

Journal of Experimental Psychology: Human Perception and Performance

Feature-Based Versus Object-Based Representation in Visual Working Memory

Ayelet Ramaty and Roy Luria

Online First Publication, September 11, 2025. <https://dx.doi.org/10.1037/xhp0001367>

CITATION

Ramaty, A., & Luria, R. (2025). Feature-based versus object-based representation in visual working memory. *Journal of Experimental Psychology: Human Perception and Performance*. Advance online publication. <https://dx.doi.org/10.1037/xhp0001367>

Feature-Based Versus Object-Based Representation in Visual Working Memory

Ayelet Ramaty¹ and Roy Luria^{1, 2}

¹ School of Psychological Sciences, Tel Aviv University

² The Sagol School of Neuroscience, Tel Aviv University

Visual working memory (WM) can hold a limited amount of information for a short interval. The current study investigated whether the features of the objects maintained in WM are represented in a dependent or independent manner. Across five experiments, we presented multifeature objects (color and shape) and investigated whether remembering one feature is correlated with remembering the other feature. To answer this question, we divided the continuous response distribution into five quintiles according to the accuracy performance, then computed the area under the curve of the continuous response of the other feature, thus calculating the area under the curve for a given feature for each quintile of the other feature. A dependent object representation predicts a correlation between these measures, indicating that remembering one feature is correlated with remembering the other feature. In all five experiments, in which we used different stimuli (triangles or polygons), different memory exposure intervals (1,200 or 300 ms), and different response procedures (sequential or simultaneous responses), we found strong evidence for a dependency between the object's features. We conclude that this current analysis was able to reveal strong feature dependency in WM. These findings support the conclusion that visual WM relies on object-based representations and that all the objects' features are represented in a dependent manner.

Public Significance Statement

Visual working memory can hold and manipulate online information. Corroborating its importance, individual differences in its capacity estimates strongly correlate with behavior and various aptitude measures. The current study investigated how visual working memory maintains its online information, specifically how objects with more than one feature (e.g., color and shape) are represented. We provide strong evidence for a dependency between the object's features, indicating that objects are represented as bound units in memory.

Keywords: visual working memory, object representation, object complexity, feature binding

Supplemental materials: <https://doi.org/10.1037/xhp0001367.supp>

Visual working memory (WM) is responsible for transient storage of task-relevant information, enabling both storage and processing of the represented visual information (Luck & Vogel, 2013). Previous studies have shown that visual WM has a very limited capacity (Alvarez & Cavanagh, 2004; Awh et al., 2007; Luck & Vogel, 1997; Vogel et al., 2001; Zhang & Luck, 2008), but that

individual differences in WM capacity are correlated with cognitive abilities and aptitude measures such as academic achievements (Alloway & Alloway, 2010), top-down attentional control (Bengson & Mangun, 2011; Kane et al., 2001; Vogel et al., 2005), and fluid intelligence (Cowan et al., 2006).

The strong connections between WM capacity and behavior have led to several lines of research investigating how items are represented within the WM workspace. Two major theories have been proposed to answer this question: an object-based model and a feature-based model. The object-based model states that we perceive an object as a whole, and this model predicts that the objects' features (e.g., its shape and color) should be highly correlated with each other, such that if we remember one feature, we would remember the other features as well (Awh et al., 2001; Luck & Vogel, 1997; Luria & Vogel, 2011). The feature-based model states that each feature of an object is remembered independently. Thus, this model predicts a null correlation between remembering the various features of an object (e.g., Fougine & Alvarez, 2011; Fougine et al., 2013). Moreover, when additional features of an object need to be remembered (e.g., both color and shape), the feature-based model predicts a decrease in WM performance because the added features should increase WM load.

The object-based model received strong initial support from a study by Luck and Vogel (2013). They presented objects that

Isabel Gauthier served as action editor.

This research was supported by the Israel Science Foundation (Grant 1589/23) awarded to Roy Luria. All the authors declare no conflicts of interest. We would like to extend our gratitude to Hagai Shemesh for his invaluable assistance in developing the Matrix Laboratory (MATLAB) code for generating a polygon circle and for implementing a dynamically changing color feature, enabling the simultaneous response of both features.

Ayelet Ramaty served as lead for formal analysis, investigation, and software. Roy Luria served as lead for funding acquisition and supervision. Ayelet Ramaty and Roy Luria contributed equally to conceptualization and writing—review and editing.

Correspondence concerning this article should be addressed to Ayelet Ramaty, School of Psychological Sciences, Tel Aviv University, Shareit Building, Floor 1, Door 236, 30 Haim Levanon Street, Tel Aviv 69987, Israel. Email: peer.ayelet@gmail.com

consisted of two features—color and shape, and showed that the participants' performance didn't change when they were asked to remember just one feature (color or shape) or when participants were asked to remember both features (color and shape). The feature-based model predicts a decrease in performance when WM maintains both features as compared to maintaining only one feature, because if each feature is remembered independently, retaining more features in WM should lead to a decrease in performance. However, since performance did not change when increasing the number of relevant features per object, Luck and Vogel concluded that the objects in WM are represented in WM as integrated units (cf. Gajewski & Brockmole, 2006; Luria & Vogel, 2011; Pratte et al., 2017; Vogel et al., 2001).

It is important to note that the object-based theory only argues that the encoded features of an object are maintained in a dependent manner. Namely, this theory does not predict that all the object's features are obligatory encoded. Thus, the object-based model predicts a correlation between the features of an object only when these features are encoded in WM. Moreover, the object-based theory doesn't necessarily predict that forgetting is object-based. It is possible that all the object's features are maintained in a dependent manner, yet forgetting is not object-based, such that forgetting disrupts the dependency between the features, resulting in a loss of one feature but not the other. In other words, the processes that are involved in forgetting might be different from the processes that are responsible for remembering.

Yet, several studies investigated object-based theories by focusing on forgetting. As explained above, finding object-based (dependent) forgetting certainly supports object-based remembering, while finding feature-based forgetting should be treated with more caution because the conclusion assumes a similar mechanism for forgetting and remembering. In the sections below, we start by reviewing previous research that investigated object-based versus feature-based forgetting, and then discuss significant factors that might have contributed to observing feature-based forgetting.

Fougnie and Alvarez (2011) studied object-based and feature-based forgetting by investigating whether forgetting one of the object's features led to forgetting the other objects' features as well. In their study, they presented five triangles for 1,200 ms, each consisting of two distinct features—color and shape. Then they asked the participants to report both the color and shape of the triangles, using the continuous report paradigm (Zhang & Luck, 2008). By first analyzing the primary response distribution for each feature, Fougnie et al. defined responses that contained information about the target versus responses that did not contain any information about the target. They treated responses that were more than 3 *SDs* away from the correct value as pure guesses, reflecting no information about the target. Analyzing only these guesses, they extracted the histogram distribution of the other feature. They argued that if the object-based model is correct, we should not see memory for the other feature when the first feature was a guess. Thus, they expected to find a uniform distribution in these secondary graphs. However, a Gaussian distribution was observed, and Fougnie et al. argued that these trials reflected guessing in one feature but some knowledge in the other, violating the prediction of the object-based view.

An important aspect of the Fougnie and Alvarez (2011) paradigm is that they used a sequential response procedure (one for each feature). This procedure might cause interference, such that the first response might affect the second response (Fukuda et al., 2022). Another important caveat of the Fougnie and Alvarez (2011) is that their analysis

ignores most of the data (all responses that are within 3 *SD* from the correct value), thus relying only on a small subset of responses.

To avoid interference from the sequential response procedure and to include all the responses in the analysis, Sone et al. (2021) introduced a new method of responding to both features simultaneously. In their first experiment, they showed that three or six triangles consisted of two features, color and shape. They asked the participants to estimate the color and shape simultaneously by clicking on a single point on the response probe containing both color and shape information (see Sone et al., 2021), thus minimizing serial response interference.

