Liesefeld, Töllner, and Müller (2017) showed that in this design the most salient object almost inevitably captures attention (if top-down influences are kept constant), even if completely irrelevant to the task (see also H. R. Liesefeld, Liesefeld, & Müller, 2019; H. R. Liesefeld & Müller, 2019a).

Thus, the memory displays employed here featured a dense array of vertical non-target bars into which several (*here*: three) tilted target bars were placed (Fig. 1e-f). In order not to make color dominate the contrast (and therefore determine saliency), all bars were drawn in a random color. We used target tilts of 12°, 28°, and 45° to achieve a strong manipulation of target saliency. Note that even the smallest tilt (12°) produced clear pop out (i.e., very efficient search) in H. R. Liesefeld et al. (2016). In contrast to previous experimental approaches to manipulate saliency (see above), this type of display provides tight control over the stimuli's saliencies without messing with the discriminability of the to-be-remembered feature (color).

To try and demonstrate the viability of our new approach and to confirm an influence of saliency on VWM encoding in a more controlled situation, we conducted two experiments in which participants were instructed to remember the color of three tilted objects with varying saliency. Our results show a strong impact of bottom-up saliency on the distribution of VWM resources to equally relevant objects and provide additional insights into the mechanisms determining the allocation of VWM resources in complex scenes. Furthermore, fitting the data to the standard Zhang and Luck (2008) mixture model revealed that saliency mainly impacts the probability that an object is remembered rather than the quality of the respective memory trace. By comparison, a third experiment demonstrates how strong the achieved effect of saliency in our displays is and how salient all objects in typical VWM displays are.

Experiment 1

Methods

Participants. For each experiment, sample size was determined via sequential testing with Bayes factors, following the recommendations by Schönbrodt and Wagenmakers (2018) with a minimum of 10 and a maximum of 60 participants. We stopped testing when sufficient evidence for either the null or the alternative ($BF \geq 6$) was reached for each critical test.

The critical tests determining the stopping rule for Experiment 1 examined whether VWM performance (the mean absolute angular distance between correct and selected response, henceforth: *recall error*) would decrease with object saliency (tilt). This resulted in a sample of 10 healthy human adults (Mean age: 26.3 ± 3.37, 4 females, all right-handed) who received either course credits or monetary remuneration (9 €/h). In this and all following experiments, all participants provided informed consent prior to the experiment, reported normal or corrected-to-normal visual acuity and normal color vision and were naïve as to the purpose of the study, and the experimental procedures were approved by the ethics committee of the Department Psychology and Pedagogics at LMU.

Stimuli, procedure & design. Stimuli were displayed on a 24" TFT-LCD monitor (ASUS VG248QE, 1920×1080 pixels, 60 Hz) at a viewing distance of 70 cm. The testing room was pitch dark and there were between one and four participants in each testing session. OpenSesame 3.2.7 (Mathôt, Schreij, & Theeuwes, 2012) with the PsychoPy (Peirce, 2008) backend was used for stimulus presentation. For CIE L*a*b* conversion to sRGB, the colormath (Taylor, 2017) Python package was used.

Each trial began with the presentation of a central fixation dot (white, 0.18° radius) against a gray background (L* = 25.3, 14.2 cd/m²). After 1 s, a sample display was presented, consisting of 33 vertical and 3 tilted (12°, 28° and 45°) colored bars subtending a visual angle of 1.30 × 0.33° each.

The bars were arranged in three concentric rings (2°, 4° and 6° radius) with respectively 6, 12 and 18 bars on each. The relevant (tilted) bars were always presented on the middle ring. Colors were randomly drawn from a circle in a luminance plane of the CIE 1976 L*a*b* (see Commission Internationale de l'Éclairage [CIE], 2019) color space (L* = 63, center: a* = 9, b* = 27, illuminant: D65, 2° standard observer) with a radius of 40 (Mean ΔE2000 between two adjacent colors: 0.43). These parameters were chosen to ensure that all colors could be mapped onto the 24-bits sRGB color space. CIE L*a*b* is a device-independent color space based on the opponent color theory (Hering, 1905/1964) that aspires to be perceptually uniform, taking into account the specificities of the human color vision system (for a more detailed overview, see Fairchild, 2013).

The memory display was presented for 350 ms, followed by a delay period of 1 s during which only the fixation dot was shown. A response display was then presented containing a randomly in 30°steps rotated color wheel (360 colors) and outlined placeholder bars at the location of each bar from the memory display. One of the placeholders was filled in black to indicate which bar to report (hereafter: *probe*), and participants were instructed to report the color they remembered for that bar by using the computer mouse to select a point on the color wheel. The color wheel had a width of 0.66°and a radius of 8°. While the mouse hovered the color wheel, the probe dynamically changed color according to the mouse position.

Each participant completed a total of 600 trials divided into blocks of 30 trials. Each condition (i.e., tilt of the probe) was randomly presented 200 times (10 times per block). After each response, a feedback line appeared at the correct location on the color wheel to show the correct response (and, by implication, how far off the actual response was) to the participant.

