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Different features are stored independently in visual working memory but mediated by object-based representations

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ABSTRACT

The question of whether visual working memory (VWM) stores individual features or bound objects as basic units is actively debated. Evidence exists for both feature-based and object-based storages, as well as hierarchically organized representations maintaining both types of information at different levels. One argument for feature-based storage is that features belonging to different dimensions (e.g., color and orientations) can be stored without interference suggesting independent capacities for every dimension. Here, we studied whether the lack of cross-dimensional interference reflects genuinely independent feature storages or mediated by common objects. In three experiments, participants remembered and recalled the colors and orientations of sets of objects. We independently manipulated set sizes within each feature dimension (making colors and orientations either identical or differing across objects). Critically, we assigned to-be-remembered colors and orientations either to same spatially integrated or to different spatially separated objects. We found that the precision and recall probability within each dimension was not affected by set size manipulations in a different dimension when the features belonged to integrated objects. However, manipulations with color set sizes did affect orientation memory when the features were separated. We conclude therefore that different feature dimensions can be encoded and stored independently but the advantage of the independent storages are mediated at the object-based level. This conclusion is consistent with the idea of hierarchically organized VWM.

1. Introduction

At every moment of our perception, we interact with different objects, each having a number of various features, such as color, shape, size, etc. A limited portion of the information about these objects and their features can be used for current tasks and maintained for a short period of time in working memory (Baddeley, 1986; Baddeley & Hitch, 1974). It is consistently established that the capacity of working memory has serious limitations (e.g., Cowan, 2001; Miller, 1956). These fundamental limits are also true for the visual subsystem of working memory (VWM) that maintains and operates visual information necessary for an ongoing task (Alvarez & Cavanagh, 2004; Luck & Vogel, 1997). However, for a correct capacity estimate, it is important to determine what is represented in VWM as a basic unit of storage. There is a long-lasting debate around this question in the VWM literature: Does VWM store whole objects or separate features?

Existing studies provide evidence that both objects (Cowan, Chen, & Rouder, 2004; Kahneman, Treisman, & Gibbs, 1992; Lee & Chun, 2001; Luck & Vogel, 1997; Luria & Vogel, 2011; Treisman, 1999; Vogel, Woodman, & Luck, 2001; Xu, 2002; Xu & Chun, 2006) and features (see Brady, Konkle, & Alvarez, 2011, for review; Wang, Cao, Theeuwes, Olivers, & Wang, 2017; Wheeler & Treisman, 2002; Shin & Ma, 2017; Fougnie & Alvarez, 2011) can be the units of VWM. In their seminal study, Luck and Vogel (1997) demonstrated a strong advantage of maintaining any number of features in a limited number of spatially bound objects (at least up to four features per object). The prevailing limiting factor for capacity, as Luck and Vogel (1997) suggested, was the number of objects (~3–4) rather than the number of features. They concluded that objects are the units of VWM, showing no limitation in VWM by a number of features. However, other studies failed to support this strong version of object-based storage suggesting that the number of stored features also can be limited (see Brady et al., 2011, for review). Two major sets of evidence are used against this purely object-based account. The first set of evidence is based on findings that increasing the number of features to be remembered within an object does cause interference. For example, the increased number of features belonging to the same dimension per object significantly decreases VWM capacity for these objects (Olson & Jiang, 2002; Wheeler & Treisman, 2002; Xu, 2002). The same was found for increasing object complexity (Alvarez & Cavanagh, 2004; Hardman & Cowan, 2015;

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Oberauer & Eichenberger, 2013). Other studies have found that remembering two features of the same objects impaired the precision of each remembered feature, whereas the capacity was seemingly intact (Fougnie, Asplund, & Marois, 2010; Fougnie & Marois, 2009). The second strong line of evidence against the purely object-based account of VWM is a number of demonstrations of relative independence between features of the same object. This independence can manifest as selective forgetting of some features rather than entire object (Fougnie & Alvarez, 2011) or as swaps between remembered features of different objects (Bays, Catalao, & Husain, 2009; Bays, Wu, & Husain, 2011; Fougnie, Cormiea, & Alvarez, 2013; Pertzov, Dong, Peich, & Husain, 2012). Whatsoever, even in the presence of these feature-based limitations, VWM still consistently benefits from object-based representations: It is easier to remember several features of one object than the same number of features distributed across several objects (Fougnie et al., 2010; Fougnie et al., 2013; Wheeler & Treisman, 2002). To account for this, theorists suggested that neither objects, nor features alone can be the units of VWM. Rather, the units are structured "feature bundles" containing both integrated object and feature representations hierarchically linked (see Brady et al., 2011, for review; Fougnie et al., 2010). Similar ideas that VWM can be constrained by both objects and features in different ways have been proposed by other authors (Olson & Jiang, 2002; Shin & Ma, 2017; Xu & Chun, 2006).

The complicated pattern of evidence for feature-based vs. object-based storage in VWM is additionally complicated by an ambiguity regarding the structure of feature memories. Specifically, it was noted that VWM performance can depend on whether remembered and tested features belong to same or different dimensions. Most experiments on features were the same dimension (Olson & Jiang, 2002; Wheeler & Treisman, 2002; Xu, 2002) which typically constitute different parts of an object (Alvarez & Cavanagh, 2004) show a significant decrement in performance with an increasing number of features per object (but see Luck & Vogel, 1997; Vogel et al., 2001 for an opposite conclusion). There is no such interference between features from the same dimension (e.g., Wheeler & Treisman, 2002). This leaves room for a theory that feature-based VWM is, in fact, a multistorage system having separate capacities for features from different dimensions. This theory was directly tested and supported in recent studies where researchers independently manipulated the memorized set size for features from two separable dimensions, color and orientation (Wang et al., 2017). They found that VWM capacity for a given feature depended on the set size in the corresponding dimension rather than joint set size in both dimensions. For example, if observers are shown six isosceles triangles, each triangle having one of two possible colors (color set size is two) and one of two possible orientations (orientation set size is also two), their ability to spot a change in either of the dimensions is rather high. If color set size becomes six (each triangle has a unique color) and orientation set size remains two, it selectively impairs change detection for color but not for orientation (and vice versa if color set size stays small and orientation set size increases). These separate storages can provide an advantage when the selective encoding of one dimension and ignoring another can be required (Shin & Ma, 2017; Woodman & Vogel, 2008).

However, it is important to note that independent set size manipulations in the experiments by Wang et al. (2017) concerned features but not objects these features belonged to. In all experiments, colors and orientations were tested in the same set of objects. If object representations facilitate feature storage in general, can they mediate the advantage of the independent feature capacities? Alternatively, these independent capacities can be purely feature-based in which case they should manifest in both unitary and separate objects.

To address this question, we have run three experiments testing VWM for color and orientation. The general approach was similar to that used by Wang et al. (2017): We orthogonally manipulated the set size within each dimension by assigning either a single or three different values and measured VWM for both dimensions. Critically, colors and orientations could be assigned to the same objects (Experiment 1), different parts of spatially integrated objects (Experiment 3), or spatially separated objects (Experiment 2). Unlike Wang et al. (2017), we used a continuous report task (Wilken & Ma, 2004; Zhang & Luck, 2008) instead of a change detection task. It is justified by a fact that the former paradigm allows parametric estimation of both capacity and fidelity of VWM (Zhang & Luck, 2008), that are both known to be sensitive to feature-based and object-based load (Fougnie et al., 2010).

2. Experiment 1

In Experiment 1, we tested VWM for colors and orientations in the same set of three objects. In different conditions of the experiment, we assigned either three different values or a single value to each object in each dimension orthogonally. This manipulation affected both within-dimension and joint set sizes in a manner similar to that in the experiments by Wang et al. (2017). Hence, the main goal of this experiment is to test whether the principal finding of independent storages for color and orientation is replicated in our paradigm.

2.1. Methods

2.1.1. Participants

Twenty students from the Higher School of Economics (17 female) participated for extra course credits. The participants ranged in age from 18 to 25 years (average age was 19.93 years) and reported having normal or corrected to normal visual acuity, no color blindness and neurological problems. Before the beginning of the experiment, they signed an informed consent form. In this and subsequent experiments, sample sizes were determined based on similar studies addressing the issue of feature storage and binding in VWM and using a continuous report task (from 10 to 16; for example, Fougnie & Alvarez, 2011; Fougnie et al., 2010; Bays et al., 2009; Pertzov et al., 2012). The planned sample size also included a few extra participants considering a possibility of technical problems or poor performance in some participants.

2.1.2. Apparatus and stimuli

Stimulation was developed and presented through PsychoPy (Pierce, 2007) for Linux Ubuntu. Stimuli were presented on a standard VGA monitor with a refresh frequency of 75 Hz and 1024 × 768-pixel spatial resolution. Stimuli were presented on a homogeneous gray field. Participants sat approximately at 47 cm from the monitor. From that distance, screen subtended approximately 42.44 × 32.5 degrees of visual angle.

Sample displays consisted of one or three colored isosceles triangles presented in randomized positions along an imagery circumference 4.35° away from a monitor center (Fig. 1). Each triangle had sides of 0.6°, 1.2°, and 1.2° in length. To set the positions of the three triangles on the imaginary circumference, we first generated a random rotational angle from 1° to 360° for a first triangle and then positioned the rest two triangles 120° and − 120° away from the first with a ± 30°-jitter. For color assignment, we used the hue wheel in the 360° HSV (hue-saturation-value) space, and for orientation assignment, we used the 360° orientational circumference. As color and orientation had the same dimensionality as spatial positions, we applied the rotational algorithm described above to set three colors and three orientations. When an experimental condition required a single color, a single orientation, or a single item to be presented, the color, orientation, or position was chosen randomly.

