Semantic Meaning Enhances Feature-Binding but not Quantity or Precision of Locations in Visual Working Memory

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Abstract

Recent studies showed that real-world items are better remembered in Visual Working Memory (VWM) than visually similar stimuli that are stripped of their semantic meaning. However, the exact nature of this advantage remains unclear. We used meaningful and meaningless stimuli in a location-reproduction VWM task. Employing a Mixture-modeling analysis, we examined whether semantic meaning enables more item locations to be remembered, whether it improves the precision of the locations stored in memory, or whether it improves binding between the specific items and their locations. Participants were presented with streams of 4 (Experiments 1 & 2) or 6 (Experiment 3) real-world items, or their scrambled, meaningless counterparts. Each item was presented at a unique location and the task was to reproduce one item's location. Overall, location memory was consistently better for real-world items compared to their scrambled counterparts. Furthermore, the results revealed that participants were less likely to make swap errors for the meaningful items but there was no effect of conceptual meaning on the guess rate or the precision of the report. In line with previous findings, these results indicate that conceptual meaning

enhances VWM for arbitrary stimulus properties such as item location, and this improvement is primarily due to a more efficient identity-location binding rather than an increase in the quantity or quality (precision) of the locations held in memory.

Introduction

Studies of visual memory have extensively investigated both the breadth and capacity limits of visual memory. Classical as well as more recent Long-Term Memory (LTM) studies found that observers can remember a vast number of items and their features or states, to the extent that, effectively, no upper bound of capacity was established (e.g., Brady et al., 2008, 2011; Konkle et al., 2010a, 2010b; Shepard, 1967; Standing 1973). Those studies used meaningful items such as real-world objects and scenes as memoranda, lending support for the important role of semantic meaning in visual LTM (e.g., Brady et al., 2019; Konkle et al., 2010; Koutstaal et al., 2003; Kramer et al., 2023; Reder et al., 2013; Shoval et al., 2023a). Indeed, when real-world objects were stripped of their semantic meaning through scrambling and distortion, visual memory capacity was shown to be dramatically reduced (Shoval et al., 2023b).

In an attempt to avoid LTM influences, however, classical visual working memory (VWM) studies have typically employed 'low-level' stimuli such as colors, line orientations, and meaningless matrix patterns (e.g., Luck &

Vogel, 1997, Phillips, 1974). In contrast to LTM findings, these studies have traditionally demonstrated a highly limited capacity system in VWM (e.g., Cowan, 2010; Luck & Vogel, 2013; Oberauer et al., 2016; Zhang & Luck, 2008). However, recent research has indicated that VWM performance is actually enhanced when the memoranda carry semantic meaning (e.g., Asp et al., 2021; Brady et al., 2016; Brady & Störmer, 2022; Chung et al., 2023a; Conci et al., 2021; Conci et al., 2023; Sahar et al., 2020; Shoval & Makovski, 2022).

For example, Sahar et al. (2020) compared VWM and the metamemory of meaningful and meaningless stimuli. The meaningful stimuli comprised of images of real-world objects (Brady et al., 2008), while the meaningless stimuli were the same images subjected to a simple image manipulation, preserving most visual properties while reducing their meaning (see, Makovski, 2018). The results revealed that participants better remembered semantically meaningful items than meaningless items, with higher confidence. The disadvantage of meaningless items was observed in following studies regardless of whether the items were "lightly" (e.g., Makovski, 2018, or "heavily" (Stojanoski & Cusack, 2014, fig. 1b) distorted (Brady & Störmer, 2022; Shoval & Makovski, 2022). Another study (Brady & Störmer, 2022) showed that meaningful items were better remembered in both serial and simultaneous presentation than blobs of colors and distorted items (see also Chung et al., 2023a). Supported by past findings of a larger CDA (Contralateral Delayed Activity) component for real-world items than

color patches (Brady et al., 2016), the authors stipulated that memory capacity is boosted for meaningful items since they receive in-depth encoding and stronger active maintenance in VWM (see, Asp et al., 2021; also, Brady et al., 2019 in LTM). While a follow-up study (Thibeault et al., 2023) was not able to pinpoint the precise locus of improvement (i.e., encoding, maintenance, or retrieval), it too, demonstrated an improvement in capacity estimates (Cowan's-K) of meaningful stimuli compared to meaningless items. The authors suggested it is the conceptual meaning rather than the visual complexity of the items that drives a VWM advantage for real-world object identities.