Analysis. For statistical analyses, JASP 0.10.2 (JASP Team, 2019; Love et al., 2019) was used with default settings for the priors. Directed Bayesian *t* tests (Rouder, Speckman, Sun, Morey, & Iverson, 2009) were conducted to analyze the differences between the different tilts. The *BF* quantifies the support for a hypothesis (first subscript) over another (second subscript), regardless of whether these models are correct. The subscript "0" always refers to the null hypothesis (H_0). When conducting undirected (two-sided) tests, the subscript "1" refers to the alternative hypothesis (H_1). When conducting directed (one-sided) tests, instead of "1", the subscripts "+" or "−" were used depending on the direction of the hypothesis (H_+ or H_-, respectively). Throughout the results, we will report the *BF* for the most favored hypothesis (e.g., if the null is more probable, BF_{01} will be reported), as we find it most intuitive to interpret.

We also conducted the traditional (frequentist) significance tests for reference and report effect sizes (d_z; Cohen, 1988) followed by their respective 95% CIs in brackets. Finally, as an exploratory analysis, we fitted the data with MemToolbox (Suchow, Brady, Fougnie, & Alvarez, 2013, https://memtoolbox.org/) – separately per participants and condition – to the mixture model of Zhang and Luck (2008) to determine whether observed effects are better explained by variation in VWM precision (*sd*) or variation in the probability that the response originated from remembering the probed item (p_{mem}).[1]

Results

As expected, our manipulation of saliency had a huge and reliable impact on VWM performance (see Fig. 2): Recall error was higher for 12° ($M \pm SD$: 59.07° ± 16.73) than for 28° probes (41.84° ± 14.06), $t(9) = 6.56$, $p < .001$, $d_z = 2.07$ [0.93, 3.19], $BF_{+0} = 551.51$, and higher for 28° than for 45° probes (28.14° ± 7.32), $t(9) = 4.66$, $p < .001$, $d_z = 1.47$ [0.54, 2.37], $BF_{+0} = 70.6$. Effect sizes were so huge that, despite the relatively small sample size (which we had defined as the minimum in our pre-registration), the Bayes factors indicated overwhelming evidence for both differences. This finding demonstrates that saliency is a major determinant for the distribution of VWM resources.

Fitting to the Zhang and Luck (2008) model revealed that p_{mem} differed significantly between 12° (44.08% ± 23.36) and 28° probes (68.89% ± 17.61), $t(9) = 6.37$, $p < .001$, $d_z = 2.01$ [0.89, 3.10], $BF_{10} = 227.57$; and between 28° and 45° probes (86.41% ± 8.50), $t(9) = 4.10$, $p = .003$, $d_z = 1.30$ [0.42, 2.14], $BF_{10} = 18.18$. However, *sd* did not significantly differ between 12° (26.93° ± 11.02) and 28° probes (25.99° ± 4.65), $t(9) = 0.315$, $p = .760$, $d_z = 0.10$ [0.52, 0.72], $BF_{01} = 3.10$; or between 28° and 45° probes (23.91° ± 2.87), $t(9) = 1.29$, $p = .230$, $d_z = 0.41$ [0.25, 1.04], $BF_{01} = 1.68$.

Discussion

Using a novel design, providing high experimental control over object saliency while mimicking the visual complexity of real-world scenes, Experiment 1 confirmed that the allocation of a limited VWM resource is strongly and parametrically dependent on saliency. Moreover, fitting a standard model of VWM performance to the data revealed that this effect is mainly due to salient objects being remembered more likely rather than more precisely. Even though we observed only moderate ($BF_{01} = 3.10$) and indecisive ($BF_{01} = 1.68$) evidence for the absence of an effect on precision, it is clear that potential effects on precision cannot explain the over-

[1] Due to a technical mistake only the response and the correct answer were stored for Exp. 2, so that we could not estimate the impact of other items on the response (*swap errors*; Bays, Catalao, & Husain, 2009) or apply other more advanced models (e.g., Brady & Tenenbaum, 2013; Oberauer & Lin, 2017).