For memory test, outline circles were presented at the locations of sample triangles, with one thick outline indicating the location of a probed item. In trials where color was probed, the test display was surrounded by an HSV color wheel 4.35° in radius (Fig. 1). In trials where orientation was probed, the test display was surrounded by a black orientational wheel with white ticks marking 30° steps (Fig. 1).

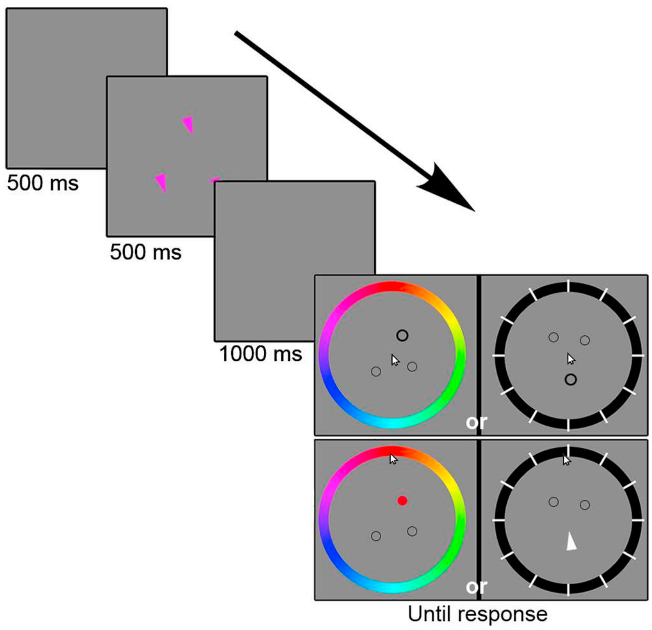

Fig. 1. The time course of a typical trial in Experiment 1.

The probed outline turned into a solid colored circle (if the color was probed) or a white-oriented triangle (if the orientation was probed) upon mouse click on a wheel (Fig. 1).

2.1.3. Procedure

Each experimental trial started with a 500-ms presentation of a sample display. Participants were instructed to memorize both the color and orientation of the triangles. The sample was followed by a 1-s delay (retention interval) that, in turn, was followed by a probe screen (Fig. 1). Clicking on a color or orientation wheel, participants had to adjust a corresponding attribute of the probe item to match the sample attribute presented at that location. At the beginning of the experiment, participants completed a practice block. The total duration of the experiment varied between 45 and 60 min.

2.1.4. Design and data analysis

Five conditions of the Sample type were tested in Experiment 1 (Fig. 2A). In four of these conditions, we orthogonally varied color and orientation set sizes in three triangles: (1) all different features (three colors and three orientations), (2) color identical (one color and three orientations), (3) orientation identical (three colors and one orientation), (4) all identical features (one color and one orientation). The latter condition can be considered a baseline estimating observers' capacity and fidelity at minimal load for each feature. Finally, condition (5) contained a single object and was used as a baseline. This baseline, in comparison with the "all identical" condition, aimed to test whether three identical feature values of three objects are indeed encoded like a single feature of one object. In a within-subject experiment, each participant was exposed to 5 (Sample type) × 2 (Probed dimension: Color vs. Orientation) × 47 repetitions = 470 trials.

For each trial, the error was calculated as an angular difference between the correct feature value and that adjusted by a participant. The distribution of errors was then analyzed using the mixture model (Zhang & Luck, 2008) implemented in MemToolbox for Matlab (Suchow, Brady, Fougnie, & Alvarez, 2013). The standard mixture model has two different parameters obtained from fitting two components of the error distribution. The first parameter is the standard deviation (*SD*) of the von Mises distributional component, that is supposed to reflect the precision of a noisy representation that is present in memory. The second parameter is the probability of random guess (P_{guess}) can be estimated as an area below the uniform component of the mixed distribution; this component is supposed to reflect randomly chosen answers when a probed item is likely to be absent in the memory (not encoded or forgotten). Reverse P_{guess} is used as an estimate for a probability that a probed element is held in VWM: $P_{memory} = 1 - P_{guess}$.

To evaluate the effect of Sample type, we applied the standard frequentist and Bayesian one-way repeated measures ANOVA to the *SD* and P_{memory} for color and orientation. The Bayes factor (BF_{10}) was calculated using JASP 0.9.0.0 (JASP Team, 2018; Wagenmakers et al., 2017) and interpreted using the standard Jeffreys's (1961) scale. The Bayesian approach estimates the odds of H_1 to H_0 (Rouder, Speckman, Sun, Morey, & Iverson, 2009).

2.2. Results and discussion

One participant was excluded from the analysis because she showed nearly 100% guess rate in all conditions. The results of Experiment 1 for P_{memory} and *SD* are summarized in Fig. 3.

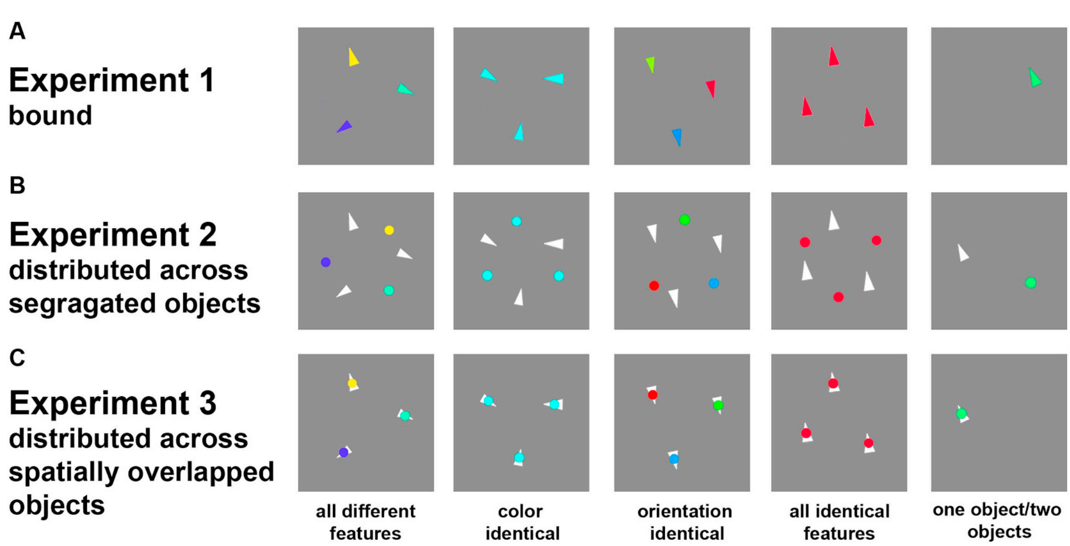

Fig. 2. Example of stimuli for three experiments for five conditions (objects with all different features, objects with different color and identical orientation, objects with different orientation and identical color, objects with all identical features, one pair of features): (A) Experiment 1 with bound features in the object, (B) Experiment 2 with features distributed across segregated objects, (C) Experiment 3 with features distributed across spatially overlapped objects.