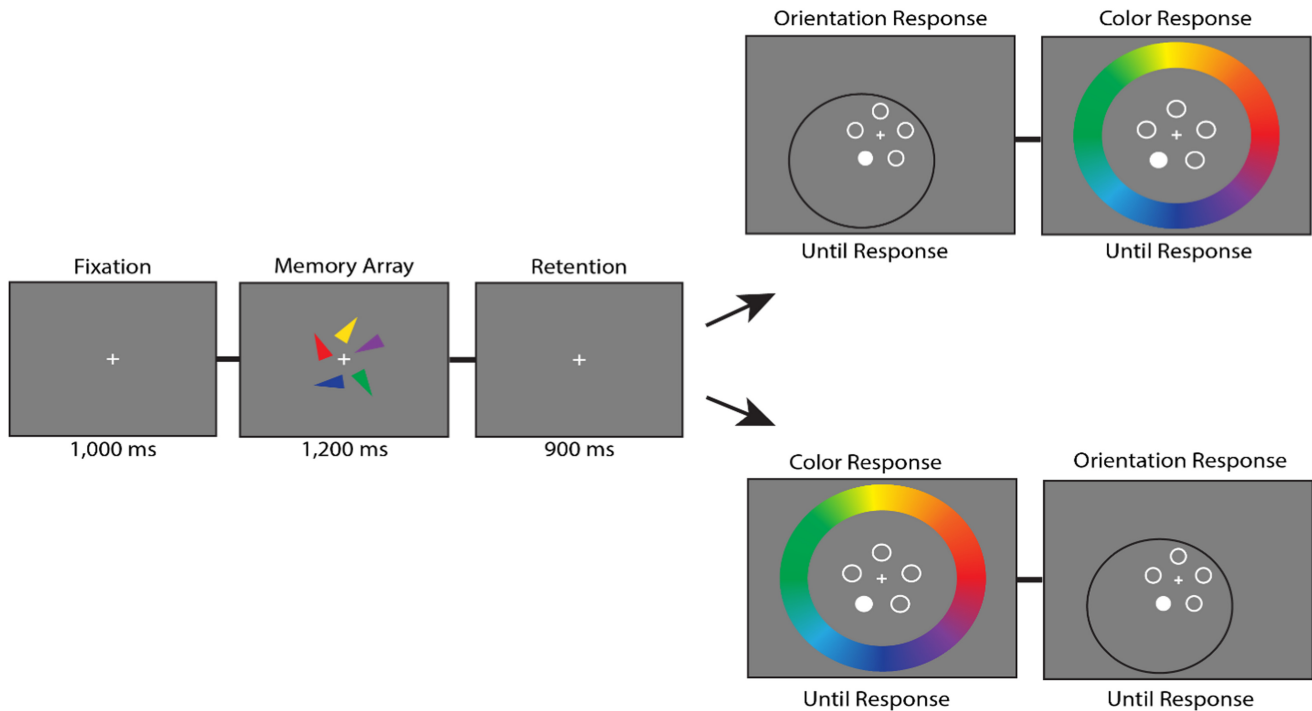
In order to quantify the dependence between the different features while including all responses, these authors divided each feature response into four quartiles according to the magnitude of absolute offsets, and for each quartile, they computed the conditional area under the cumulative distribution function (area under the curve [AUC]) for each feature as a function of the representational quality of the other feature. Then they computed the AUC of the other feature in each quartile as a conditional AUC of the first feature. This procedure allowed Sone et al. (2021) to check whether color and shape are stored dependently, as the object-model predicts, or independently. If the conditional feature is positively correlated with the other feature (rather than randomly split between the four quartiles), it supports the dependency between both features as the object model predicts, because a more accurate response in one feature leads to a more accurate response in the other. Their results indeed showed a dependency between both features of the same object. Next, they compared sequential and simultaneous response estimation procedures and found that both procedures produced significant dependency between the features. However, the dependence was more pronounced in the simultaneous estimation procedure, indicating that the object-based dependence can be weakened by the sequential response procedure.

Fougnie and Alvarez (2011) and Fougnie et al. (2013) used a sequential response procedure and analyzed only a small proportion of the data (responses that are more than 3 *SD* from the mean). It is possible that these trials represent a very small number of cases in which only one feature was encoded or forgotten, which doesn't necessarily contradict the object-based account. In contrast, Sone et al. (2021) used simultaneous responses and analyzed the full data set, providing a more comprehensive and robust measure of feature dependency. While these differences may explain the conflicting conclusions, note that Sone et al. only used a limited set of stimuli and encoding intervals. There are arguments that the stimuli type and the encoding interval might affect objecthood (e.g., Alvarez & Cavanagh, 2004).

In our study, in contrast to Fougnie and Alvarez (2011), but similar to Sone et al. (2021), we analyzed all the data. By including all trials, we investigated both memory and forgetting processes. We used a similar approach to Sone et al. and calculated the degree of dependency between the object's features by plotting the performance for both features across the various quintiles (see below). If there is no dependency between the features, we expect to see a straight line, and as the slope becomes steeper, it indicates a stronger dependency between the features.

Our study builds directly on these findings. First, we replicated Fougnie and Alvarez (2011) using this novel analysis and found evidence for dependency between color and shape, and then we investigated the robustness of this dependency by manipulating several

Figure 1
Trial Timeline for Experiment 1



Note. See the online article for the color version of this figure.

parameters such as the presentation time, the type of stimuli, and the response procedure.

Experiment 1: Presenting Five Triangles for 1,200 ms

Experiment 1 was a replication of Fougne and Alvarez (2011). We presented five colored random triangles for 1,200 ms and used sequential responses (see Figure 1). To investigate within-object feature dependency, we analyzed the results following Sone et al. (2021) by dividing the response distribution into 5 quintiles (since we had 540 trials instead of 360 as in the original study, we were able to use quintiles instead of quartiles). To reveal evidence for dependence between the features, for each quintile, we computed the dependent accuracy of the other feature. For each feature, we then computed the AUC for each of the five quintiles. The AUC represents the quality of the memory for each quintile.

If the features are represented independently, we expect a null relationship between the features' performance in each quintile, because accuracy in one feature should not be related to accuracy in the other feature. Conversely, as the slope becomes steeper, it supports a dependent feature representation, because remembering one feature is correlated with remembering the other feature.

Materials and Method

Participants

Sixteen naive participants participated in Experiment 1. The participants are Tel Aviv students aged 20–35, 10 women and six men. An a priori power analysis was conducted using G*Power3.1.9.2 (Faul et al.,

2007) to test the difference between the different conditions using a repeated measures analysis of variance (ANOVA). We used an effect size of $f=0.3$, based on the ANOVA for quartiles reported in Sone et al. (2021), who found a large effect size ($\eta_p^2=.66$, $F=65$). However, we chose a more conservative estimate because our design used quintiles instead of quartiles and included a broader range of stimuli and experimental conditions that were not tested in previous studies. We used a correlation of .5 among repeated measures and an alpha of .05. Results showed that a total sample of 15 was required to achieve a power of 0.8. All participants gave informed consent following the procedures of a protocol approved by the Ethics Committee at Tel Aviv University. The participants were Tel Aviv University students who received 40 NIS (approximately \$11) per hour for participation. All participants had normal or corrected-to-normal vision and normal color vision. The data for this experiment were collected during 2018.

Transparency and Openness

Data analysis of each experiment used the `circ_r` matlab functions developed by Berens (2009). All data, analysis code, and research materials are available at <https://osf.io/u7yqg/>. We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study. This study's design and its analysis were not preregistered.

Stimuli

On each trial, the memory array consisted of five randomly chosen triangle stimuli, each defined by a unique color and

orientation. The five triangles were equally spaced along an imaginary circle (2.5° radius) centered on a fixation dot. Each triangle subtended approximately 30° , 75° , and 75° of visual angle. The orientation of each triangle was independently randomized from a continuous set ranging from 2° to 360° , sampled in 2° increments, with a minimum angular separation of 44° between them to ensure perceptual distinctiveness. The colors were selected from a set of 720 equally luminant colors in the international commission on illumination *Lab** color space (centered at $L = 54$, $a = 18$, $b = -8$, radius = 59), ensuring that the chosen colors were distinct from one another. This randomization ensured that the memory array varied on each trial.

Trial Procedure

A trial began with 1,000 ms fixation, then 1,200 ms presentation of the memory stimulus of five triangles with randomly chosen colors and shapes, followed by a 900 ms retention interval which included only a white fixation dot in the middle of the screen, then a filled white circle appeared at the probed triangle's location, and hollow circles appeared at nonprobed locations. Participants were asked to report the color and shape (at a random order) of the filled circle. For color reports, a wide color wheel (7° radius, centered on fixation) made of 720 equally luminant colors was presented in the middle of the screen, and the participants were asked to click with the mouse along the color wheel at the exact color they think was presented earlier on that cued location. After this report, participants were given feedback on how accurate their response was. The color feedback was a circle which was presented for 600 ms at the cued location and consisted of an inner circle of the true color and an outer circle of their chosen color. That way, participants could briefly see how exact their response was. For shape reports, a black thin response wheel was presented, centered on the cued-location probe. Participants were asked to click with the mouse along the response wheel where they think was the exact shape of the earlier presented triangle at the cued location (we can imagine the triangle is an arrow, and they were asked to click on the color wheel location where the arrow was pointing). The shape feedback was presented for 600 ms and showed simultaneously the original shape of the triangle at that cued location (in black color), and a small white circle marked the actual response on the wheel. Responses were unspeeded. Each participant completed 540 trials.