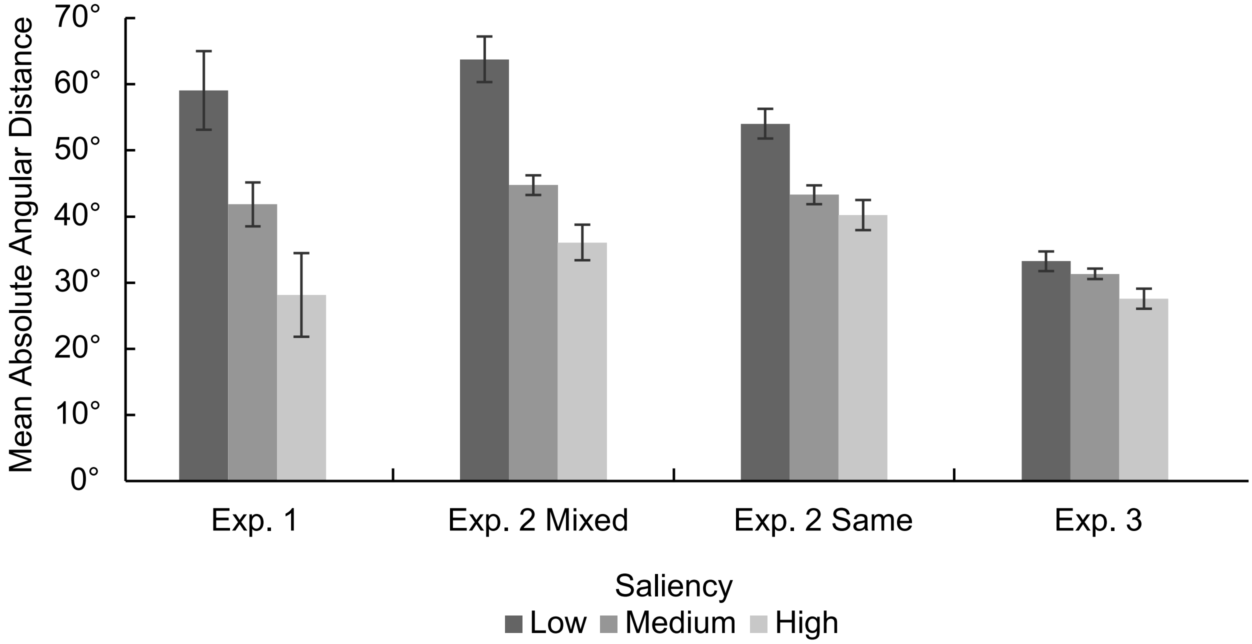

Figure 2. *Summary of Results From all Three Experiments.*
Note. For Experiments 1 and 2, Saliency "Low" refers to 12° probes, "Medium" to 28° probes and "High" to 45°-probes. For Experiment 3, Saliency "Low" refers to 6° eccentricity, "Medium" to 4° eccentricity and "High" to 2° eccentricity. Error bars represent 95% within-subject CIs (Morey, 2008).

whelming evidence for an effect of saliency on recall error (BF_{+0} = 551.51 and BF_{+0} = 70.6).

Experiment 2

If saliency indeed determines the distribution of the limited VWM resource (VWM slots), the 45° tilted object received particularly much of this resource by virtue of the other two tilted bars being less salient, and, correspondingly, the 12° tilted object received particularly little of this resource due to the other two tilted bars being more salient. By contrast, when all targets within a display are equally salient, the VWM resource should be distributed equally. This means that each 45°-tilted object in a display with only 45°-tilted objects among vertical bars (*same* displays) would receive less resource and each 12°-tilted object in a display with only 12°-tilted objects would receive more resource compared to the *mixed* displays in Experiment 1. To test this prediction of the hypothesis that saliency determines the allocation of the limited VWM resource, displays in Experiment 2 contained either three objects of the same or three objects of different tilts.

A potential alternative is that saliency determines how well the resource can be allocated to only the relevant objects in the scene (rather than being consumed by the irrelevant vertical bars, for example). This would predict that even in displays with only 12°-tilted bars, each 12°-tilted bar receives less resource than each 45°-tilted bar in displays with only 45°-tilted bars. In other words, the overall amount of resource allocated to the relevant (tilted) objects might be lower for 12°- compared to 45° *same* displays. These two possibilities are not mutually exclusive, and, in contrast to an earlier study (Klink et al., 2017), our results indicate that both mechanisms are at play in the present design.

Methods

In Experiment 2, the critical tests determining the stopping rule for the sequential testing procedure examined whether recall error would increase with object saliency (as in Experiment 1) for both *same* and *mixed* displays and (additionally) whether recall error would differ, for the *same* probe tilt, between *mixed* and *same* displays, with an increase for 45° and a decrease for 12° probes. This resulted in a sample of 31 healthy human adults (Mean age: 26.4 ± 5.44, 25 female, 4 left-handed). Three participants had already participated in Experiment 1 and three others had participated in Experiment 3 (which was run before Experiment 2). Experiment 2 was modeled after Experiment 1 with the main difference being that one of two types of memory displays could be presented on each trial:

1. *Mixed* displays (Fig. 1e) were identical to the displays of Experiment 1 in all relevant aspects and differed only in that the fixation dot and the radius of the color wheel were slightly smaller (0.16° rather than 0.18°, and 7.8° rather than 8°, respectively).

2. *Same* displays (Fig. 1f) were similar to *mixed* displays except that the tilted bars all shared the same tilt (either 12°, 28° or 45°).

Each participant completed a total of 600 trials divided into blocks of 30 trials. Each condition (i.e., type of display × tilt of the probe) was randomly presented 100 times (5 times per block). Experiment 2 was written in JavaScript and HTML5 and run in Mozilla Firefox (68.0), using the d3.js (Bostock, Ogievetsky, & Heer, 2011) library for color conversion.