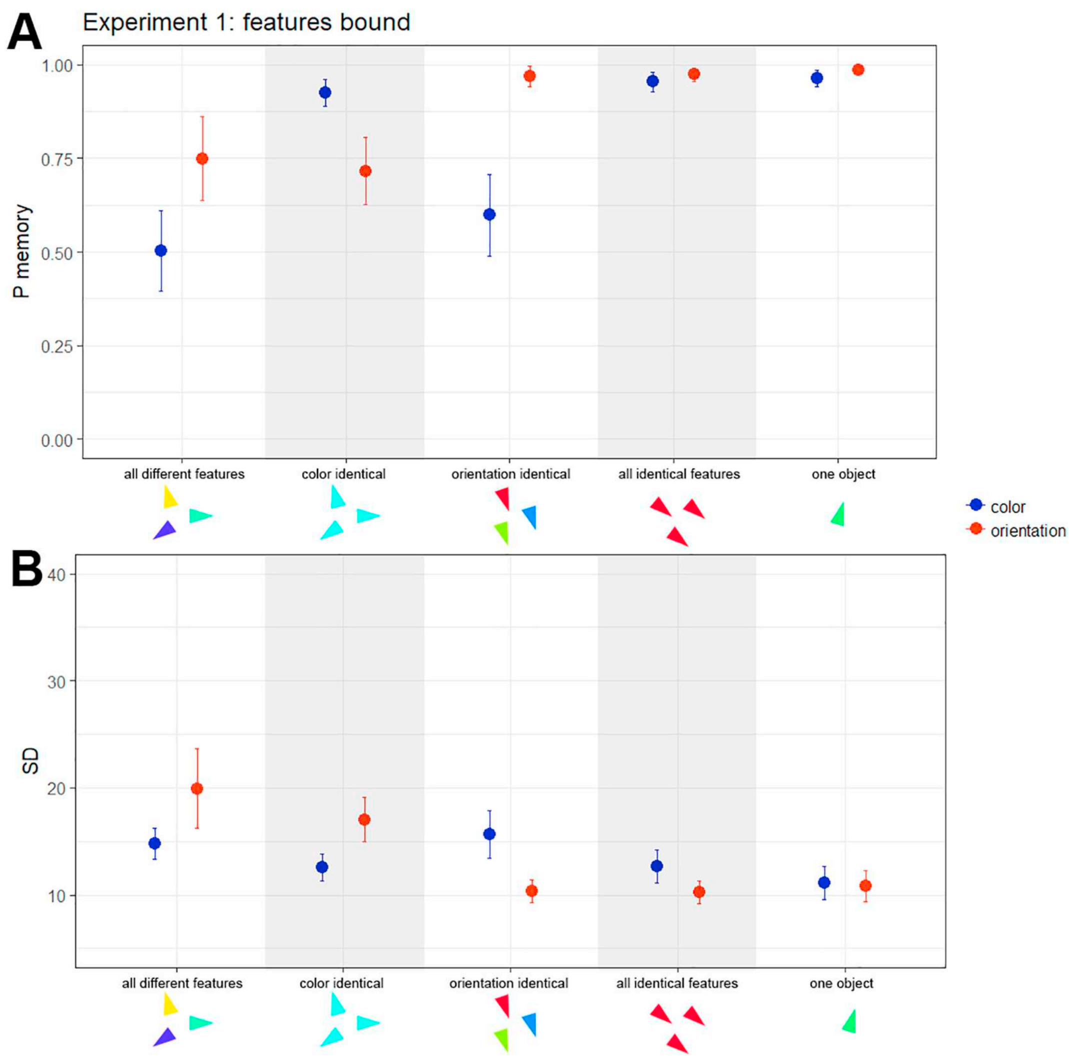

Fig. 3. Results of Experiment 1: (A) P_{memory} and (B) *SD* as a function of Sample type. Error bars depict 95% CIs.

2.3. P_{memory} for color

We found a strong effect of Sample type on P_{memory} for color (F (4, 72) = 65.92, $p < .001$, $\eta^2 = 0.786$, $BF_{10} > 10^{20}$). P_{memory} was greater in conditions where the color was identical across objects (color identical, all features identical, and one object) compared to conditions where colors differed across (all different features and orientation identical) $-7.348 \leq t(18) \leq 9.739$, $p < .001$, Bonferroni corrected $\alpha = 0.005$, $1.686 \leq$ Cohen's $d \leq 2.234$, $10^4 < BF_{10} < 10^{18}$. There were no significant differences between conditions with identical color across objects (color identical, all features identical, and one object – see Appendix A for the exact results of statistical evaluation) and also between conditions with different color across objects (all different features and orientation identical – see Appendix A). Note that, when the colors were identical, P_{memory} was always near 100% ceiling (Fig. 1A) suggesting the perfect capacity to remember one color regardless of variations in the number of orientations and the total number of physically presented objects.

2.4. P_{memory} for orientation

We found a strong effect of Sample type on P_{memory} for orientation (F (4, 72) = 28.53, $p < .001$, $\eta^2 = 0.613$, $BF_{10} > 10^{10}$). P_{memory} was greater in samples where orientation was identical across objects (orientation identical, all identical features, and one object) compared to samples where orientation differed across objects (all different features and color identical) – $4.537 \leq t(18) \leq 7.376$, $p < .001$, Bonferroni corrected $\alpha = 0.005$, $1.041 \leq$ Cohen's $d \leq 1.692$, $122 < BF_{10} < 10^9$. There were no significant differences between conditions with identical orientation across objects (orientation identical, all identical features, and one object – see Appendix A for the exact results of statistical evaluation) and also between conditions with different orientation across objects (all different features and color identical – see Appendix A). Again, P_{memory} for orientations was at ceiling in all conditions with identical orientation, suggesting perfect VWM capacity for a single orientation regardless of any variations of the number of colors or objects in total.

2.5. SD for color

We found a strong effect of Sample type on *SD* for color (F (4, 72) = 6.115, $p < .001$, $\eta^2 = 0.254$, $BF_{10} = 217.3$). In all different features and in identical orientations, *SD* for color was greater compared to color identical ($t(18) = 3.312$, $p = .0039$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.760$, $BF_{10} = 11.53$) and one object (t (18) = 3.312, $p = .0004$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 1.003$, $BF_{10} = 88.89$). In all other comparisons there were no significant differences (see Appendix A).

2.6. SD for orientation

We found a strong effect of Sample type on *SD* for orientation (F (4, 72) = 30.66, $p < .001$, $\eta^2 = 0.630$, $BF_{10} > 10^{10}$). *SD* was lower in samples where orientation was the same across objects (only orientation identical, all features identical and one object) compared to conditions where orientation was different through objects (all features different and only color identical): $5.327 \leq t(18) \leq 8.269$, $p < .001$, Bonferroni corrected $\alpha = 0.005$, $1.222 \leq$ Cohen's $d \leq 1.897$, $559 < BF_{10} < 10^{11}$. There were no significant differences between conditions with identical orientation across objects (orientation identical, all identical features, and one object – see Appendix A for the exact results of statistical evaluation) and also between conditions with different orientations across objects (all different features and color identical – see Appendix A).

In total, in Experiment 1 we observed a consistent pattern across both probed dimensions and both estimated VWM parameters. Specifically, we found that a greater P_{memory} (roughly corresponding to capacity in items) and a lower *SD* (corresponding to better precision) take place in those clusters of conditions where the tested features have been identical across objects or where a memorized object has been physically alone. More importantly, within these clusters, there was no effect of whether a second dimension had been represented by identical or different features. Hence, we found that both P_{memory} and *SD* for a given dimension depended only on the set size within that dimension and not on the joint set size. Additionally, we found that all identical features are encoded as efficiently as a corresponding feature in one object. Overall, the results of Experiment 1 replicate Wang et al.'s (2017) finding in favor of independent storages for features from different dimensions.

3. Experiment 2

In Experiment 2, we modified stimuli so that colors and orientations belonged to different spatially separated objects (exactly like in Fougnie et al., 2010). This would allow us to test whether dimension independence is preserved when there is no object-based advantage for storing the features together and when object-based load is increased.

3.1. Methods

3.1.1. Participants

Nineteen students from the Higher School of Economics (14 female) participated for extra course credit. They ranged in age from 18 to 22 years (average age is 18.52 years) and reported having normal or corrected to normal visual acuity, no color blindness and no neurological problems. Before the beginning of the experiment, they signed an informed consent form.

3.1.2. Apparatus and stimuli

Apparatus and stimuli were similar to Experiment 1, except that colors and orientations were distributed across spatially separated objects. This led to duplicated numbers of objects from Experiment 1 (from three to six and from one to two). Objects were located along an imaginary circumference with a radius of 4.35°. If there were six objects on a screen, each object was separated by 60° of rotation ± 15° jitter from its neighbors (Fig. 2B). When there were two objects on a screen, each object was separated by 180° of rotation from another (presented symmetrically across the center of the screen, Fig. 2B). There were two types of objects depending on which dimension was relevant for memorization. "Color" objects were the circles whose colors were set using the coloring algorithm from Experiment 1. "Orientation" objects were the isosceles triangles whose orientations were set using the orientation rotation algorithm from Experiment 1. "Color" objects alternated with "orientation" objects on the imaginary circumference forming two overlapping triangular groups (this was exactly the same method of positioning as that used by Fougnie et al., 2010, Fig. 2B). When two objects were presented, one was a "color" object and another was an "orientation" object.

3.1.3. Procedure

The procedure of Experiment 2 was the same as in Experiment 1, except for a difference in instruction. Participants were instructed to memorize only orientations of white triangles and only colors of color circles.

3.1.4. Design and data analysis

The design of Experiment 2 was the same as that of Experiment 1 in terms of Sample types, two tested dimensions, and a number of trials. The only nominal change was that the baseline "one object" condition from Experiment 1 was renamed to "two objects" for clarity (but they were equal in terms of feature set sizes). Data analysis was identical to Experiment 1.

3.2. Results and discussion

The results of Experiment 2 for P_{memory} and *SD* are summarized in Fig. 4.

3.3. P_{memory} for color

We found a strong effect of Sample type on P_{memory} for color (F (4, 72) = 69.53, $p < .001$, $\eta^2 = 0.794$, $BF_{10} > 10^{20}$). P_{memory} for was greater in samples where color was identical across "color" objects (color identical, all identical features) or belonged to a single "color" object compared to samples where colors were different across objects (all features different and orientation identical): $8.426 \leq t(18) \leq 9.129$, $p < .001$, Bonferroni corrected $\alpha = 0.005$, $1.993 \leq$ Cohen's $d \leq 2.094$, $BF_{10} > 10^6$. There were no significant differences between conditions with identical color across objects (color identical, all features identical, and single "color" object – see Appendix A for the exact results of statistical evaluation) and also between conditions with different color across objects (all different features and orientation identical – see Appendix A). This result replicates the respective pattern from Experiment 1.