The *semantic meaning* of an (visual) item can be defined from various perspectives. Here, we consider the semantics of an object as typically derived from its basic-level category, namely, the level at which the item can be labeled. It's important to note that a label or a name encapsulates a set of critical features defining the item (Rosch, 1975; see, Gasparri & Marconi, 2021), yet the manner in which these features contribute to visual memory remains largely unclear. That is, how idiosyncratic non-visual information (i.e., conceptual meaning) contributes to the enhancement of visual information in memory is quite remarkable and not yet fully explained.

There are several, not mutually exclusive, explanations for the advantage of semantic meaning in VWM. In some studies, semantic meaning has been described as a "hook", or a "scaffold" for visual detail (e.g., Chung et al., 2023a; Konkle et al., 2010). More specifically, it was suggested that real-

world objects are stored in memory at both feature and object-based levels, with the latter linked to conceptual knowledge. This hierarchical organization provides a valuable structure (or 'scaffold') for low-level visual features and a higher-dimensional representation, thereby enhancing VWM (e.g., Chung et al., 2023a, Wyble et al., 2016). From a neurophysiological perspective, meaningful items may activate brain regions that support the formation of more vivid visual memories, compared to meaningless stimuli (e.g., Asp et al., 2021; Brady & Alvarez, 2015; Shoham et al., 2022). Relatedly, some argued that prior knowledge about an object enables the "chunking" of information, thereby reducing capacity limitations and enabling observers to maintain more features and information (e.g., Brady et al., 2009; Conci et al., 2021).

Previous existing knowledge is also tied to stimulus familiarity, with familiar items benefiting from better consolidation of items into VWM (Blalock, 2015; Shoval & Makovski, 2021; Xie & Zhang, 2017, 2018). In alignment with this perspective, other views have proposed that familiarity contributes to visual memory performance by freeing attentional resources to encode more visual information and facilitate feature-to-feature binding (Popov & Reder, 2020; Popov et al., 2022; Reder et al., 2013). Another way in which meaning might play a role in VWM is through the engagement of verbal LTM or labeling. When participants are given the option to use a term that describes the visual stimulus (i.e., a label), VWM performance improves both in terms of quantity and quality compared to a condition involving meaningless

articulatory suppression (Souza & Skóra, 2017). Labeling has been shown to boost VWM performance by allowing to maintain and protect a detailed representation in VWM (Overcott & Souza, 2022, 2023). However, conceptual meaning does not *necessitate* explicit verbal encoding. It was suggested that meaningful visual items might activate some form of conceptual, and perhaps prototypical, knowledge irrespective of verbal encoding (Bae et al., 2015; Sahar et al., 2020; Souza et al., 2021; Markov & Utochkin, 2022). Given the intimate connection between perceptual and conceptual information in everyday objects, it is often highly challenging to separate the two and isolate 'perceptual' memory *per se* (see Konkle et al., 2010, in LTM). Notably, the type of visual information being tested might affect one's conclusions. For instance, A feature might be easier to encode and consolidate into VWM if it aligns with pre-existing knowledge (Olsson & Poom, 2005; Bae et al., 2015), or if it is diagnostic of the object's nature/identity (e.g., distinguishing between a green and yellow banana, or recognizing the colors of a familiar flag, e.g., Conci et al., 2021). In the present study, we therefore asked whether conceptual knowledge can affect memory for visual details that are not associated with an item's core essence. Specifically, we investigated whether meaning can enhance VWM of an *arbitrary* object feature, such as its spatial location.