Results

The *mixed* condition of Experiment 2 replicated the results of Experiment 1 (see Fig. 2). Recall error was higher for 12° (63.77° ± 14.21) than for 28° probes (44.74° ± 13.49), $t(30) = 10.57$, $p < .001$, $d_z = 1.90$ [1.30, 2.49], $BF_{+0} = 1.44e+9$, and higher for 28° than for 45° probes (36.06° ± 11.12), $t(30) = 5.83$, $p < .001$, $d_z = 1.05$ [0.60, 1.48], $BF_{+0} = 1.68e+4$.

Crucially, and as expected, performance was better for 12° probes, $t(30) = 6.02$, $p < .001$, $d_z = 1.08$ [0.63, 1.52], $BF_{+0} = 2.69e+4$ and worse for 45° probes, $t(30) = 2.88$, $p = .004$, $d_z = 0.52$ [0.89, 0.13], $BF_{-0} = 11.56$, in *same* compared to *mixed* displays. This difference was only weak and unreliable for 28° probes (for which we had no specific hypotheses as mentioned in our pre-registration), $t(30) = 1.57$, $p = .128$, $d_z = 0.28$ [0.08, 0.64], $BF_{01} = 1.75$. Mean recall error across tilts was lower in *same* (45.83° ± 11.35) compared to *mixed* (48.19° ± 12.86) displays, $t(30) = 3.220$, $p = .003$, $d_z = 0.58$ [0.19, 0.96], $BF_{10} = 12.25$.

Despite the observed convergence in performance for the different tilts, even in *same* displays, saliency affected VWM performance. Recall error was higher for 12°- (54.02° ± 12.93) than for 28° probes (43.29° ± 13.31), $t(30) = 7.79$, $p < .001$, $d_z = 1.40$ [0.90, 1.89], $BF_{+0} = 2.39e+6$, and higher for 28°- than for 45° probes (40.19° ± 14.71), $t(30) = 3.10$, $p = .002$, $d_z = 0.56$ [0.17, 0.93], $BF_{+0} = 18.85$ (see Fig. 2). Replicating Experiment 1, results from the Zhang and Luck (2008) mixture model again showed that salience influenced mainly p_{mem} in both *mixed* and *same* displays (see Supplement). In the comparison between *mixed* and *same* displays, the effect for 12° probes was mainly reflected in p_{mem} and the effect for 45° probes was mainly reflected in *sd*.

Discussion

Results of Experiment 2 confirm the prediction that the amount of VWM resource an object receives depends on its relative saliency with respect to the other objects in the scene. Furthermore, we found that even when all objects within a display are of the same saliency, more salient objects still receive more resource than their less salient counterparts, indicating that in addition to *relative* saliency, *absolute* saliency also plays a role in the distribution or availability of VWM resources. While the former conclusion is in line with previous reports that when a salient item is present less-salient items receive proportionally less VWM resource (see also Bays et al., 2011; Klink et al., 2017; Melcher & Piazza, 2011; Pedale & Santangelo, 2015; **?**), the latter conclusion might conflict with some of these studies (see the General Discussion for details).

Experiment 3

Experiment 3 was a more prototypical VWM task in which we manipulated the eccentricity of probed objects. This served various purposes: (a) to demonstrate by comparison to our design that saliency in typical VWM task is very high; (b) to demonstrate that some of the variability in typical VWM displays stems from random variation in seemingly irrelevant display characteristics (eccentricity); and (c) to demonstrate by comparison that the saliency effect observed in our design is indeed huge.

Regarding (a), typical VWM displays are very simple in that only a few and only relevant stimuli are shown on the screen (e.g., H. R. Liesefeld, Liesefeld, Pollmann, & Müller, 2019; Luck & Vogel, 1997; Zhang & Luck, 2008). Due to their contrast to the background and the absence of any other non-target stimuli (that could probably reduce saliency), these stimuli's contrast is usually very high. Thus Experiment 3 serves to demonstrate how strongly the laboratory situation differs from the real-world situation in which relevant objects are shown among many irrelevant objects.

Regarding (b), influential recent work (Brady, Konkle, & Alvarez, 2011; Fougnie et al., 2012; van den Berg et al., 2012) has pointed out that the apparently unsystematic variability of VWM performance across trials is much stronger than the systematic variability typically examined (e.g., the effect of set size). One factor that might systematically influence VWM performance, and that – following the influential work of Luck and Vogel (1997) – is often not controlled for in VWM studies, is the probed object's distance from fixation (*eccentricity*). Visual-search studies have repeatedly found that – all else being equal – objects further in the periphery are harder to find (Carrasco & Frieder, 1997) and that objects closer to fixation tend to attract attentional resources more readily (Woodman & Luck, 1999).