Data Analysis

The data from each participant consisted of a set of distances between the original color value and the reported color value in each trial, which reflects the degree of error for each response. We created histograms of these error values to visualize the distribution of responses. To quantify performance while avoiding pre-assumptions on our model, we used circular statistic. To compute circular statistic, we used a circular statistic toolbox for matlab, called "CircStat" toolbox for Matrix Laboratory (Berens, 2009). For more information on statistics in circular space, see Zar (2010). In this toolbox, we used the function called "circ_r.m" that computes the mean resultant vector length (MRVL) of the distribution. MRVL reflects the variability of the data points, scaling from 0 = *no information about the item* to 1 = *perfect information*

about the item. We first computed the absolute error for one feature, then divided each feature into five quantiles according to the absolute accuracy. Subsequently, we computed the mean accuracy of the other feature for each quantile. For example, to compute the color feature, the first group contained 20% of the trials that were most accurate in shape, the second group contained 20% of the trials that were second most accurate in shape, and so on until the fifth group contained 20% of the trials that were most inaccurate in shape. This approach allowed us to assess feature dependency as a function of representational quality.

All analyses were performed using Matrix Laboratory R2017a (MathWorks Inc., Natick, Massachusetts, United States) and Statistica 8. Figures (e.g., timeline illustrations) were created using Adobe Illustrator 2021, and references were managed with Zotero. The experiment itself was programmed and executed using Presentation software (Neurobehavioral Systems).

Results and Discussion

Histograms displaying the degree of accuracy distributions for color and shape are shown in Figure 2A and 2B, respectively. We divided each feature into five quintiles according to the accuracy and then computed the accuracy of the other feature in this quantile to investigate the dependence of the memory of both features of the item. Figure 2E shows plots of the average AUC for each feature of the five quantiles. We performed a separate repeated measure ANOVA for color and shape, with quintiles as the independent variable, which yielded significant main effects of quintiles for both features; color: $F(4, 60) = 75.34$, $\eta_p^2 = .83$, $MSE = 0.005$, $p < .001$. Planned comparisons showed significant linear trends for color: $F(1, 15) = 289.70$, $\eta_p^2 = .95$, $MSE = 0.005$, $p < .001$; and for shape: $F(1, 15) = 179.9$, $\eta_p^2 = .92$, $MSE = 0.01$, $p < .001$. The slope for color feature was -0.49 , and it was statistically significant from zero, $t(15) = -17.02$, $p < .001$, and the slope for shape was -0.49 , and it was statistically significant from zero, $t(15) = -13.41$, $p < .001$.

The results of Experiment 1 revealed that when using a different analysis than Fougny and Alvarez (2011), which included all responses, we found evidence for dependency between the two features.

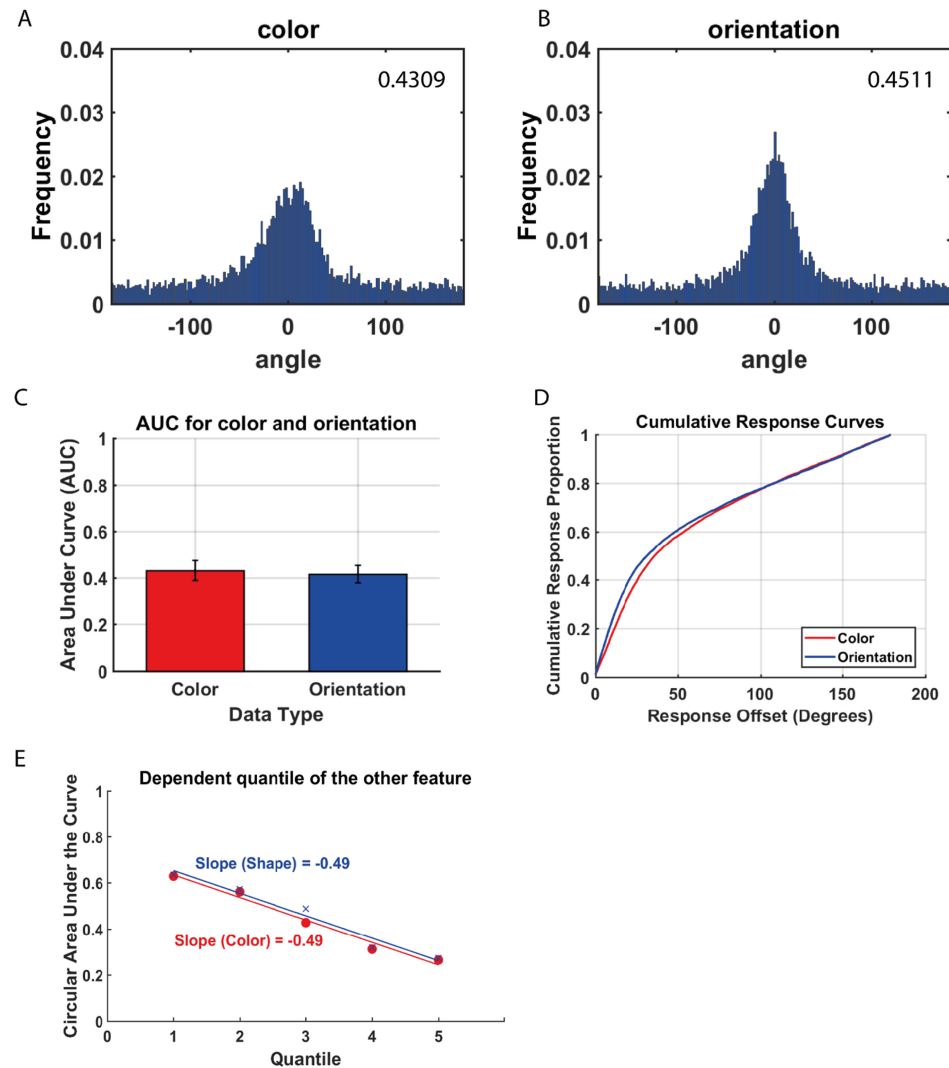
Experiment 2: Presenting Five Triangles for 300 ms

In Experiment 2, we shortened the memory array presentation time from 1,200 to 300 ms. We reasoned that 1,200 ms is a relatively long encoding interval that might encourage verbal encoding (Ramaty & Luria, 2018). Note that previous research indicated that 300 ms is ample time to encode simple objects (Alvarez & Cavanagh, 2004; Lin & Luck, 2012; Luria et al., 2010; Vogel et al., 2001; Zhang & Luck, 2008), but the role of the encoding period on the feature's dependency is still unknown. Thus, the goal of Experiment 2 was to investigate whether shortening the memory array interval would eliminate the dependency between the features.

Materials and Method

The design of Experiment 2 was similar to Experiment 1, but the memory array was presented for 300 ms instead of 1,200 ms.

Figure 2
Color and Orientation Accuracy and Dependency Analysis in Experiment 1



Note. (A–B) Histograms displaying error frequencies for color (A) and orientation (B). (C) Bar plot showing the AUC for color and orientation dependency, with color dependency in red and orientation dependency in blue. The value at the top right of each bar represents the circular AUC. (D) Cumulative response curves for color (red [dark gray] bars) and orientation (blue [light gray] bars), depicting response accuracy over increasing offset bins. (E) Mean dependency of the nonreported feature, separated by accuracy quantiles of the reported feature (i.e., feature dependency as a function of response precision). Error bars represent ± 1 standard error of the mean. AUC = area under the curve. See the online article for the color version of this figure.