If meaning does indeed enhance location memory performance, we aimed to observe whether this enhancement operates in terms of memory resolution or other factors. The results of Chung et al. (2023a), demonstrating that

memory for an arbitrary color is enhanced for meaningful items, already suggest that the influences of meaning might not be restricted to the item's identity. Yet, it is not clear whether this result can be generalized to other dimensions that are not directly related to the item's intrinsic features. Critically, in the context of the current study, location serves as an arbitrary feature that is independent of the item's identity.

Furthermore, testing spatial location memory is essential because many researchers have argued that location constitutes a unique feature, playing a key role in attention, perception, and VWM (e.g., Golomb et al., 2014; Lamy & Tsal, 2001; Makovski 2016; Pertzov & Husain, 2014; Treisman & Gelade, 1980), specifically in the binding of different features together (Oberauer & Lin, 2017; Schneegans & Bays, 2017, but see Li et al., 2022). The goal of the study was thus to test the effects of meaning on spatial memory, by comparing performance for meaningful (i.e., intact, real-world) with meaningless (i.e., scrambled) objects (see Figure 1). Furthermore, using a mixture-modeling approach (Bays, et al., 2009), we were able to test which parameters were specifically affected by the item's meaning (for a similar approach, see Markov & Utochkin, 2022; Popov et al., 2022). There are several possible outcomes to the mixture-modeling approach (see graphical illustration in Figure 2, right): (1) An effect on the SD parameter (i.e., smaller SDs for meaningful items) would suggest better location memory precision. That is, meaning creates a more precise location representation. (2) An effect on the Guess-rate would suggest that meaning boosts the number of

locations stored in VWM. (3) Fewer swap errors for meaningful items would suggest a stronger linkage between arbitrary spatial location and identity. Note that the combination of Guess-rate and the Swap rate indexes the number of correct object locations stored in memory: If meaning boosts the number of locations stored in VWM, then we should expect a higher rate of correct target responses given the item's identity (i.e., fewer errors due to guesses and swaps) for the meaningful stimuli.

It is also noteworthy that any combination of these outcomes is possible and that these possibilities do not necessarily refute the suggested theories and accounts. This is because the theories can be modified to accommodate any of the (parameters) outcomes. For example, if all items have an accessible memory signal but it is weakly bound to their specific locations, "increased capacity" could be expressed as fewer swap errors. The current study, therefore, was not designed to pit the different theoretical views against each other, but rather to ask *which* aspects of memory performance (i.e., parameters in the model) would be mostly affected by stimulus meaning.

To preview our results, Experiment 1 found that meaning had a large effect on VWM performance that translated to an effect on *swap* errors, while there was no effect on the guess rate or the precision rate (SD). Experiment 2 replicated Experiment 1's results, even though it included masks that impaired overall performance, negating the possibility that the lack of an

effect on precision might have resulted from a ceiling effect. Experiment 3

further tested VWM for a larger memory set size, and yet the main results

remained the same: meaning reduced swap errors but did not affect the

guess rate or the precision factor. Since all experiments share the same

general method, we report them all collectively.

Method

The stimuli, tasks, data, and analyses are available at the Open Science

Framework: https://osf.io/za3bm

Sample-size

We adopted an open-ended Bayesian design (Schönbrodt & Wagenmakers,

2018). We set the minimal sample size at 20 participants. This sample size

allows us to detect a large effect (Cohen's d = .7, p-value = .05) with 85%

statistical power. Due to the exploratory nature of Experiment 1, we allowed

a larger sample size to make sure we could detect an effect (if any) on each

parameter and adopted a stricter criterion to stop collecting data (i.e., BF >

100 for H_0 or H_1). In Experiments 2 and 3, given the observed effects of

Experiment 1, we adopted a looser criterion for stopping the collection of

data: when a two-sided Bayesian paired samples t-test for the average

absolute error (i.e., Meaningful vs. Meaningless) showed a BF[1] above 3 (for

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[1] In the results section BF_{10} denotes the Bayes Factor in favor of a difference (i.e., an effect present) while BF_{01} denotes the Bayes Factor in favor of a no-difference (i.e., the absence of an effect). The two measures are reciprocal and easily interchangeable:

either H_0 or, H_1). The mixture modeling was performed only after the data collection was completed.