Regarding (c), in addition to attentional factors (which are probably maxed out in typical VWM displays), VWM representations of more eccentric stimuli should have a lower resolution due to purely physiological reasons. In particular, as the density of cone receptors in the retina sharply drops with eccentricity (Curcio et al., 1990; Legras et al., 2018; Østerberg, 1935; Park et al., 2013), color perception – and consequently the detail of information that is initially available to be transferred to VWM – decreases with eccentricity. Thus, effects of eccentricity should provide an interesting benchmark against which we will compare the strength of saliency effects examined above.

Methods

In Experiment 3, the critical tests determining the stopping rule for the sequential testing procedure examined whether recall error would increase with object eccentricity. The sequential testing procedure resulted in a sample of 34 healthy human adults (Mean age: 24.4 ± 4.44, 27 female, 2 left-handed). Experiment 3 was modelled after Experiment 1 with the following differences: Rather than tilted bars among irrelevant vertical bars, to-be-remembered targets were three isolated squares subtending a visual angle of 0.65 × 0.65° each as in prototypical VWM tasks (Luck & Vogel, 1997; Zhang & Luck, 2008). The squares were arranged in three concentric rings (2°, 4° and 6° radius) with one square at each eccentricity in each display, thus implementing a parametric within-display manipulation comparable to Experiment 1 and the *mixed* displays of Experiment 2. On each ring, the square was randomly placed at one of 6, 12 or 18 positions, respectively. The positions on the middle ring were identical to those in Experiments 1 and 2. Each participant completed a total of 600 trials divided into blocks of 30 trials. Each target eccentricity was randomly probed 200 times (10 times per block).

Results and Discussion

As expected, our manipulation of eccentricity influenced VWM performance (see Fig. 2). Recall error was higher for objects on the outer (33.24° ± 8.19) than on the middle ring (31.33° ± 7.55), $t(33) = 2.56$, $p = .008$, $d_z = 0.44$ [0.08, 0.79], $BF_{+0} = 6.04$, and higher for objects on the middle than on the inner ring (27.58° ± 6.96), $t(33) = 4.78$, $p < .001$, $d_z = 0.82$ [0.43, 1.21], $BF_{+0} = 1308.45$. As evident from Figure 2, this effect was much weaker than our direct manipulation of saliency in Experiments 1 and 2. Effects of tilt and effects of eccentricity are, of course, not directly comparable, but linearly extrapolating from the present results, one would need eccentricities far beyond the typical range used in VWM tasks and beyond the retinal area that provides color vision (12° into the periphery) to reach similar-sized effects as with our tilt manipulation. A comparison with data combined across Experiments 1 and 2 (Recall error: 46.04° ± 11.90°) indicated much better average performance in Experiment 3 (30.72° ± 6.90), $t(65.94) = 6.95$, $p < .001$, $d_z = 1.58$ [1.04, 2.10], $BF_{+0} = 3.61\text{e+}6$, even if analysis was restricted to the middle ring[2] (31.34° ± 7.56; the exact same eccentricity as in Experiments 1 and 2), $t(68.69) = 6.48$, $p < .001$, $d_z = 1.47$ [0.95, 1.99], $BF_{+0} = 7.52\text{e+}5$.

Respective analyses on the Zhang and Luck (2008) model parameters (see Supplement) revealed that the difference between outer and middle ring was mainly explained by *sd*, whereas the difference between middle and inner ring was mainly explained by p_{mem}. Importantly, the difference in performance between Experiments 1 and 2 on the one and Experiment 3 on the other hand was almost exclusively explained by p_{mem}.

General Discussion

We set out to demonstrate an influence of saliency on performance in a VWM task that mimics the complexity of real-world scenes while providing high experimental control and comparability to the main thrust of laboratory VWM studies. In Experiments 1 and 2, we showed that the distribution of the limited VWM resource depends on object saliencies in that (a) more salient objects receive more resource then less salient objects, (b) salient objects receive more resource if presented among less salient objects rather than among equally salient objects, and (c) the overall amount of resource allocated to relevant objects is higher for salient than less salient objects. Experiment 3 served to demonstrate that (d) objects in the traditionally employed, simple displays are highly salient, (e) eccentricity also modulates VWM performance, and (f) the effect of saliency observed in Experiments 1 and 2 is huge in comparison. The major additional insight from applying the Zhang and Luck (2008) mixture model to these data was that effects of saliency and the difference in performance between our design (Experiments 1 and 2) and a more traditional VWM design (Experiment 3) were almost exclusively explained by differences in the probability that the probed objects was in memory (p_{mem}). That the same model parameter (p_{mem}) explains within-experiment effects of saliency and the superior performance in the more prototypical Experiment 3 supports our hypothesis that the between-experiment difference is due to differences in saliency and that in typical VWM experiments saliency is (unrealistically) high.