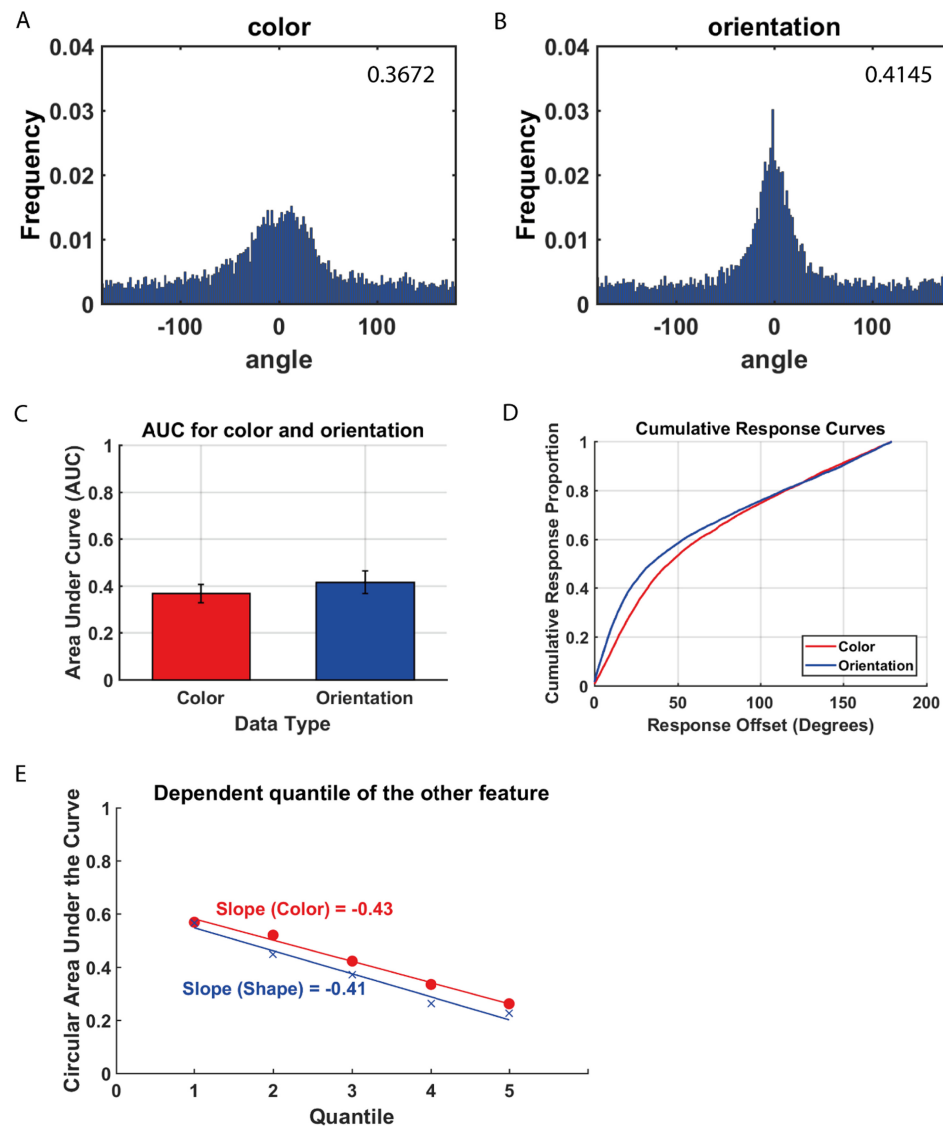
Participants

Sixteen naive participants (nine women, seven men) aged 20–35 from Tel Aviv University participated in Experiment 2. All had normal or corrected-to-normal vision and normal color vision. Power analysis and compensation were identical to Experiment 1.

Results and Discussion

Histograms displaying the degree of accuracy distributions for color and shape are shown in Figure 3A and 3B, respectively. Plots of the average area under the curve for each feature of the

five quantiles are shown in Figure 3E. A repeated measure ANOVA with the Quintiles as the independent variable yielded significant main effects of Quantile for both features; color: $F(4, 60) = 35.65$, $\eta_p^2 = .7$, $MSE = 0.009$, $p < .001$; and shape: $F(4, 60) = 51.14$, $\eta_p^2 = .77$, $MSE = 0.005$, $p < .001$. Planned comparisons showed significant linear trends for color: $F(1, 15) = 208.14$, $\eta_p^2 = .9328$, $MSE = 0.005771$, $p < .001$; and for shape: $F(1, 15) = 153.11$, $\eta_p^2 = .91$, $MSE = 0.01$, $p < .001$. The slope for color was -0.43 , and it was statistically significant from zero, $t(15) = -14.42$, $p < .001$, and the slope for shape was -0.41 , and it was statistically significant from zero, $t(15) = -12.37$, $p < .001$.

Figure 3*Color and Orientation Accuracy and Dependency Analysis in Experiment 2*

Note. (A–B) Histograms displaying error frequencies for color (A) and orientation (B). (C) Bar plot showing the AUC for color and orientation dependency, with color dependency in red and orientation dependency in blue. The value at the top right of each bar represents the circular AUC. (D) Cumulative response curves for color (red [dark gray] bars) and orientation (blue [light gray] bars), depicting response accuracy over increasing offset bins. (E) Mean dependency of the nonreported feature, separated by accuracy quantiles of the reported feature (i.e., feature dependency as a function of response precision). Error bars represent ± 1 standard error of the mean. AUC = area under the curve. See the online article for the color version of this figure.

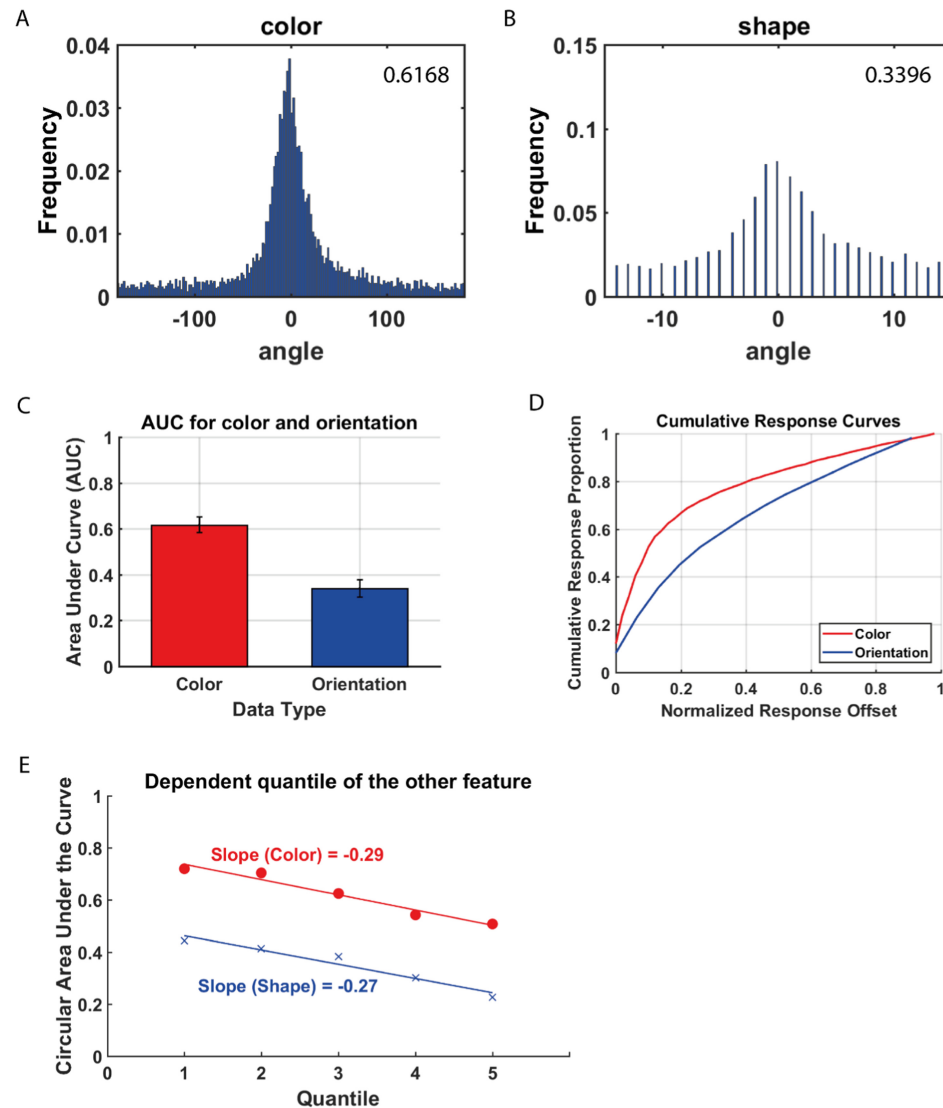
The results of Experiment 2 still revealed a strong dependency between color and shape, similar to the findings of Experiment 1. Thus, shortening the encoding time from 1200 to 300 ms did not affect the dependency between the features.

Experiment 3: Presenting Three Random Polygons for 1,200 ms

Previous research has shown lower behavioral performance when using unfamiliar and complex objects such as random polygons

(e.g., Alvarez & Cavanagh, 2004; Gao et al., 2009; Luria et al., 2010). However, it is not clear whether unfamiliar stimuli would show a dependency with a familiar feature (color). In Experiment 3, we decided to use random polygons, which previous research has demonstrated is above the average WM capacity (Alvarez & Cavanagh, 2004; Luria et al., 2010). Thus, in Experiment 3, we presented colored random polygons with a continuous report method for both features, to further investigate whether the color feature and an unfamiliar shape will be maintained in WM as dependent or independent features. Note that there were only 30 values for

Figure 4
Color and Orientation Accuracy and Dependency Analysis in Experiment 3



Note. (A–B) Histograms displaying error frequencies for color (A) and orientation (B). (C) Bar plot showing the AUC for color and orientation dependency, with color dependency in red and orientation dependency in blue. The value at the top right of each bar represents the circular AUC. (D) Cumulative response curves for color (red [dark gray] bars) and orientation (blue [light gray] bars), depicting response accuracy over increasing offset bins. (E) Mean dependency of the nonreported feature, separated by accuracy quantiles of the reported feature (i.e., feature dependency as a function of response precision). Error bars represent ± 1 standard error of the mean. AUC = area under the curve. See the online article for the color version of this figure.

the polygon's circular response (see Figure 4) because of space limitations, we generated 30 morphologically distinct polygon shapes, evenly spaced along a circular morph continuum.

Materials and Method

The main differences from previous experiments were the use of unfamiliar stimuli (random polygons) and the reduction in set size to three items. Each polygon was selected from a continuous set of 30 unique shapes. The memory array was presented for 1,200 ms.

Participants

Sixteen naive participants (11 women, five men), aged 20–35, from Tel Aviv University participated. Power analysis, inclusion criteria, and compensation were the same as in Experiment 1. The data for this experiment were collected in 2019.