3.4. P_{memory} for orientation

We found an effect of Sample type on P_{memory} for orientation (F (4, 72) = 19.03, $p < .001$, $\eta^2 = 0.514$, $BF_{10} > 10^8$). As in Experiment 1, P_{memory} was greater in samples with all identical features or in a single "orientation" object (two objects) compared to conditions where orientations differed across objects (all different features and color identical; comparison: $3.375 \leq t(18) \leq 5.838$, $p \leq .0034$, Bonferroni corrected $\alpha = 0.005$, $0.774 \leq$ Cohen's $d \leq 1.339$, $12.981 < BF_{10} < 10^4$). However, unlike Experiment 1, we found that P_{memory} for orientation suffered from the increased color set size (orientation identical condition). Specifically, P_{memory} in that condition ($M = 0.91$) was lower than in all identical features ($M = 0.96$) condition ($t(18) = 3.368$, $p = .0018$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.842$, $BF_{10} = 7.431$) but greater than in the two conditions with three different orientations (all different features ($M = 0.82$) and color identical ($M = 0.83$); comparisons: $3.375 \leq t(18) \leq 5.838$, $p \leq .0034$, Bonferroni corrected $\alpha = 0.005$, $0.774 \leq$ Cohen's $d \leq 1.339$, $12.981 < BF_{10} < 10^4$). We also found some evidence (basically, from effect size and Bayes factor estimates) that the orientation P_{memory} in the orientation identical trials ($M = 0.91$) was lower than that in the two object trials ($M = 0.97$), though this evidence was not conclusive, since the significance level did not fall below the strictly Bonferroni corrected critical ($t(18) = 3.075$, $p = .0065$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.705$, $BF_{10} = 22.689$). Overall, we conclude that orientation P_{memory} in the orientation identical condition was high, yet, we observed some evidence for slight impairment due to color

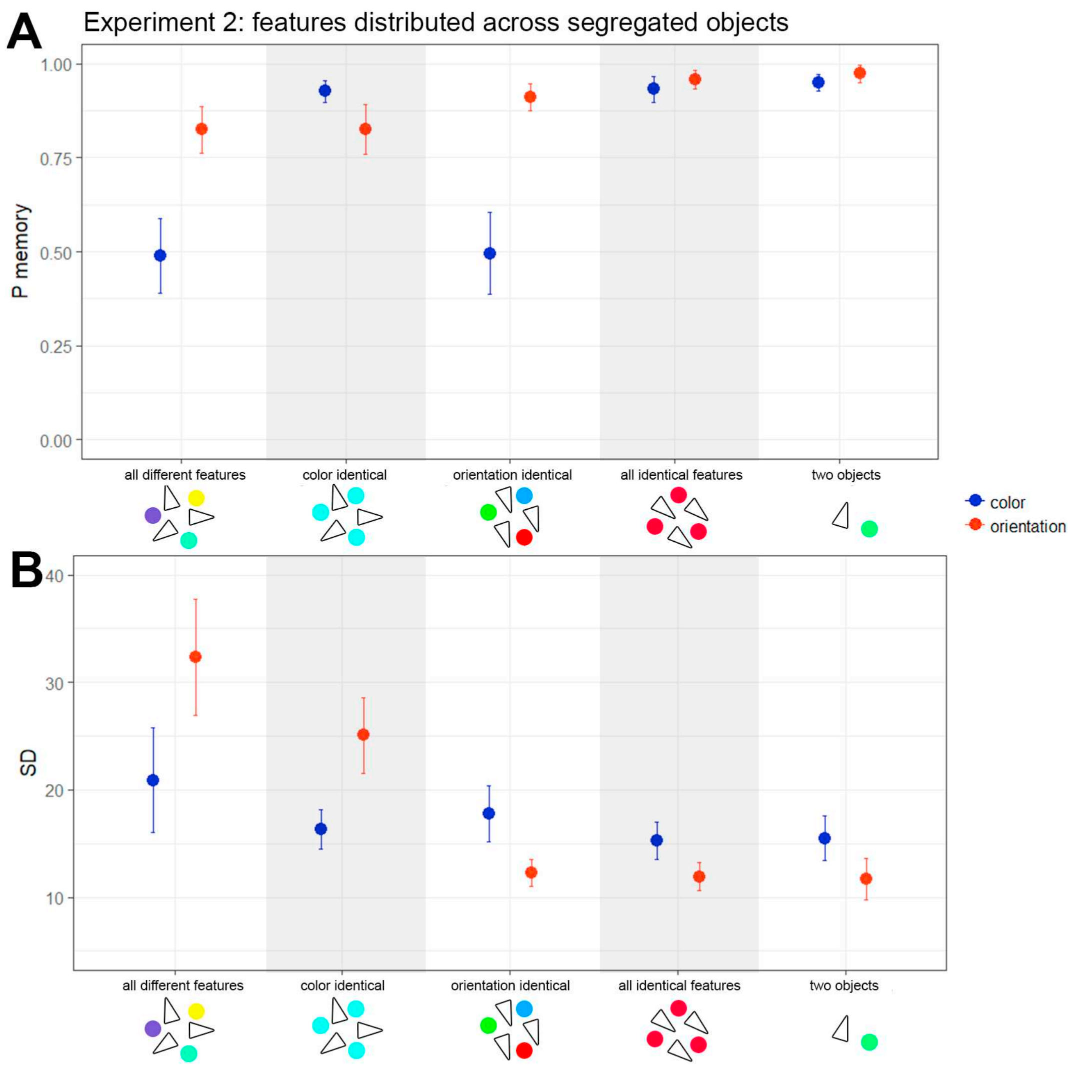

Fig. 4. Results of Experiment 2: (A) P_{memory} and (B) *SD* as a function of Sample type. Error bars depict 95% CIs.

memory load. In all other comparisons, we found no significant differences (see Appendix A).

3.5. SD for color

We did not find convincing evidence for a reliable effect of Sample type on *SD* for color (F (4, 72) = 2.865, p = .029, η^2 = 0.137, BF_{10} = 2.735). We conclude, therefore, that memory set size manipulation did not have a strong effect on the precision of color encoding. As we will show later, by direct comparison of results across Experiments 1–3, the lack of the effect can be associated with overall drop in color memory precision in Experiment 2.

3.6. SD for orientation

We found a strong effect of Sample type on the *SD* for orientation (F (4, 72) = 71.02, p < .001, η^2 = 0.798, $BF_{10} > 10^{12}$). Like in Experiment 1, *SD* was lower in the samples where orientations were identical across "orientation" objects (identical orientation and all identical features) or belonged to a single "orientation" object (two objects condition) compared to the samples where orientations were different across objects (all different features and identical color; comparisons: $8.059 \le t(18) \le 10.197$, p < .001, Bonferroni corrected $\alpha = 0.005$, $1.849 \le$ Cohen's $d \le 2.335$, $10^5 < BF_{10} < 10^6$). We also found that, in the identical color samples (but different orientations), *SD* was smaller than in samples with all different features (t (18) = 3.867, p = .0011, Bonferroni corrected $\alpha = 0.005$, Cohen's d = 0.887, BF_{10} = 33.281), that suggests that color set size interfered with the precision of VWM for orientation. In all other comparisons, we found no significant differences (see Appendix A).

Overall, in Experiment 2 we replicated the finding from Experiment 1 and from the literature (Fougnie et al., 2010; Wang et al., 2017; Zhang & Luck, 2008) that the set size increment within the same dimension makes P_{memory} for that dimension dropping and *SD* for that dimension raising. It is also quite evident that, like in Experiment 1, the VWM parameters for a given dimension depended on memory load in that dimension more than on memory load in another dimension. For example, P_{memory} for orientations dropped strongly when the orientation set size increased (all identical features vs. identical color comparison, Fig. 4A) and it dropped slightly when the color set size increased (all identical features vs. identical orientation comparison, Fig. 4A). Therefore, this result supports an idea that observers kept storing colors and orientations relatively independently, even despite a serious increment in the number of spatially separated objects.

However, unlike Experiment 1, we found some evidence for slight detrimental effects of VWM load in one dimension on feature storage in another dimension. Specifically, when orientation load was kept low but color load increased (all identical features vs. orientation identical) it impaired P_{memory} for orientations. Also, when orientation load was high and color load increased (color identical vs. all different features) the precision of orientation estimates decreased substantially (Fig. 4B). Following the interpretational logic of the mixture model for VWM (Zhang & Luck, 2008), this pattern suggests that storing more colors decreases the probability that the orientation would be remembered, whereas storing more orientations (when color set size is already big) causes the subsequent loss in the precision of each orientation memory. Another recent framework (Schurgin, Wixted, & Brady, 2018) does not make a strong qualitative difference between the *SD* and the P_{memory} parameters suggesting a single source of degradation for both these parameters, namely, the distinctiveness of familiarity signals provided by available test alternatives. In this framework, the drop of P_{memory} and *SD* of orientation memory under high color load might reflect gradual decrement in the quality of familiarity signals for orientation.

This detrimental effect of color memory load on orientation memory was not mirrored in an effect of orientation memory load on color memory. One possible explanation of this asymmetry could be that colors were more prioritized for encoding, so it did not suffer from overall feature load as much as less prioritized orientation memory. One finding can seemingly contradict to this interpretation, namely, the fact that P_{memory} for color drops much stronger when color set size increases than P_{memory} for orientation drops when orientation set size increases (Fig. 4A). However, this fact may suggest that remembering three colors is generally a more difficult task than remembering three orientations. This suggestion does not rule out the possibility that observers put a higher priority to color (note that in Experiment 1, the relative P_{memory} decrement for color was also greater despite the absence of interference between color and orientation set sizes, Fig. 3A). Color priority could be partially explained by the additional focus on colored objects, because of the match between its shape and the shape of location cues in their initial states, before observers clicked on a color or orientation wheel (Fig. 1). Although this asymmetry between color and orientation needs further research, our major result indicates that there is interference between color VWM and orientation VWM when these features are distributed between different objects.