Pedale and Santangelo (2015) observed that when objects much more salient than the rest were present in a scene, over-

[2] Both *t* tests are Welch's *t* test (Welch, 1947) as variances were unequal.

all performance declined, indicating that high-saliency objects exhaust VWM resources (see also Krüger, Tünnermann, & Scharlau, 2017). "Exhausting resources" when saliencies are highly heterogeneous within a display could mean one of two (nonexclusive) things: First, resources are re-distributed in that salient objects capture more resource, leaving less for the remaining ones, or second, some resource is indeed wasted in that less information is stored in total. Due to their binary measure of whether an object was later on reported or not, Pedale and Santangelo could not differentiate between these two possibilities: in line with the first option, redistribution might have pushed some medium-saliency items below some reporting threshold and memory for the most salient objects was anyway so far above that threshold, so that the extra boost did not impact its recall. As a consequence observed results would mimicking those predicted by the second option. Owing to the sensitivity of the continuous-report task for fine changes in the distribution of VWM resource our data provide evidence for the second option (without excluding the first): overall performance was higher in the *same* (= homogeneous) than in the *mixed* (= heterogeneous) condition of Experiment 2, indicating that less overall resource was allocated to relevant objects in 12° *same* displays compared to 45° *same* displays. This could mean that either less resource was available or that resource was more likely allocated to non-targets.

The latter assumption of improved selection efficacy for salient objects is more intuitive to us, because it allows assuming that the amount of available VWM resource is constant. Interpreting our results in terms of improved selection efficacy would also explain the apparent discrepancy to earlier findings. In particular, Klink et al. (2017) found that the effect of saliency vanished completely when all relevant objects within a display were of the same saliency (see also Bays et al., 2011, Exp. 4). As discussed in more detail above and similar to most VWM studies, Klink et al. had participants remember isolated objects (Gabor patches on a gray background, Fig. 1c). Thus, in contrast to the present study and in contrast to real-world scenes, Klink et al. displays did not contain any irrelevant objects that could potentially draw VWM resource.

Notwithstanding the above, participants' ability to select relevant information as measured with other tasks (*filtering ability*) is correlated with performance in standard VWM tasks, even if only a handful of isolated, all relevant objects is presented (Gaspar, Christie, Prime, Jolicœur, & McDonald, 2016; A. M. Liesefeld et al., 2014; McNab & Klingberg, 2008). This has been interpreted as indicating that some VWM resource is wasted on other aspects of the environment (Awh & Vogel, 2008) or mind wandering (Adam, Mance, Fukuda, & Vogel, 2015). Examining to which degree the vertical bars in our design are processed might provide a means to quantify the former consumption of VWM resource by irrelevant aspects of the visual environment in future studies.

Having established an effect of saliency on the distribution of VWM resource, we may speculate on the reasons for this effect, also drawing from the exploratory mixture-model analysis: One possibility is that all objects are processed in parallel but with faster processing rates for more salient objects, so that by the time the display vanishes (from iconic memory) more information has been accumulated for more salient objects and these are therefore represented more precisely (Bays et al., 2011; Magnussen, Greenlee, & Thomas, 1996; Wilken & Ma, 2004). This idea would, however, predict an effect of saliency on *sd* rather than the observed effect on p_{mem} (see below for a parallel-processing theory that predicts an effect on p_{mem}). While this mismatch might alternatively indicate that the applied model is invalid, our results do at least not strongly support this possibility.

Another possibility in line with an effect on p_{mem} and based on a serial-processing model is that the more strongly tilted objects are found and attended earlier, so that they are more likely processed and/or consolidated (see Gegenfurtner & Sperling, 1993; Shibuya & Bundesen, 1988; Vogel, Woodman, & Luck, 2006; Woodman & Vogel, 2005). Indeed, it has been shown that saliency determines the order of attention allocations if all attended objects are task-relevant (Christie, Spalek, & McDonald, 2018; Woodman & Luck, 1999) and sometimes even if the more salient object is task-irrelevant (H. R. Liesefeld et al., 2017). As a consequence, time might have often been insufficient to attend and process the lower-saliency objects at all, thus producing an effect on p_{mem}.

In line with a temporal bottleneck, previous studies have found that effects of saliency decrease and eventually vanish with prolonged encoding times (Bays et al., 2011; Klink et al., 2017). Future studies examining this issue with our design should keep in mind that effects of encoding time would also be predicted if the initial influence of bottom-up factors is overcome by top-down factors after a while (Theeuwes, 2004; Ye et al., 2017) and that with long encoding durations the influence of categorical (probably non-visual) representations might increase (Bae & Luck, 2019; Hardman et al., 2017). In any case, the 350 ms employed here are about as much if not more than a typical fixation lasts, so that our task would mimic the temporal limits on VWM encoding typical in real life (Aagten-Murphy & Bays, 2018; Schneider, 2013).

These temporal limitations are also typical for the bulk of previous VWM studies, so that the apparently unsystematic variation across trials prominently pointed out before (Fougnie et al., 2012; van den Berg et al., 2012) might, in fact, be in large part due to variations in saliency. The small effects in Experiment 3 showed that variation in eccentricity does likely not contribute much to this variability. However, if not manipulated systematically, variation in color (that is necessary when VWM for color is probed) might result in strong variation in saliency due to variation in contrast to the background and due to interactions between adjacent objects. This possible contribution of uncontrolled variation in saliency to variation in VWM performance needs to be addressed in future studies.