Transparency and Openness

Data analysis of each experiment used the `circ_r` matlab functions developed by Berens (2009). All data, analysis code, and research

materials are available at <https://osf.io/u7yqg/>. We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study. This study's design and its analysis were not preregistered.

Stimuli

Participants were asked to remember the color and the shape of three random polygons that were positioned randomly on the screen (and sufficiently away from each other, with at least 84° between the chosen shape of the polygons). The colors were chosen from a set of 720 equally luminant colors in the international commission on illumination $L^*a^*b^*$ color space (centered at $L = 54$, $a = 18$, $b = -8$, with a radius of 59), such that they were distinct enough from one another.

In this experiment, polygon shapes were selected from a circular morph wheel consisting of 30 (or 20 in Experiment 5) smoothly transitioning polygons. The morphing continuum forms a circular feature space in which both shape and orientation change gradually along the wheel. On each trial, three polygons were randomly sampled with the constraint that any two shapes were separated by at least seven steps along the wheel. Since the full wheel spans 360° , this corresponds to a minimum angular separation of approximately 84° , ensuring that the selected shapes remained perceptually distinct.

The polygons were selected from a circular morphing continuum of 30 (or 20 in Experiment 5) smoothly transitioning polygon shapes. This morph wheel represents a circular feature space in which both shape and orientation gradually change along the wheel. Although the polygons themselves were not explicitly rotated, the morphing process included changes in both shape and orientation, and the use of the circular wheel ensured variability in presentation.

Trial Procedure

A trial began with 1,000 ms fixation, then 1,200 ms presentation of the memory stimulus of three random polygons with randomly chosen colors and shape, followed by a 900 ms retention interval which included only a white fixation dot in the middle of the screen, then a filled white circle appeared at the probed polygon's location, and hollow circle appeared at nonprobed location. Participants were asked to report the color and shape (at a random order) of the filled circle. For color reports, a color wheel (7° radius, centered on fixation) made of 720 equally luminant colors was presented in the middle of the screen, and the participants were asked to click with the mouse along the color wheel at the exact color they think was presented earlier on that cued location. After this report, participants were given feedback on how accurate their response was. The color feedback was a circle which was presented for 600 ms at the cued location and consisted of an inner circle of the true color, and an outer circle of their chosen color. That way, participants could briefly see how exact their response was. For polygon reports, a polygon wheel made of 30 continuous black polygons was presented in the middle of the screen. Participants were asked to click with the mouse along the response wheel where they think was the exact polygon they saw earlier. The polygon feedback was presented for 600 ms and showed the polygon wheel, in which all of the polygons were in black color, except the true polygon that was in white color, and the chosen polygon that was shown in broken white color. Responses were unspeeded. Each participant completed 540 trials.

Results and Discussion

Histograms displaying the degree of accuracy distributions for color and shape are shown in Figure 4A and 4B, respectively. Plots of the average area under the curve for each feature are shown in Figure 4E. An ANOVA with the within variable. Quintiles yielded significant main effects for both features; color: $F(4, 60) = 28.74$, $\eta_p^2 = .66$, $MSE = 0.005$, $p < .001$; and shape: $F(4, 60) = 22.62$, $\eta_p^2 = 0.6$, $MSE = 0.005$, $p < .001$. Planned comparisons showed significant linear trends for color: $F(1, 15) = 42.30$, $\eta_p^2 = .74$, $MSE = 0.013$, $p < .001$; and for shape: $F(1, 15) = 41.29$, $\eta_p^2 = .73$, $MSE = 0.01$, $p < .001$. The slope for color was -0.29 , and it was statistically significant from zero, $t(15) = -6.50$, $p < .001$, and the slope for shape was -0.27 , and it was statistically significant from zero, $t(15) = -6.43$, $p < .001$.

The results of Experiment 3 revealed a dependency between a color and an unfamiliar shape feature. This is particularly noteworthy since we presented three polygons that exceeded the average WM capacity, and the continuous response included only 30 options. Experiment 3 used a relatively long encoding interval of 1,200 ms, and it might be the case that the results observed in this experiment depend on this long encoding interval. Thus, the goal of Experiment 4 was to test feature dependency when using novel stimuli but when presenting the polygons for only 300 ms (Alvarez & Cavanagh, 2004; Luria et al., 2010).

In Experiment 4, we presented the polygons for only 300 ms (relative to 1,200 ms) to further investigate if, under these conditions, we could still find evidence for independence between the features.

Experiment 4: Presenting Three Random Polygons for 300 ms

In this experiment, we investigated whether reducing the encoding time to 300 ms affected feature dependency for colored polygons. In Experiment 4, we presented the three random colored polygons for 300 ms instead of 1,200 ms. If encoding the stimuli as coherent objects takes time, we might be able to find evidence for independence when restricting the encoding interval for above-capacity unfamiliar set of stimuli.

Materials and Method

The design of Experiment 4 was similar to Experiment 3, but the memory array was presented for 300 ms instead of 1,200 ms.

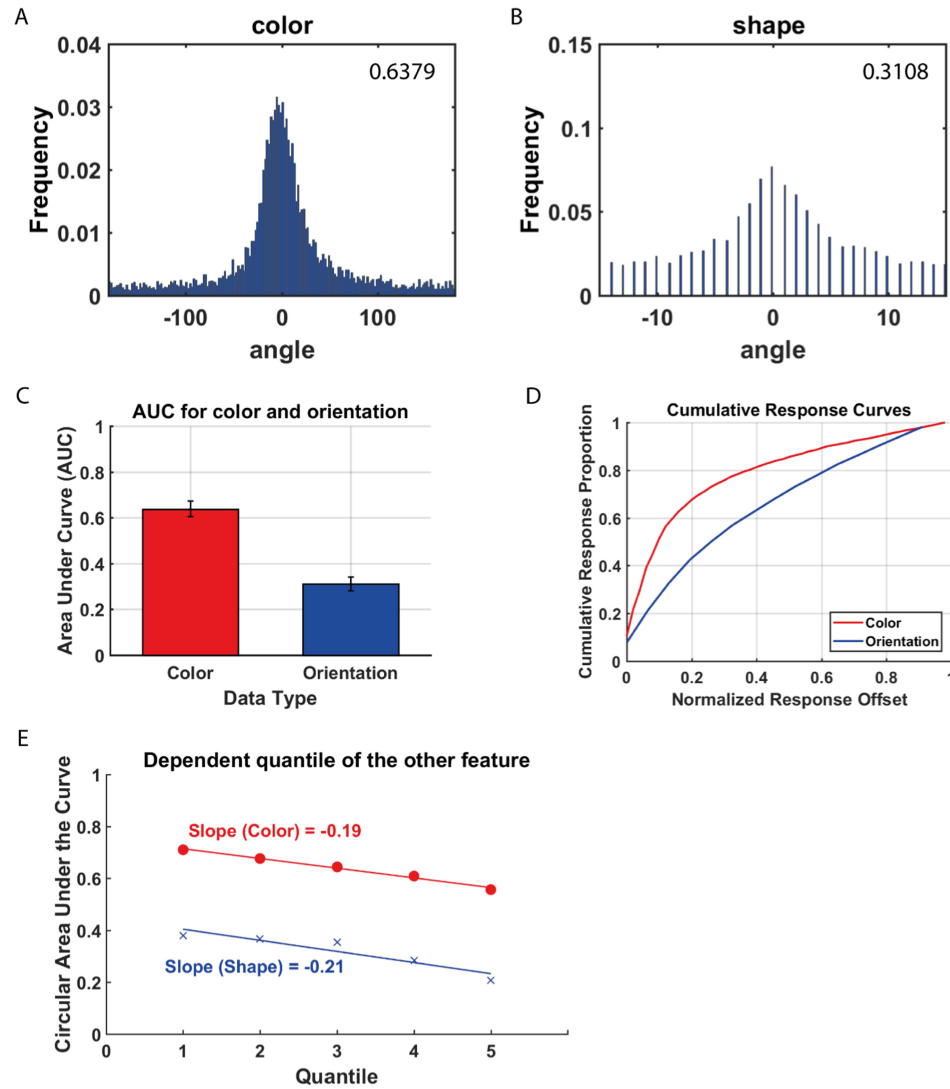
Participants

Sixteen naive participants (10 women, six men), aged 20–35, from Tel Aviv University participated. Power analysis, inclusion criteria, and compensation were the same as in Experiment 1. The data for this experiment were collected in 2019.