Participants

Participants in all experiments were the Open University of Israel undergraduate students who took part in the experiments for course credit (age range: 18-40). All signed an informed consent, and had normal or corrected vision, normal color vision, and lacked any neurological or attention deficits. The study was approved by the ethics committee of the Education and Psychology department at the Open University. Experiment 1 tested 35 participants (18 females, 10 males, 7 other/not responded, mean age = 29.4), Experiment 2 tested 24 participants (22 females, 2 males, mean age = 26), and Experiment 3 tested 25 participants (12 females, 13 males, mean age = 27.3)

Materials

The task was implemented with PsychoPy (version 2020.1.3; Peirce et al., 2019), running on a Standard PC with a 23.5" LCD Eizo Foris monitor (1920 x 1080, 120Hz refresh rate). Analyses were performed using JASP (version 0.15, JASP team, 2021) with the Standard prior (Caucy~.707). Mixture-modeling analyses and model comparisons were performed using the Memtoolbox package (Suchow et al., 2013). All stimuli appeared against a white background (RGB = [0, 0, 0]). All experiments included a starting

fixation display (a black cross, 50 pix). Stimuli appeared on an invisible circle with a radius of 380 pix (11.4°, except in Experiment 3 in which it was visible and appeared in black (RGB = [255, 255, 255]). Each image size was 160 x 160 pix (4.8° x 4.8°), except for Experiment 3 in which the image size was 100 x 100 pix (3° x 3°). The image set (for each participant) included 600 randomly sampled intact images of everyday objects from a previously published set (which contains 1600 images, Brady et al., 2008). The distorted images were a subset of 600 scrambled versions of intact images, also sampled from the larger pool (of 1600 scrambled images). Thus, images in the two conditions were roughly matched across participants. Scrambling was performed by diffeomorphic transformations (Stojanoski & Cusack, 2014) that distorted the images' meaning while keeping most of the visual statistics intact (Brady & Störmer, 2022; Shoval & Makovski, 2022; Shoval et al., 2023b). An image of a multi-colored circle was presented before the first and after the last items so each trial sequence started and ended with the colored-squares image. The mask image was a circle filled with multi-colored squares, of the same dimensions as the images. The locations of the memory items were achieved by presenting the stimuli in a radial orientation ranging from 1° to 360° in steps of 1°. Each image (160 x 160 pix) appeared in a random, unique position with the restriction of a minimum distance of 30° between the images. Participants responded to the memory-location task by using the mouse to adjust a response probe to the target's location. The response probe was a white circle (radius Experiments 1 and 2: 80 pix, 2.4°;

Experiment 3: 50 pix, 1.5̊) that appeared on a visible black circle (RGB =

[255, 255, 255]), of the same dimensions as the objects presented during

encoding. After the response, participants received written feedback ("your

error is X degrees", RGB = [0,0,0], Helvetica, 30pix) presented inside the

response circle, 80 pix below the probe. In addition, the correct target

location appeared on the circle with a red "X", and the participant's response

appeared simultaneously with a blue "O" (40 pix).

Procedure

Experiment 1

The task of the participants was to remember the location of four images so

they could adjust the probe to match the target's location. Four unique

images, either Intact (Meaningful) or Distorted (Meaningless), were randomly

sampled and each image was used only once throughout the experiment.