4. Experiment 3

The interference pattern that we found in Experiment 2 for orientation memory under the increasing color memory load, can have an alternative explanation apart from the spatial separation of colors and orientations. Overall stimulus complexity was greater than in Experiment 1 that could become an extra source of noise (some items were circles and some were triangles, some were white and some had different colors). Moreover, the instruction requiring to selectively encode different features in different objects could be also more difficult than in Experiment 1. To control for these possible confounds, we have run Experiment 3. Here, we presented participants with spatially integrated objects and asked to remember the color and orientation information about each of the object, like we did in Experiment 1. However, each of the objects consisted of two overlapping parts, one corresponding to a “color” object and another corresponding to the “orientation” object from Experiment 1 (for similar manipulations, see Fougnie et al., 2010; Xu, 2002). So, each object presented in Experiment 3 had the same amount of complexity as two separate objects in Experiment 2. Also, the instruction in Experiment 3 required selective encoding of orientation information from one part of an object and of color information from another part.

4.1. Methods

4.1.1. Participants

Nineteen students from the Higher School of Economics (14 female) participated for extra course credits. They ranged in age from 18 to 22 years (average age is 19.03 years) and reported having normal or corrected to normal visual acuity, no color blindness and no neurological problems. Before the beginning of the experiment, they signed an informed consent form.

4.1.2. Apparatus, stimuli, and procedure

In general, apparatus and stimuli were the same as in two previous experiments with some differences. Each object consisted of two parts: an oriented white triangle overlaid with a color circle (see Fig. 2C for examples). Object positioning was the same as in Experiment 1. The procedure was the same as in Experiment 1 with an addition that participants were instructed to remember the color of the circular part and the orientation of the triangular part of each object.

Design and data analysis were the same as in Experiment 1

5. Results and discussion

The data from four participants were excluded from analysis because they showed nearly 100% guess rate in all conditions. The results of Experiment 3 for P_{memory} and *SD* are summarized in Fig. 5.

5.1. P_{memory} for color

We found the strong effect of Sample type on P_{memory} for color (F (4, 56) = 69.53, $p < .001$, $\eta^2 = 0.808$, $BF_{10} > 10^{20}$). P_{memory} for color was higher in all conditions where color was identical across objects (color identical, all identical features, and one object) compared to the conditions where color differed across objects (all different features and orientation identical; comparisons: $7.916 \leq t(14) \leq 8.898$, $p < .001$, Bonferroni corrected $\alpha = 0.005$, $2.044 \leq$ Cohen's $d \leq 2.298$, $BF_{10} > 10^5$). In all other comparisons, we found no significant differences (see Appendix A).

5.2. P_{memory} for orientation

We found the strong effect of Sample type on P_{memory} for orientation (F (4, 56) = 14.37, $p < .001$, $\eta^2 = 0.506$, $BF_{10} > 10^6$). P_{memory} was greater in all conditions where orientation was identical across objects (identical orientation, all identical features and one object) compared to the conditions where orientations differed across objects (all different features and identical color; comparisons: $3.450 \leq t(14) \leq 4.191$, $p \leq .0039$, Bonferroni corrected $\alpha = 0.005$, $0.891 \leq$ Cohen's $d \leq 1.081$, $12.18 < BF_{10} < 42.123$). In all other comparisons, we found no significant differences (see Appendix A).

5.3. SD for color

We found no effect of Sample type on the color *SD* (F (4, 56) = 0.726, $p = .578$, $\eta^2 = 0.049$, $BF_{10} = 0.139$). There were no significant differences in SD for color between conditions.

5.4. SD for orientation

We found the strong effect of Sample type on the orientation *SD* (F (4, 56) = 40.92, $p < .001$, $\eta^2 = 0.745$, $BF_{10} > 10^{13}$). *SD* was lower in all conditions where orientation was identical across objects (identical orientations, all identical features, and one object) compared to the conditions where orientation differed across objects (all different features and identical colors; comparisons: $6.008 \leq t(14) \leq 10.397$, $p < .001$, Bonferroni corrected $\alpha = 0.005$, $1.551 \leq$ Cohen's $d \leq 2.684$, $781 < BF_{10} < 10^6$). In all other comparisons, we found no significant differences (see Appendix A).

Therefore, the results of Experiment 3 basically replicated the principal results of Experiment 1 regarding the absence of interference between color and orientation VWM parameters. We conclude that VWM can support the independent storage of features from different dimensions in spatially integrated objects.

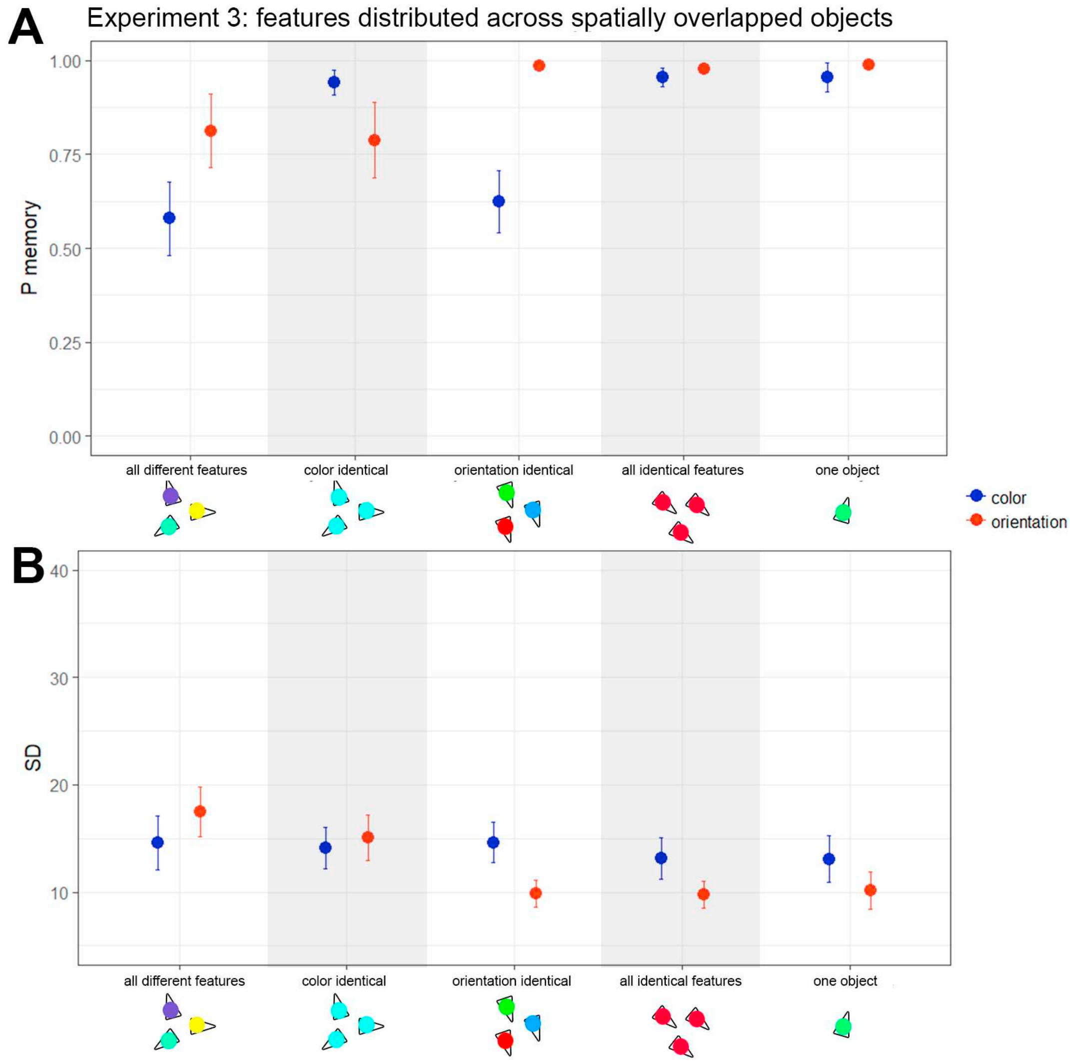

Fig. 5. Results of Experiment 3: (A) P_{memory} and (B) *SD* as a function of Sample type. Error bars depict 95% CIs.

5.5. Comparisons between experiments

To get a more comprehensive picture of the effects of feature separation vs. feature integration on VWM for both color and orientation, we directly compared the results of all three experiments. Data from 53 participants were analyzed. In Fig. 6, we plotted the results of all experiments together.

There were no significant differences between experiments in P_{memory} for both colors ($F(2, 50) = 1.434$, $p = .248$, $\eta^2 = 0.054$, $BF_{10} = 0.106$) and orientations ($F(2, 50) = 0.699$, $p = .502$, $\eta^2 = 0.027$, $BF_{10} = 0.123$). Yet, these differences were substantial in *SD* for both color ($F(2, 50) = 15.67$, $p < .001$, $\eta^2 = 0.054$, $BF_{10} = 415$) and for orientation ($F(2, 50) = 14.51$, $p < .001$, $\eta^2 = 0.367$, $BF_{10} = 246$). These differences were provided by Experiment 2 (Fig. 5B) where *SD*'s were overall greater than in Experiment 1 (color SD: $t = 5.242$, $p < .001$, Bonferroni corrected $\alpha = 0.017$, Cohen's $d = 0.720$, $BF_{10} = 20{,}176$; orientation SD: $t = 4.224$, $p < .001$, Bonferroni corrected $\alpha = 0.017$, Cohen's $d = 0.580$, $BF_{10} = 218$) and Experiment 3 (color SD: $t = 4.196$, $p < .001$, Bonferroni corrected $\alpha = 0.017$, Cohen's $d = 0.576$, $BF_{10} = 213$; orientation SD: $t = 4.936$, $p < .001$, Bonferroni corrected $\alpha = 0.017$, Cohen's $d = 0.678$, $BF_{10} = 3293$). Together these results demonstrate that both color and orientation were encoded and stored with a substantial loss in precision when they belonged to different rather than same objects. This finding is in line with the previous evidence for object-based advantage for storing features in VWM (Fougnie et al., 2010; Fougnie et al., 2013; Wheeler & Treisman, 2002).