Results and Discussion

Histograms displaying the degree of accuracy distributions for color and shape are shown in Figure 5A and 5B, respectively. Plots of the average area under the curve for each feature of the five quantiles are shown in Figure 5E. A repeated measure ANOVA with the factor. Quintiles yielded significant effect in both color: $F(4, 60) = 14.46$, $\eta_p^2 = .49$, $MSE = 0.004$, $p < .001$; and shape: $F(4, 60) = 13.34$,

Figure 5
Color and Orientation Accuracy and Dependency Analysis in Experiment 4



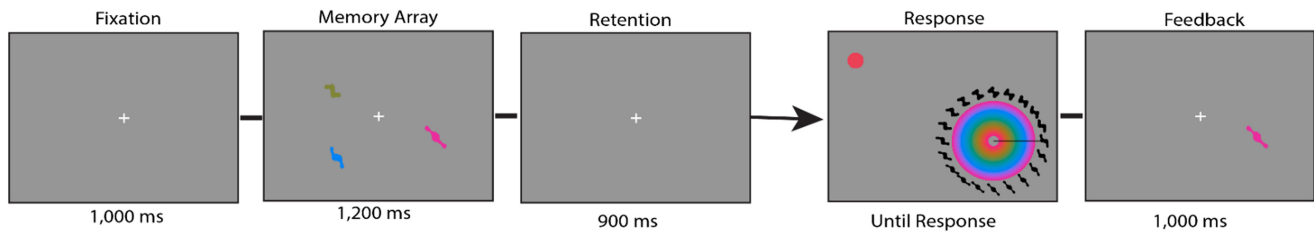
Note. (A–B) Histograms displaying error frequencies for color (A) and orientation (B). (C) Bar plot showing the AUC for color and orientation dependency, with color dependency in red and orientation dependency in blue. The value at the top right of each bar represents the circular AUC. (D) Cumulative response curves for color (red [dark gray] bars) and orientation (blue [light gray] bars), depicting response accuracy over increasing offset bins. (E) Mean dependency of the nonreported feature, separated by accuracy quantiles of the reported feature (i.e., feature dependency as a function of response precision). Error bars represent ± 1 standard error of the mean. AUC = area under the curve. See the online article for the color version of this figure.

$\eta_p^2 = .47$, $MSE = 0.006$, $p < .001$. Planned comparisons showed significant linear trends for color: $F(1, 15) = 34.01$, $\eta_p^2 = .69$, $MSE = 0.01$, $p < .001$; and for shape: $F(1, 15) = 30.01$, $\eta_p^2 = .67$, $MSE = 0.01$, $p < .001$. The slope for color was -0.19 , and it was statistically significant from zero, $t(15) = -5.83$, $p < .001$, and the slope for shape was -0.21 , and it was statistically significant from zero, $t(15) = -5.48$, $p < .001$.

Experiment 4 replicated the dependency between the unfamiliar and familiar features even for above-capacity arrays were presented for only 300 ms.

Experiment 5: Presenting Three Random Polygons With Concurrent Response for 1,200 ms

In a recent study, Sone et al. (2021) demonstrated that the sequential response procedure used in the present study (and also by previous studies, e.g. Fougner & Alvarez, 2011) decreased the apparent dependency between the object's features. Sone et al. used a simultaneous response procedure allowing a single response to both features and demonstrated increased feature dependency relative to the sequential response procedure. They argued that this novel

Figure 6*Trial Timeline for Experiment 5*

Note. See the online article for the color version of this figure.

procedure can minimize the interference that the first response may cause on the second response. Importantly, Sone et al. only investigated simple stimuli (colored triangles), and the goal of our next experiment was to test whether this simultaneous procedure (see Figure 6) would affect the dependency of unfamiliar stimuli such as random polygons.

Materials and Method

Same as Experiment 3, with the following differences: responses were made simultaneously for both features using a single mouse movement and click. A polygon-color wheel was shown at the probed item's location, allowing selection of both features in one action. The polygon wheel contained 20 options (reduced from 30 due to layout constraints).

Participants

Sixteen naive participants (11 women, five men), aged 20–35, from Tel Aviv University participated. Power analysis, inclusion criteria, and compensation were the same as in Experiment 1. The data for this experiment were collected during 2021.

Trial Procedure

A trial began with 1,000 ms fixation, then 1,200 ms presentation of the memory stimulus of three random polygons with randomly chosen colors and shape, followed by a 900 ms retention interval which included only a white fixation dot in the middle of the screen, then a polygon wheel and inside a filled color wheel circle appeared at the probed polygon's location, and dot appeared at the upper left corner of the screen. The polygon wheel was made of 20 continuous black polygons, and inside it was a color wheel (7° radius, centered on fixation) made of 720 equally luminant colors. The reduction in the number of polygons in the polygon wheel from 30 in previous experiments to 20 in this experiment was due to a change in the experimental setup. In this experiment, the polygon wheel was not centered in the middle of the screen but instead moved across the screen, as its center aligned with the selected polygon. This adjustment was necessary due to the simultaneous response procedure. This means that the polygon wheel needed to be adjusted to fit the size of the screen. Consequently, the size of the polygon wheel was smaller, resulting in fewer polygons being included. Participants were asked to report both color and shape of the polygon by adjusting a black line. Using the black line, they can point at a single polygon and “jump” from one polygon to another. While

moving the mouse along the line's length, they can see the color change, and to better view the changed color a dot appeared at the upper left corner of the screen and changed its color according to the movement of the mouse along the line's length. The participants were asked to click with the mouse along the black line at the exact color they think was presented earlier on that cued location, and point the black line to the exact polygon they think was presented earlier on that cued location—meaning both color and shape were reported at a single response. After this report, participants were given feedback on how accurate their response was. The feedback was the original polygon with the original color, which was presented for 1,000 ms at the cued location. That way, participants could briefly see how exact their response was. Responses were unspeeded. Each participant completed 540 trials.

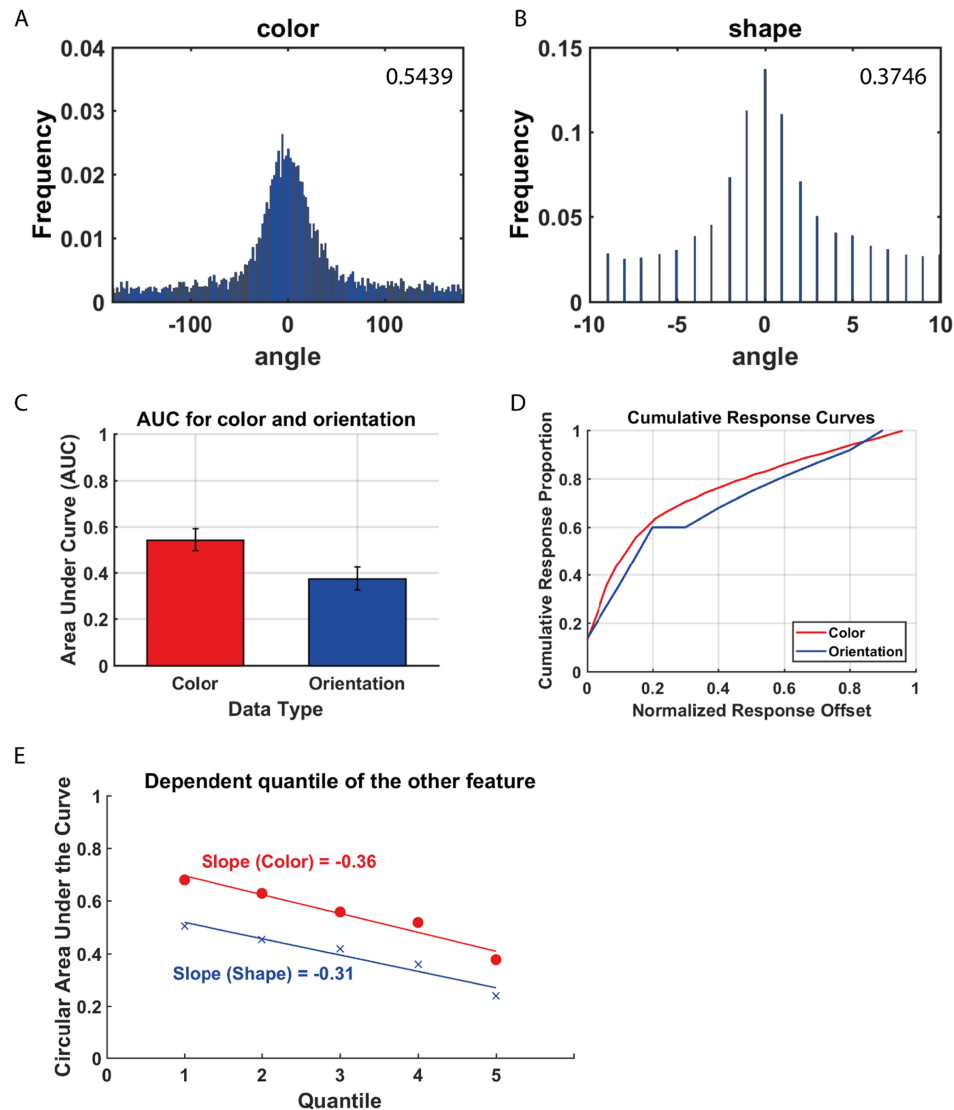
Results and Discussion

Histograms displaying the degree of accuracy distributions for color and shape are shown in Figure 7A and 7B, respectively. Plots of the average area under the curve for each feature of the five quantiles are shown in Figure 7E. A repeated measure ANOVA with the factor. Quintiles yielded significant effect in both color: $F(4, 60) = 32.42$, $\eta_p^2 = .68$, $MSE = 0.007$, $p < .001$; and shape: $F(4, 60) = 19.02$, $\eta_p^2 = .56$, $MSE = 0.008$, $p < .001$, analyses. Linear contrast for color: $F(1, 15) = 75.55$, $\eta_p^2 = .83$, $MSE = 0.01$, $p < .001$; and for shape: $F(1, 15) = 36.21$, $\eta_p^2 = .71$, $MSE = 0.02$, $p < .001$. The slope for color is -0.36 , and it was statistically significant from zero, $t(15) = -8.70$, $p < .001$, and the slope for shape was -0.31 , and it was statistically significant from zero, $t(15) = -6.02$, $p < .001$.