The probably most comprehensive account of our results comes from the *Theory of Visual Attention* (*TVA*, Bundesen, 1990; Bundesen et al., 2005, 2011; Schneider, 2013), which is compatible with our findings to a surprisingly high degree (given that we did not set out to test the TVA). Indeed, with its central notion of a priority map determining the rate of processing, TVA provides an excellent framework to interpret the data from our newly devised task: According to TVA, the rate of processing during a parallel race determines whether an object gets one of the limited slots that hold objects in VWM. As the number of relevant objects in our study (3) is below the number of memory slots assumed by the TVA (4), the critical bottleneck here is likely not the overall available amount of VWM resource (slots) but the time it takes to fill each individual slot (to distribute the VWM resource). Previous TVA studies have estimated processing capacity for highly overlearned and categorical letter stimuli at around 60 Hz (objects/s) (parameter C; Krüger, Tünnermann, & Scharlau, 2016; Krüger et al., 2017; Nordfang, Dyrholm, & Bundesen, 2013). Thus, if only relevant objects were processed and if processing was equally fast, the available time would be sufficient to process all objects (only 50 ms would be needed). This would indicate that processing capacity is lower for the continuous color of objects (the feature that was probed here, and in many typical VWM studies) compared to the letter identity probed in typical TVA studies. Furthermore, the irrelevant, vertical bars might also consume processing capacity or VWM slots (as already speculated above). Future studies will have to examine the impact of irrelevant non-salient objects and the interaction between saliency and the temporal dynamics of loading VWM.

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Supplement

The analyses in the main article focus on the raw recall error. Another approach to analyze this type of data (which is not without critiques, see Ma, 2018) is to fit a model to the data to disentangle the sources of recall error. One particular model (Zhang & Luck, 2008) assumes that the recall error arises from two sources represented by two parameters. The first parameter is the probability that the probed object is present in memory (p_{mem}). If the probed object is in memory, the second parameter reflects the precision of its representation (*sd*); higher *sd*s indicating lower precision. If the probed object is not in memory, the response will be made randomly. Statistical analyses on the parameters of this model (using the MemToolbox; Suchow et al., 2013, https://memtoolbox.org/) are described in the paper for Experiment 1, and given here for Experiment 2 and Experiment 3.

Experiment 2

In *mixed* displays (Table S1, S3), the results for p_{mem} replicated those of Experiment 1, with the p_{mem} for 12° probes being lower than for 28° probes and p_{mem} for 28° probes being significantly lower than for 45° probes. However, while no significant effect on *sd* was observed in Experiment 1, here we found a significant difference in *sd* between 28° probes and 45° probes (this effect was non-significant and Bayesian evidence was indecisive in Exp. 1). Notwithstanding this small effect, the results also clearly show that the huge effect in response error reported in the main text is largely due to an effect on the probability that the probed object was in memory rather than an effect on the precision of this representation.

For *same* displays (Table S1, S4), the only significant difference was in p_{mem} between 12° and 28° probes. Although the effect on p_{mem} between 12° and 28° probes was non-significant and inconclusive, it was still clearly larger than the respective effect in *sd*. In fact, we found moderate evidence in favor of the null hypothesis suggesting that there was no difference in *sd* either between 12° and 28° probes or between 28° and 45° probes.

When comparing the two types of displays (Table S1, S5), there was a significant and highly convincing difference for p_{mem} in 12° displays and a significant difference (moderately convincing) for *sd* in 45° displays. Finally, there was moderate evidence for the null hypotheses for p_{mem} in 28° displays and for *sd* both in 12° displays and 28° displays.

Table S1

Estimated Model Parameters for Experiment 2.

Param − Tilt	Display	Mean	*SD*	95% CI Lower	95% CI Upper
p_{mem} − 12°	*Mixed*	40.09%	20.67	32.95	47.22
	Same	52.51%	18.71	45.38	59.65
p_{mem} − 28°	*Mixed*	66.41%	19.41	59.28	73.55
	Same	68.39%	21.67	61.25	75.52
p_{mem} − 45°	*Mixed*	75.02%	15.53	67.88	82.16
	Same	71.82%	21.94	64.68	78.95
sd − 12°	*Mixed*	29.75°	12.95	26.56	32.94
	Same	26.53°	8.60	23.34	29.71
sd − 28°	*Mixed*	27.84°	10.43	24.65	31.02
	Same	27.74°	8.30	24.56	30.93
sd − 45°	*Mixed*	23.63°	4.65	20.44	26.81
	Same	26.76°	6.52	23.58	29.95

Experiment 3

For Experiment 3 (Table S2, S6), there was a significant difference in p_{mem} between the middle and the inner ring. There was also a significant difference in *sd* between the outer and the middle ring. Finally, there was moderate evidence for the null hypothesis of no difference in p_{mem} between the outer and the middle ring.