We found evidence for a small effect of Sample type × Experiment on P_{memory} for orientations ($F(8, 38) = 2.640$, $p = .009$, $\eta^2 = 0.046$, $BF_{10} = 4.457$). It is provided by a smaller P_{memory} found for trials with identical orientations (and different colors) in Experiment 2 compared to Experiments 1 ($t(36) = 2.633$, $p = .012$, Bonferroni corrected $\alpha = 0.017$, Cohen's $d = 0.854$, $BF_{10} = 4.234$) and 3 ($t(32) = 3.721$, $p < .001$, Bonferroni corrected $\alpha = 0.017$, Cohen's $d = 1.285$, $BF_{10} = 38.705$). This result suggests that the probability of not having an orientation in VWM is slightly impaired by increasing color load but only when colors and orientations belong to spatially separated objects. To remind, this very decrement was earlier supported by the within-experiment comparison between the identical orientation and the all identical displays in Experiment 2. We also found evidence for an effect of Sample type × Experiment on the *SD* for orientations ($F(8, 200) = 12.58$, $p < .001$, $\eta^2 = 0.127$, $BF_{10} > 10^{11}$). The effect was mostly provided by disproportional absolute increment of the *SD* as a function of the sample type in Experiment 2 compared to Experiments 1 and 3 (Fig. 6B). When observers had to remember a single orientation in Experiments 1 or 3 (samples: one object, all identical features, or identical orientation) the orientation SD were ~10°, and they reached only ~12° in Experiment 2 showing a bare or no statistical evidence of growth ($0.77 \le t \le 2.87$, $0.007 \le p \le .45$, Bonferroni corrected $\alpha = 0.017$, $0.249 \le$ Cohen's $d \le 0.991$, $BF_{10} < 7$). When observers

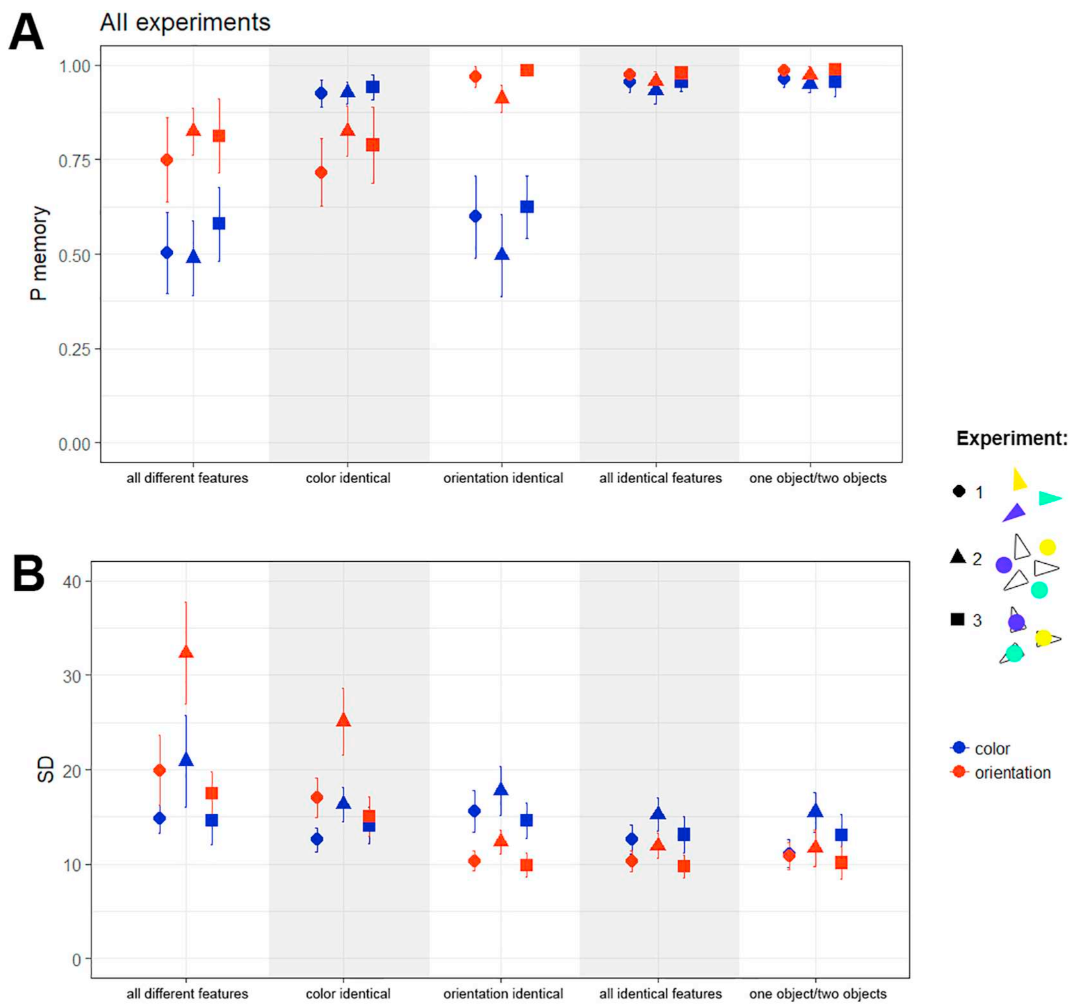

Fig. 6. Results of Experiments 1–3: (A) P_{memory} and (B) *SD* as a function of Sample type and Experiment. Error bars depict 95% CIs.

had to remember three orientations, the growth in orientation SD was much substantial in Experiment 2 compared to Experiments 1 and 3: from ~15 to 17° to ~25° in identical colors (*t*'s ≥ 4.1, $p < .001$, Bonferroni corrected $\alpha = 0.017$, Cohen's $d \geq 1.3$, $BF_{10} \geq 91$), and from ~18–19° to ~32° in all different features (*t*'s ≥ 3.9, $p < .001$, Bonferroni corrected $\alpha = 0.017$, Cohen's $d \geq 1.3$, $BF_{10} \geq 78$). In other words, memory precision for a single orientation almost did not suffer from assigning this orientation to a set of objects separate from a "color" set. Together with the insensitivity of the orientation SD to manipulating the color size (see the comparisons between all identical and identical orientation displays in Experiment 2), this keeps supporting the independent storage of colors and orientations regardless of object integration. However, orientation precision suffers much more from object separation when three orientations are to be remembered. This suggests that, under high load, the task to remember both colors and orientations becomes more detrimental, at least for the orientation memory, if the colors and orientations are spatially separated. Together with the demonstration that higher color load stronger impairs the orientation *SD* in separated objects (see the comparisons between identical color and all different features displays in Experiment 2), this suggests that spatial separation of features limits their independent storage.

6. General discussion

Our principal research question was about the relationship between feature-based and object-based unit organization in VWM. In particular, we tested whether the finding that features from two different dimensions, color and orientation, can be stored without substantial interference (Wang et al., 2017; Wheeler & Treisman, 2002) is related to object-based coordination between these features. In other words, we tested whether the absence of interference is due to the fact that each particular color goes with a certain orientation within a unitary object (Duncan, 1984; Luck & Vogel, 1997). In our experiments, we implemented the same approach as Wang et al. (2017) used in their work to test independence or interdependence of VWM resources for color and orientation. This approach is based on the orthogonal manipulation with set sizes in each dimension. Our critical addition to this manipulation was spatial separation vs. spatial integration of features from different dimensions in a paradigm very much resembling that used by Fougnie et al. (2010). It is supposed that spatial separation would cause features to be perceived and encoded as belonging to different objects, whereas spatial integration would cause the features to be encoded as belonging to the same objects. One could question object unity in Experiment 3 where two geometrical shapes were overlaid, but in fact spatial overlap seems to be a strong factor that aids the formation of object-like units (Rensink, 2000; Trick & Pylyshyn, 1993; Wolfe & Bennett, 1997; Xu, 2002). Overlaying could indeed create single object representation (Xu, 2002), but connections between different dimensions represented by different parts of the object are weaker than connections between different features represented by one object (Fougnie et al., 2010; Xu, 2002). We suggest that overlapped objects are still able to create a two-part representation of a more complex object, similar to beachball-like or Saturn-like objects in Xu's (2002) study, so that the originally separate features of the more elementary objects can become the features of a single complex objects.