The results of Experiment 5 indicated a between-feature dependency for polygons and color features using a single response, corroborating the results for Sone et al. (2021) also for polygon stimuli, which had much less circular values. Overall, we replicated the finding of feature dependency across various sets of conditions and stimuli. The motivation for Experiment 5 was to extend the investigation of feature dependency by presenting complex stimuli and a single response. Previous experiments (Sone et al., 2021) only used simple stimuli with the single response design, while the current experiment investigated feature dependency with complex stimuli, overloading WM capacity limit.

Response Order Analysis (Experiments 1–4)

To examine whether the order in which participants reported the two features influenced memory precision, we conducted a post hoc analysis across the four sequential-report experiments (Experiments 1–4).

Figure 7*Color and Orientation Accuracy and Dependency Analysis in Experiment 5*

Note. (A–B) Histograms displaying error frequencies for color (A) and orientation (B). (C) Bar plot showing the AUC for color and orientation dependency, with color dependency in red and orientation dependency in blue. The value at the top right of each bar represents the circular AUC. (D) Cumulative response curves for color (red [dark gray] bars) and orientation (blue [light gray] bars), depicting response accuracy over increasing offset bins. (E) Mean dependency of the nonreported feature, separated by accuracy quantiles of the reported feature (i.e., feature dependency as a function of response precision). Error bars represent ± 1 standard error of the mean. AUC = area under the curve. See the online article for the color version of this figure.

For each feature—color and orientation/shape—we computed the circular concentration (MRVL, circ_r) separately for trials in which the feature was reported first and trials in which it was reported second. This analysis tested the hypothesis that sequential reporting may introduce interference, particularly degrading the memory quality of the second-reported feature.

Across all four experiments, we observed a consistent pattern: memory precision was generally higher when a feature was reported first compared to when it was reported second. Paired-sample t tests confirmed this pattern statistically. In Experiment 1 (triangles,

1,200 ms), color was significantly better remembered when reported second, $t(15) = -4.27$, $p = .0007$, and orientation was better remembered when reported first, $t(15) = -4.74$, $p = .0003$. In Experiment 2 (triangles, 300 ms), color was again better remembered when reported second, $t(15) = -3.31$, $p = .0047$, and orientation when reported first, $t(15) = -5.12$, $p = .0001$. In Experiment 3 (polygons, two responses, 1,200 ms), the same pattern held: color was better remembered when reported second, $t(15) = -2.47$, $p = .0259$, and orientation when reported first, $t(15) = -2.53$, $p = .0229$. In Experiment 4 (polygons, two responses, 300 ms),

Table 1

Mean Memory Performance (Circular Concentration) Values for Each Feature by Report Order, Across Experiments 1–4

Experiment	Color	Orie	Color first	Orie second	Color second	Orie first
Five triangles, 1,200 ms	0.43	0.45	0.37	0.41	0.5	0.49
Five triangles, 300 ms	0.37	0.41	0.33	0.37	0.41	0.46
Three polygons, 1,200 ms	0.62	0.34	0.6	0.32	0.64	0.36
Three polygons, 300 ms	0.64	0.31	0.62	0.3	0.66	0.33

Note. Orie = orientation.

the effect directions were consistent, although the differences did not reach significance: $t(15) = -2.07$, $p = .0559$ for color, and $t(15) = -1.79$, $p = .0937$ for orientation.

These findings suggest that sequential responding imposes measurable interference on visual WM, selectively impairing the feature that is reported second. This result complements prior evidence (e.g., Sone et al., 2021) and supports the rationale for using simultaneous report procedures, such as the one implemented in Experiment 5, to minimize such interference and more faithfully assess feature dependency (Table 1).

General Discussion

The goal of this study was to investigate whether features are represented in memory in an “object-based” or “feature-based” model. To address this question, we performed five different experiments, using different stimuli (simple as triangles or complex as polygons), manipulated the encoding duration (1,200 ms vs. 300 ms), and manipulated the response procedure (responding to both features sequentially vs. simultaneously). As opposed to previous studies, we analyzed all the data and extracted a plot for each feature, divided into five quantiles accordingly.

Across all experiments and conditions, we consistently found strong evidence for dependency between object features. First, we replicated the design used by Fougny and Alvarez (2011), applying the AUC slope analysis developed by Sone et al. (2021), and found evidence for dependency between color and shape. We then shortened the encoding interval from 1,200 to 300 ms but still observed evidence of dependency. We then used unfamiliar stimuli (random polygons) and found a dependency between the polygon’s shape and its color, across short and long encoding intervals. This result is interesting because in these experiments, we presented a memory array that included an above-capacity number of stimuli, which should severely limit performance. Yet, this did not disturb the feature’s dependency.

The current investigation adds important findings to the ongoing debate regarding whether visual working memory stores object features as integrated units or as independent components. While Sone et al. (2021) introduced a powerful framework to study this question, other recent findings remained mixed (e.g., Liu et al., 2022; Markov et al., 2021). The importance of the present findings is that we used a powerful AUC slope analysis and tested the competing theories using several nontrivial conditions. By extending the analysis to unfamiliar stimuli, above-capacity set sizes, and shorter encoding durations, our study provides converging evidence for object-based representations and advances the current debate. For example, the findings from Experiment 4, which presented three polygons for only 300 ms and still found strong evidence for dependency, go

beyond our current knowledge. Note that this experiment used novel stimuli, with a set size that exceeded WM capacity and encoding interval that was not sufficient to encode all the items.

The current study corroborated the findings by Sone et al. (2021), extending their results to other conditions and stimuli. This is in contrast to other research that failed to find evidence for within-object feature dependency (Fougny & Alvarez, 2011; Markov et al., 2021; Utochkin & Brady, 2020). One possible reason for this discrepancy lies in methodological differences. Our use of full-data analysis, rather than relying only on a subset of “guess” trials, may have allowed us to better capture the structure of memory representations. Importantly, a null effect in feature dependency does not provide affirmative evidence for independence—it may instead reflect limitations in sensitivity or analysis.

It is also important to note that object-based models do not argue that all of the object’s features are mandatorily encoded. For example, when color is the task-relevant feature, it is possible to encode it without the stimulus shape, even when presenting different shapes (Luria et al., 2010). This is important because several previous studies evaluated feature dependency without verifying that all of the objects’ features were indeed encoded.

While the current work revealed strong evidence for feature dependency, the observed correlations were not perfect. There are several possible mechanisms that might be responsible for observing imperfect correlation between the object’s features. It is plausible that object dependency is a continuum, rather than being all-or-none (Ngiam, 2024). However, the exact processes responsible for finding only partial dependency between two features are not clear. Another possible mechanism is that feature dependency is all-or-none, but the percentage of fully dependent and fully independent objects varies across the experimental situations. Another possibility is that the object’s features are independently bound to the same spatial location, and the imperfect feature–feature dependency is mediated by two separate feature-to-location dependencies. Note, however, that this last possibility was directly tested and ruled out by Sone et al. (2021, Experiment 3).

We argue that the current set of results could be explained either by an all-or-none mechanism in which in most trials, the features are completely dependent, and in the minority of trials, the features are completely independent or by some weak object mechanism, suggesting that the features are remembered as dependent but could be forgotten independently (Ngiam, 2024). This account could naturally explain why analyzing the results according to Fougny and Alvarez (2011) reveals a small proportion of trials that demonstrate a memory trace only in one of the object’s features (see the current online supplemental materials). Note that while there are many alternatives as to how the features are dependent, the independent account makes the clear prediction that the

memory trace for one feature should not be correlated with the memory trace of the other feature. Thus, evidence that the features are represented hierarchically (e.g., Utochkin & Brady, 2020) supports the dependent account, as it allows predicting memory of one feature based on memory of the other feature.

The results from the response order analysis (Experiments 1–4) further supported the notion that sequential reporting introduces interference, selectively reducing precision for the second-reported feature. This reinforces the rationale for using simultaneous report procedures, as implemented in Experiment 5.