Finally, when comparing the pooled results from Experiment 1 and 2 to the results from Experiment 3 (Table S7), p_{mem} was significantly higher in Experiment 3 but *sd* did not differ reliably. This holds true even if the pooled results were compared to the middle ring (the eccentricity on which the tilted bars were presented) of Experiment 3.

Table S2

Estimated Model Parameters for Experiment 3.

Param − Ring	Mean	*SD*	95% CI Lower	95% CI Upper
p_{mem} − Outer	81.04%	10.92	77.87	84.21
p_{mem} − Middle	81.94%	9.53	78.77	85.11
p_{mem} − Inner	86.25%	6.72	83.08	89.42
sd − Outer	26.64°	4.17	25.10	28.17
sd − Middle	24.58°	4.02	23.04	26.11
sd − Inner	23.59°	5.10	22.05	25.12

Table S3

Paired Samples t *Tests on Model Parameters for* Mixed *Displays*

		Test	statistic	*df*	*p*	d_z
p_{mem} 12°	p_{mem} 28°	Student's *t*	9.66	30	< .001	1.73 [1.17, 2.29]
		BF_{10}	9.83e+7			
p_{mem} 28°	p_{mem} 45°	Student's *t*	4.71	30	< .001	0.85 [0.43, 1.25]
		BF_{10}	456.21			
sd 12°	*sd* 28°	Student's *t*	0.87	30	.390	0.16 [−0.20, 0.51]
		BF_{01}	3.68			
sd 28°	*sd* 45°	Student's *t*	2.41	30	.023	0.43 [0.06, 0.80]
		BF_{10}	2.26			

Table S4

Paired Samples t *Tests on Model Parameters for* Same *Displays*

		Test	statistic	*df*	*p*	d_z
p_{mem} 12°	p_{mem} 28°	Student's *t*	6.84	30	< .001	1.23 [0.75, 1.69]
		BF_{10}	1.11e+5			
p_{mem} 28°	p_{mem} 45°	Student's *t*	1.83	30	.077	0.33 [−0.04, 0.69]
		BF_{01}	1.19			
sd 12°	*sd* 28°	Student's *t*	−0.68	30	.504	−0.12 [−0.47, 0.23]
		BF_{01}	4.23			
sd 28°	*sd* 45°	Student's *t*	0.73	30	.468	0.13 [−0.22, 0.48]
		BF_{01}	4.07			

Table S5

Paired Samples t *Tests on Model Parameters for* Mixed *vs* Same *Displays*

Mixed	***Same***	Test	statistic	*df*	*p*	d_z
p_{mem} 12°	p_{mem} 12°	Student's *t*	4.38	30	< .001	0.79 [0.38, 1.19]
		BF_{10}	201.01			
p_{mem} 28°	p_{mem} 28°	Student's *t*	−0.73	30	.472	0.13 [−0.48, 0.22]
		BF_{01}	4.09			
p_{mem} 45°	p_{mem} 45°	Student's *t*	1.36	30	.185	0.24 [−0.12, 0.60]
		BF_{01}	2.27			
sd 12°	*sd* 12°	Student's *t*	1.04	30	.307	0.19 [−0.17, 0.54]
		BF_{01}	3.19			
sd 28°	*sd* 28°	Student's *t*	0.04	30	.969	0.01 [−0.35, 0.36]
		BF_{01}	5.22			
sd 45°	*sd* 45°	Student's *t*	−2.26	30	.012	−0.48 [−0.85, −0.10]
		BF_{10}	3.70			

Table S6

Paired Samples t *Tests on Model Parameters for Experiment 3*

		Test	statistic	*df*	*p*	d_z
Outer p_{mem}	Middle p_{mem}	Student's *t*	0.83	33	.413	0.14 [−0.20, 0.48]
		BF_{01}	3.96			
Middle p_{mem}	Inner p_{mem}	Student's *t*	3.60	33	.001	0.62 [0.25, 0.98]
		BF_{10}	31.12			
Outer *sd*	Middle *sd*	Student's *t*	3.51	33	.001	0.60 [0.23, 0.96]
		BF_{10}	25.24			
Middle *sd*	Inner *sd*	Student's *t*	1.89	33	.067	0.32 [−0.02, 0.67]
		BF_{01}	1.11			

Table S7

Independent Samples t *Test on Model Parameters for Experiments 1 & 2 vs. Experiment 3*

All rings	**Test**	**statistic**	***df***	***p***	**Cohen's *d***
p_{mem}	Welch's t	6.90	58.44	$< .001$	1.55 [1.01, 2.08]
	BF_{10}	1.01e+6			
sd	Welch's t	−0.84	70.85	.403	−0.20 [−0.65, 0.26]
	BF_{01}	3.08			
Middle ring					
p_{mem}	Welch's t	6.29	64.53	$< .001$	1.42 [0.90, 1.93]
	BF_{10}	1.47e+5			
sd	Welch's t	−1.10	71.14	.277	−0.25 [−0.71, 0.20]
	BF_{01}	2.49			