Using the continuous report paradigm, we replicated the basic finding made by Wang et al. (2017) in the change detection paradigm. When colors and orientations belonged to the same set of objects (Experiments 1 and 3), we found no evidence of cross-dimensional interference. Both capacity (P_{memory}) and precision (*SD*) for colors stayed intact when the number of orientations increased, and vice versa. Together with intra-dimensional interference remarkably growing with a set size, this supports the conclusion about the independent capacities for features from different dimensions (Shin & Ma, 2017; Wang et al., 2017; Wheeler & Treisman, 2002). Moreover, the pattern was mirrored quite consistently by another parameter, *SD* indicating the precision of a VWM trace. Together, these findings corroborate the robustness of the main conclusion made by Wang et al. (2017). It is also important to note that this pattern is still observable in Experiment 2 (Fig. 6) when colors and orientations were distributed between spatially separated objects. This supports the idea that observers could selectively extract different relevant features from different objects and "put" these features to relatively separate storages. This selective encoding could be aided by the way the objects were organized in Experiment 2 (see also Fougnie et al., 2010). The round shape of "color" objects made them "orientation-free", and the white color of "orientation" objects made them "color-free". Moreover, shape differences between the "color" and the "orientation" objects could provide stronger grouping between all objects of the same type and weaker grouping between objects of different types, thus encouraging independent feature encoding. Apart from our main topic, it is an interesting question for future research whether observers are capable of selective encoding of different features from different objects when the objects are variable in both dimensions. Whatsoever, the basically consistent pattern across all three experiments suggests that observers are more efficient in dealing with an increased VWM load across feature dimensions than within these dimensions, both within spatially integrated and spatially separated objects. This conclusion supports multiple feature-based storages in VWM.

Having said that, we also found that the prevailing pattern of the independent color and orientation storages was modulated by the spatial separation of these features in Experiment 2. Here, we found some signs of cross-dimensional interference, although they manifested only in the orientation domain. Moreover, we found that the precision of orientation reports is substantially more prone to the detrimental effect of the increased orientation set size when colors are to be remembered from different rather than same objects. This can indicate that object separation limits the totally independent storage of features from different dimensions.

This pattern of results leads us to a conclusion that may seem paradoxical. On one hand, we demonstrated that features from different dimensions can be stored independently from each other. On the other hand, this independence is better supported by their belongingness to shared objects. In general, this supports the idea both separate features and integrated feature "bundles" can be hierarchically stored by VWM (Brady et al., 2011; Fougnie et al., 2010, 2013) in such a way that the "bundles" facilitate the encoding and retrieval of features. Interpreting their results from the paradigm similar to our present paradigm, Wang et al. (2017) also speculated about the possibility of the hierarchically organized memories about features and objects. Our experimental manipulations with feature separation and integration provided empirical support for this suggestion.

How can the object-based advantage mediate the feature independence? One possibility is that, when features are separated between different objects, observers have to spread their attention and VWM resources across a greater number of locations and, thus, each feature representation is noisier than when two features are integrated into one location. We did find evidence that all features, in general, were represented with the greater noise in Experiment 2 with feature separation (see also Fougnie et al., 2010). Viewing the noise as an important source of interference in VWM (Bays, 2015; Wilken & Ma, 2004), we could explain the cross-dimensional interference in spatially separated features by overall noisier representations. In this view, adding a new spatially separable item involves increased firing in a neural population with receptive fields corresponding to the location of this item during the entire retention interval (Buschman, Siegel, Roy, & Miller, 2011; Sprague, Ester, & Serences, 2014). The firing rate within each population is normalized (divided) by the activity in the rest of firing populations that respond to other encoded objects, thus attenuating responses in each population and reducing the signal-to-overall noise ratio of each encoded item (Bays, 2014, 2015). However, this explanation can be insufficient. Most importantly, it does not account for interference specificity towards a feature dimension. Therefore, structural links between individual feature representations can be important for understanding the difference between integrated and separated features. Our experiments were not designed to explore particular structures. Future theoretical analysis and following experiments would be necessary for that field to advance our understanding of VWM beyond the dichotomous "feature-based vs. object-based" scale.

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Contributions

Y.A.M. designed the experiments, prepared the experimental scripts, collected and analyzed data, and wrote the manuscript. N.A.T. collected and analyzed data and wrote the manuscript. I.S.U. conceptualized the basic ideas, designed the experiments and wrote the manuscript.

Appendix A

In Appendix A, additional statistical results are provided showing the exact estimates of effects mentioned as non-significant in Result sections of Experiments 1–3.

Experiment 1

P_{memory} for color

There were no significant differences between conditions with identical color across objects (color identical vs all identical: $t(18) = 2.819$, $p = .0114$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.647$, $BF_{10} = 0.801$; color identical vs one object: $t(18) = 2.281$, $p = .0349$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.523$, $BF_{10} = 4.091$; all identical vs one object: $t(18) = 0.565$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.13$, $BF_{10} = 0.257$) and also between conditions with different color across objects (all different features vs orientation identical: $t(18) = 2.938$, $p = .0088$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.674$, $BF_{10} = 2.265$).

P_{memory} for orientation

There were no significant differences between conditions with identical orientation across objects (orientation identical vs all identical features: $t(18) = 0.473$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.109$, $BF_{10} = 2.287$; orientation identical vs one object: $t(18) = 2.011$, $p = .0595$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.461$, $BF_{10} = 16.141$; all identical vs one object: $t(18) = 2.428$, $p = .0259$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.557$, $BF_{10} = 4.222$) and also between conditions with different orientation across objects (all different features vs color identical: $t(18) = 0.964$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.221$, $BF_{10} = 0.280$).

SD for color

There were no significant differences between following conditions (all different features vs orientation identical: $t(18) = 0.632$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.145$, $BF_{10} = 0.186$; all different features vs all identical: $t(18) = 2.653$, $p = .0162$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.609$, $BF_{10} = 10.277$; color identical vs orientation identical: $t(18) = 3.063$, $p = .0067$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.703$, $BF_{10} = 1.32$; color identical vs all identical: $t(18) = 0.063$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.015$, $BF_{10} = 0.271$; color identical vs one object: $t(18) = 1.482$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.34$, $BF_{10} = 0.888$; orientation identical vs all identical: $t(18) = 2.096$, $p = .0505$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.481$, $BF_{10} = 18.888$; orientation identical vs one object: $t(18) = 3.094$, $p = .0063$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.71$, $BF_{10} = 10.975$; all identical vs one object: $t(18) = 1.988$, $p = .0622$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.456$, $BF_{10} = 0.202$).

SD for orientation

There were no significant differences between conditions with identical orientation across objects (orientation identical vs all identical features: $t(18) = 0.228$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.052$, $BF_{10} = 0.221$; orientation identical vs one object: $t(18) = 0.997$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.229$, $BF_{10} = 0.15$; all identical vs one object: $t(18) = 1.102$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.253$, $BF_{10} = 0.195$) and also between conditions with different orientation across objects (all different features vs color identical: $t(18) = 1.817$, $p = .0859$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.417$, $BF_{10} = 430.193$).

Experiment 2

P_{memory} for color

There were no significant differences between conditions with identical color across objects (color identical vs all identical: $t(18) = 0.287$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.066$, $BF_{10} = 0.246$; color identical vs one object: $t(18) = 1.666$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.382$, $BF_{10} = 0.762$; all identical vs two objects: $t(18) = 1.104$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.253$, $BF_{10} = 0.404$) and also between conditions with different color across objects (all different features vs orientation identical: $t(18) = 0.168$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.039$, $BF_{10} = 0.241$).

P_{memory} for orientation

We found no significant differences between following conditions (all different features vs color identical: $t(18) = 0.007$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.002$, $BF_{10} = 0.237$; all identical vs two objects: $t(18) = 1.474$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.338$, $BF_{10} = 0.6$).

SD for orientation

We found no significant differences between following conditions (orientation identical vs all identical: $t(18) = 0.861$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.198$, $BF_{10} = 0.33$; orientation identical vs two objects: $t(18) = 1.068$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.245$, $BF_{10} = 0.391$; all identical vs two objects: $t(18) = 0.427$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.098$, $BF_{10} = 0.258$).

Experiment 3

P_{memory} for color

There were no significant differences between conditions with identical color across objects (color identical vs all identical: $t(14) = 0.878$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.227$, $BF_{10} = 0.366$; color identical vs one object: $t(14) = 0.71$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.183$, $BF_{10} = 0.327$; all identical vs one object: $t(14) = 0.022$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.006$, $BF_{10} = 0.262$) and also between conditions with different color across objects (all different features vs orientation identical: $t(14) = 1.446$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.373$, $BF_{10} = 0.624$).

P_{memory} for orientation

There were no significant differences between conditions with identical orientation across objects (orientation identical vs all identical: $t(14) = 1.447$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.374$, $BF_{10} = 0.624$; orientation identical vs one object: $t(14) = 0.334$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.086$, $BF_{10} = 0.276$; all identical vs one object: $t(14) = 1.469$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.379$, $BF_{10} = 0.64$) and also between conditions with different orientation across objects (all different features vs color identical: $t(14) = 1.284$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.331$, $BF_{10} = 0.524$).

SD for orientation

There were no significant differences between conditions with identical orientation across objects (orientation identical vs all identical: $t(14) = 0.379$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.098$, $BF_{10} = 0.28$; orientation identical vs one object: $t(14) = 0.495$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.128$, $BF_{10} = 0.292$; all identical vs one object: $t(14) = 0.639$, $p = .1$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.165$, $BF_{10} = 0.314$) and also between conditions with different orientation across objects (all different features vs color identical: $t(14) = 2.014$, $p = .0636$, Bonferroni corrected $\alpha = 0.005$, Cohen's $d = 0.52$, $BF_{10} = 1.278$).