A related issue is the distinction between investigating memory processes and investigating forgetting processes. Several previous studies investigated whether forgetting is a dependent process, but then concluded how these objects were represented in memory (e.g., Balaban et al., 2019; Fougne & Alvarez, 2011; Markov et al., 2021; Utochkin & Brady, 2020). We argue that the finding that forgetting is feature-dependent supports that the features were also remembered in a dependent manner; however, the reverse conclusion is valid only if similar processes support both forgetting and remembering, which is still an open question. One of the advantages of the current paradigm is that we analyzed all responses, thus relying on remembering processes and not only forgetting.

Another potential advantage of the current paradigm is that the slope between the quintile performance of the two features indicates the dependency strength between these features, such that a steeper slope suggests a stronger feature dependency. While the current sample size was chosen to detect an effect, future research can use the current methodology and investigate the factors that affect the features' dependency strength. For example, numerically we observed a decrease in the dependency strength when presenting three colored polygons for only 300 ms, but this observation should be verified with an adequate sample size, preferably in the within-study design.

Evidence for object-based representations corroborates many findings regarding object-based attention (Baldauf & Desimone, 2014; Chen, 2012; Gao et al., 2017). However, findings that support object-based representations do not rule out that the object's features are also represented, perhaps at earlier processing stages (Ester et al., 2013), as it only undermines arguments that found evidence for feature representations and then concluded that this is the only possible representation, such that these features don't ever integrate, even at a later level of the processing stream.

To conclude, using a novel analysis method, the current work provides strong evidence for feature dependency under various conditions, supporting object-based representations in visual WM. These findings demonstrate that features such as color, shape, and orientation are not stored independently but are bound together within the same memory representation. This evidence highlights the integral role of feature dependency in shaping how visual WM organizes and maintains information.

References

- Alloway, T. P., & Alloway, R. G. (2010). Investigating the predictive roles of working memory and IQ in academic attainment. *Journal of Experimental Child Psychology*, 106(1), 20–29. <https://doi.org/10.1016/j.jecp.2009.11.003>
- 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*, 15(2), 106–111. <https://doi.org/10.1111/j.0963-7214.2004.01502006.x>
- Awh, E., Barton, B., & Vogel, E. K. (2007). Visual working memory represents a fixed number of items regardless of complexity. *Psychological Science*, 18(7), 622–628. <https://doi.org/10.1111/j.1467-9280.2007.01949.x>
- Awh, E., Dhaliwal, H., Christensen, S., & Matsukura, M. (2001). Evidence for two components of object-based selection. *Psychological Science*, 12(4), 329–334. <https://doi.org/10.1111/1467-9280.00360>
- Balaban, H., Drew, T., & Luria, R. (2019). Neural evidence for an object-based pointer system underlying working memory. *Cortex*, 119, 362–372. <https://doi.org/10.1016/j.cortex.2019.05.008>
- Baldauf, D., & Desimone, R. (2014). Neural mechanisms of object-based attention. *Science (New York, N.Y.)*, 344(6182), 424–427. <https://doi.org/10.1126/science.1247003>
- Bengson, J. J., & Mangun, G. R. (2011). Individual working memory capacity is uniquely correlated with feature-based attention when combined with spatial attention. *Attention, Perception, & Psychophysics*, 73(1), 86–102. <https://doi.org/10.3758/s13414-010-0020-7>
- Berens, P. (2009). Circstat: A MATLAB Toolbox for circular statistics. *Journal of Statistical Software*, 31(10), 1–21. <https://doi.org/10.18637/jss.v031.i10>
- Chen, Z. (2012). Object-based attention: A tutorial review. *Attention, Perception, & Psychophysics*, 74(5), 784–802. <https://doi.org/10.3758/s13414-012-0322-z>
- Cowan, N., Fristoe, N. M., Elliott, E. M., Brunner, R. P., & Sauls, J. S. (2006). Scope of attention, control of attention, and intelligence in children and adults. *Memory & Cognition*, 34(8), 1754–1768. <https://doi.org/10.3758/BF03195936>
- Ester, E. F., Anderson, D. E., Serences, J. T., & Awh, E. (2013). A neural measure of precision in visual working memory. *Journal of Cognitive Neuroscience*, 25(5), 754–761. https://doi.org/10.1162/jocn_a.00357
- Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, 39(2), 175–191. <https://doi.org/10.3758/BF03193146>
- Fougne, 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), Article 3. <https://doi.org/10.1167/11.12.3>
- Fougne, 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>
- Fukuda, K., Pereira, A. E., Saito, J. M., Tang, T. Y., Tsubomi, H., & Bae, G.-Y. (2022). Working memory content is distorted by its use in perceptual comparisons. *Psychological Science*, 33(5), 816–829. <https://doi.org/10.1177/09567976211055375>
- Gajewski, D. A., & Brockmole, J. R. (2006). Feature bindings endure without attention: Evidence from an explicit recall task. *Psychonomic Bulletin & Review*, 13(4), 581–587. <https://doi.org/10.3758/BF03193966>
- Gao, Z., Li, J., Liang, J., Chen, H., Yin, J., & Shen, M. (2009). Storing fine detailed information in visual working memory—Evidence from event-related potentials. *Journal of Vision*, 9(7), Article 17. <https://doi.org/10.1167/9.7.17>
- Gao, Z., Wu, F., Qiu, F., He, K., Yang, Y., & Shen, M. (2017). Bindings in working memory: The role of object-based attention. *Attention, Perception, & Psychophysics*, 79(2), 533–552. <https://doi.org/10.3758/s13414-016-1227-z>
- Kane, M. J., Bleckley, M. K., Conway, A. R. A., & Engle, R. W. (2001). A controlled-attention view of working-memory capacity. *Journal of Experimental Psychology: General*, 130(2), 169–183. <https://doi.org/10.1037/0096-3445.130.2.169>
- Lin, P.-H., & Luck, S. (2012). Proactive interference does not meaningfully distort visual working memory capacity estimates in the canonical change detection task. *Frontiers in Psychology*, 3, Article 42. <https://doi.org/10.3389/fpsyg.2012.00042>

- Liu, X., Liu, R., Guo, L., Astikainen, P., & Ye, C. (2022). Encoding specificity instead of online integration of real-world spatial regularities for objects in working memory. *Journal of Vision*, 22(9), 8. <https://doi.org/10.1167/jov.22.9.8>
- 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>
- Luck, S. J., & Vogel, E. K. (2013). Visual working memory capacity: From psychophysics and neurobiology to individual differences. *Trends in Cognitive Sciences*, 17(8), 391–400. <https://doi.org/10.1016/j.tics.2013.06.006>
- Luria, R., Sessa, P., Gotler, A., Jolicoeur, P., & Dell'Acqua, R. (2010). Visual short-term memory capacity for simple and complex objects. *Journal of Cognitive Neuroscience*, 22(3), 496–512. <https://doi.org/10.1162/jocn.2009.21214>
- 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>
- Markov, Y. A., Utochkin, I. S., & Brady, T. F. (2021). Real-world objects are not stored in holistic representations in visual working memory. *Journal of Vision*, 21(3), Article 18. <https://doi.org/10.1167/jov.21.3.18>
- Ngiam, W. X. Q. (2024). Mapping visual working memory models to a theoretical framework. *Psychonomic Bulletin & Review*, 31(2), 442–459. <https://doi.org/10.3758/s13423-023-02356-5>
- Pratte, M. S., Park, Y. E., Rademaker, R. L., & Tong, F. (2017). Accounting for stimulus-specific variation in precision reveals a discrete capacity limit in visual working memory. *Journal of Experimental Psychology: Human Perception and Performance*, 43(1), 6–17. <https://doi.org/10.1037/xhp0000302>
- Ramaty, A., & Luria, R. (2018). Visual working memory cannot trade quantity for quality. *Frontiers in Psychology*, 9, Article 719. <https://doi.org/10.3389/fpsyg.2018.00719>
- Sone, H., Kang, M.-S., Li, A. Y., Tsubomi, H., & Fukuda, K. (2021). Simultaneous estimation procedure reveals the object-based, but not space-based, dependence of visual working memory representations. *Cognition*, 209, Article 104579. <https://doi.org/10.1016/j.cognition.2020.104579>
- Utochkin, I. S., & Brady, T. F. (2020). Individual representations in visual working memory inherit ensemble properties. *Journal of Experimental Psychology: Human Perception and Performance*, 46(5), 458–473. <https://doi.org/10.1037/xhp0000727>
- Vogel, E. K., McCollough, A. W., & Machizawa, M. G. (2005). Neural measures reveal individual differences in controlling access to working memory. *Nature*, 438(7067), 500–503. <https://doi.org/10.1038/nature04171>
- Vogel, E. K., Woodman, G. F., & Luck, S. J. (2001). Storage of features, conjunctions, and objects in visual working memory. *Journal of Experimental Psychology: Human Perception and Performance*, 27(1), 92–114. <https://doi.org/10.1037/0096-1523.27.1.92>
- Zar, J. H. (2010). *Biostatistical analysis*. Prentice Hall.
- 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>

Received May 12, 2024

Revision received May 13, 2025

Accepted June 16, 2025 ■