References

Alvarez, G. A., & Cavanagh, P. (2004). The capacity of visual short-term memory is set both by visual information load and by number of objects. *Psychological Science: A Journal of the American Psychological Society/APS, 15*(2), 106–111. https://doi.org/10.1167/2.7.273.

Baddeley, A. D. (1986). *Working memory.* Oxford, UK: Clarendon Press.

Baddeley, A. D., & Hitch, G. J. (1974). Working memory. In G. A. Bower (Ed.). *The psychology of learning and motivation: Advances in research and theory* (pp. 47–89). New York: Academic.

Bays, P. M. (2014). Noise in neural populations accounts for errors in working memory. *Journal of Neuroscience, 34*(10), 3632–3645. https://doi.org/10.1523/jneurosci.3204-13.2014.

Bays, P. M. (2015). Spikes not slots: Noise in neural populations limits working memory. *Trends in Cognitive Sciences, 19*(8), 431–438. https://doi.org/10.1016/j.tics.2015.06.004.

Bays, P. M., Catalao, R. F., & Husain, M. (2009). The precision of visual working memory is set by allocation of a shared resource. *Journal of Vision, 9*(10), 1–11. https://doi.org/10.1167/9.10.7.

Bays, P. M., Wu, E. Y., & Husain, M. (2011). Storage and binding of object features in visual working memory. *Neuropsychologia, 49*(6), 1622–1631. https://doi.org/10.1016/j.neuropsychologia.2010.12.023.

Brady, T. F., Konkle, T., & Alvarez, G. A. (2011). A review of visual memory capacity: Beyond individual items and toward structured representations. *Journal of Vision, 11*(5), 4. https://doi.org/10.1167/11.5.4.

Buschman, T. J., Siegel, M., Roy, J. E., & Miller, E. K. (2011). Neural substrates of cognitive capacity limitations. *Proceedings of the National Academy of Sciences of USA, 108*(27), 11252–11255. https://doi.org/10.1073/pnas.1104666108.

Cowan, N. (2001). The magical number 4 in short term memory. A reconsideration of storage capacity. *Behavioral and Brain Sciences, 24*(4), 87–186. https://doi.org/10.1017/S0140525X01003922.

Cowan, N., Chen, Z., & Rouder, J. N. (2004). Constant capacity in an immediate serial-recall task: A logical sequel to Miller (1956). *Psychological Science, 15*(9), 634–640. https://doi.org/10.1111/j.0956-7976.2004.00732.x.

Duncan, J. (1984). Selective attention and the organization of visual information. *Journal of Experimental Psychology: General, 113*(4), 501–517. https://doi.org/10.1037/0096-3445.113.4.501.

Fougnie, D., & Alvarez, G. A. (2011). Object features fail independently in visual working

memory: evidence for a probabilistic feature-store model. *Journal of Vision, 11*(12), https://doi.org/10.1167/11.12.3 3. doi:10.1167/11.12.3.
Fougnie, D., Asplund, C. L., & Marois, R. (2010). What are the units of storage in visual working memory? *Journal of Vision, 10*(12), 27. https://doi.org/10.1167/10.12.27.
Fougnie, D., Cormiea, S. M., & Alvarez, G. A (2013). Object-based benefits without object-based representations. *Journal of Experimental Psychology: General, 142*(3), 621–626. https://doi.org/10.1037/a0030300.
Fougnie, D., & Marois, R. (2009). Attentive tracking disrupts feature binding in visual working memory. *Visual Cognition, 17*(1–2), 48–66. https://doi.org/10.1080/13506280802281337.
Hardman, K. O., & Cowan, N. (2015). Remembering complex objects in visual working memory: Do capacity limits restrict objects or features? *Journal of Experimental Psychology: Learning, Memory, and Cognition, 41*(2), 325–347. https://doi.org/10.1037/xlm0000031.
JASP Team (2018). *JASP (Version 0.9.0.0).* [Computer software].
Jeffreys, H. (1961). *Theory of probability* (*3rd ed.*). Oxford: Oxford University Press.
Kahneman, D., Treisman, A., & Gibbs, B. J. (1992). The reviewing of object files: Object-specific integration of information. *Cognitive Psychology, 24*(2), 175–219. https://doi.org/10.1016/0010-0285(92)90007-O.
Lee, D., & Chun, M. M. (2001). What are the units of visual short-term memory, objects or spatial locations? *Perception & Psychophysics, 63*(2), 253–257. https://doi.org/10.3758/BF03194466.
Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature, 390*(6657), 279–281. https://doi.org/10.1038/36846.
Luria, R., & Vogel, E. K. (2011). Shape and color conjunction stimuli are represented as bound objects in visual working memory. *Neuropsychologia, 49*(6), 1632–1639. https://doi.org/10.1016/j.neuropsychologia.2010.11.031.
Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review, 101*(2), 343–352. https://doi.org/10.1037/h0043158.
Oberauer, K., & Eichenberger, S. (2013). Visual working memory declines when more features must be remembered for each object. *Memory and Cognition, 41*(8), 1212–1227. https://doi.org/10.3758/s13421-013-0333-6.
Olson, I. R., & Jiang, Y. (2002). Is visual short-term memory object based? Rejection of the "strong-object" hypothesis. *Perception & Psychophysics, 64*(7), 1055–1067. https://doi.org/10.3758/BF03194756.
Pertzov, Y., Dong, M. Y., Peich, M. C., & Husain, M. (2012). Forgetting what was where: The fragility of object-location binding. *PLoS One, 7*(10), https://doi.org/10.1371/journal.pone.0048214.
Pierce, J. W. (2007). PsychoPy – Psychophysics software in python. *Journal of Neuroscience Methods, 162*, 8–13.
Rensink, R. A. (2000). The dynamic representation of scenes. *Visual Cognition, 7*(1–3), 17–42. https://doi.org/10.1080/135062800394667.
Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian t tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review, 16*(2), 225–237. https://doi.org/10.3758/PBR.16.2.225.
Schurgin, M. W., Wixted, J. T., & Brady, T. F. (2018). Psychological Scaling Reveals a Single Parameter Framework For Visual Working Memory. *BioRxiv,* 325472. https://doi.org/10.1101/325472.
Shin, H., & Ma, W. J. (2017). Visual short-term memory for oriented, colored objects. *Journal of Vision, 17*(9), 1–19. https://doi.org/10.1167/17.9.12.
Sprague, T. C., Ester, E. F., & Serences, J. T. (2014). Reconstructions of information in visual spatial working memory degrade with memory load. *Current Biology, 24*(18), 2174–2180. https://doi.org/10.1016/j.cub.2014.07.066.
Suchow, J. W., Brady, T. F., Fougnie, D., & Alvarez, G. A. (2013). Modeling visual working memory with the MemToolbox. *Journal of Vision, 13*(10), 9. https://doi.org/10.1167/13.10.9.
Treisman, A. (1999). Solutions to the binding problem: Progress through controversy and convergence. *Neuron, 24*(1), 105–110. https://doi.org/10.1016/S0896-6273(00)80826-0.
Trick, L. M., & Pylyshyn, Z. W. (1993). What enumeration studies can show us about spatial attention: Evidence for limited capacity preattentive processing. *Journal of Experimental Psychology: Human Perception and Performance, 19*(2), 331–351. https://doi.org/10.1037/0096-1523.19.2.331.
Vogel, E. K., Woodman, G. F., & Luck, S. J. (2001). Storage of features, conjunctions and objects in visual working memory. *Journal of Experimantal Psychology: Human Perception and Performance, 27*(1), 92–114. https://doi.org/10.1037//0096-1523.27.1.92.
Wagenmakers, E.-J., Love, J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., ... Morey, R. D. (2017). Bayesian inference for psychology. Part II: Example applications with JASP. *Psychonomic Bulletin & Review,* 1–19. https://doi.org/10.3758/s13423-017-1323-7.
Wang, B., Cao, X., Theeuwes, J., Olivers, C. N. L., & Wang, Z. (2017). Separate capacities for storing different features in visual working memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 43*(2), 226–236. https://doi.org/10.1037/xlm0000295.
Wheeler, M. E., & Treisman, A. M. (2002). Binding in short-term visual memory. *Journal of Experimental Psychology. General, 131*(1), 48–64. https://doi.org/10.1037//0096-3445.131.1.48.
Wilken, P., & Ma, W. J. (2004). A detection theory account of change detection. *Journal of Vision, 4*(12), 11. https://doi.org/10.1167/4.12.11.
Wolfe, J. M., & Bennett, S. C. (1997). Preattentive object files: Shapeless bundles of basic features. *Vision Research, 37*(1), 25–43. https://doi.org/10.1016/S0042-6989(96)00111-3.
Woodman, G. F., & Vogel, E. K. (2008). Selective storage and maintenance of an object's features in visual working memory. *Psychonomic Bulletin and Review, 15*, 223–229. https://doi.org/10.3758/PBR.15.1.223.
Xu, Y. (2002). Encoding color and shape from different parts of an object in visual short-term memory. *Perception & Psychophysics, 64*(8), 1260–1280. https://doi.org/10.3758/BF03194770.
Xu, Y., & Chun, M. M. (2006). Dissociable neural mechanisms supporting visual short-term memory for objects. *Nature, 440*(7080), 91–95. https://doi.org/10.1038/nature04262.
Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature, 453*(7192), 233–235. https://doi.org/10.1038/nature06860.