Each trial began with a 700 ms fixation display- a black plus sign (50 pix)

that remained visible throughout the trial. The first colored circle appeared

at the center of the screen for 1000 ms. Then, each of the four images

appeared in their location, in isolation, for 500 ms, followed by a 500 ms

blank screen. After the presentation of all four images, the colored-circle

image appeared again at the center of the screen for 1000 ms. Then, after

another blank screen of 1000 ms, the target image appeared at the center of

a black circle (drawn in the same radius as the presentation sequence). The

target was one of the four images from the trial's sequence and its serial position was evenly and randomly assigned across trials. Once the participant clicked with the mouse on the circle, the response probe, a white circle, appeared at the clicked location on the circle's perimeter. The participant adjusted the probe (using the mouse) and validated her response by pressing the spacebar key on the keyboard. Notably, there was no time limit and participants could not validate their response without moving the mouse first. Afterward, the feedback display appeared for 1000 ms (Figure 3a). Importantly, 96 trials of Meaningful items were randomly intermixed with 96 trials of Meaningless items trials (with each trial consisting of same-type objects only). For practice, participants performed a few test trials to ensure they understood the task. These trials were not recorded, and their images were not included in the experimental trials.

Experiment 2

The design, procedure, and stimuli were the same as in Experiment 1 except for the following changes (see Figure 3b). Each item appeared for 350 ms, followed by a mask image of the same object size, that appeared immediately after each of the objects in their location, for 650 ms. This was done in order to replicate Experiment 1's results under more demanding encoding conditions.

Experiment 3

To rule out the possibility that the lack of an SD (precision) effect was due to ceiling performance, as well as to directly test whether semantic meaning allows more locations to be stored in VWM for meaningful items, the memory set size was enlarged to six items. Increasing the number of potential target locations necessitated the use of smaller items and a larger circle, thus stimuli size was reduced to 100 x 100 pix. Note that this adjustment also creates more space for an SD effect. The black circle, serving as a landmark, remained visible throughout the trial while the items appeared on its perimeter. Finally, to shorten the experiment, the initial fixation display and the final fixation display were presented for 500ms only. The colored circle at the end of the sequence was not presented (see Figure 3c). There was a total of 180 trials, 90 in each condition (i.e., Meaningful/Meaningless). In all other respects, the experiment was identical to Experiment 1.

Mixture-Model Analysis

On each trial, we calculated the error magnitude, that is, the difference between the adjusted probe location and the target location. The error magnitude ranged from ±180°. Modeling was performed with *Memtoolbox* (Suchow et al., 2013) and we used the Swap model (Bays et al., 2009). This model received the lowest AIC and BIC scores (Corrected Alkalian's Information Criteria, and Bayesian Information Criteria, respectively) against the Standard model (Zhang & Luck, 2008), and the Variable Precision model (Van den Berg et al., 2012). The Swap model consists of three parameters: (1) Standard Deviation (*SD*): The standard deviation of target responses,

reflecting the precision of the target's report in degrees, (2) Proportion of swap responses (B): the proportion of trials where participants mistakenly reported the location of one of the distractor items instead of the target item, (3) Proportion of guess responses (G): proportion of trials with a large magnitude error originating from a uniform distribution, and unrelated to any of the distractors' location. For each participant, each condition (i.e., meaningful, meaningless) was modeled separately. Each of the three parameters was aggregated across participants to create an overall model for each condition[2]. In general, the model computes the SD based on errors around 0 (target). This estimate of SD is then applied around the center of each distractor. This holds that participants had the same 'target' precision but only misreported the location of the item. Because the items were widely separated, low-precision reports (within the range of the estimated SD) would fall within the appropriate item. Unrelated location reports would fall between items, and most likely would be classified as "guesses".

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[2]Recently, criticism was raised against some of the theoretical assumptions of mixture modeling approach (Williams et al., 2022; Brady et al., 2023; Schurgin et al., 2020). Yet, not all researchers are convinced by these claims (e.g., Tomić & Bays, 2022). Moreover, the methodological assumptions of the mixture-modeling are met in the present study; radial location is a linear variable (unlike color) and there is sufficient error space for the classification of both swaps and guesses (e.g., Bays, 2016). Furthermore, an empirical model comparison of the data showed that the swap model (Bays et al., 2009) provided the best fit, even against the variable precision model (which holds other theoretical assumptions).

Results

Results from all experiments are detailed in Figure 4. To quickly overview, as

can be seen in Figure 4a, the model-free Mean Absolute Error (MAE) shows

an effect of meaning across all experiments: a smaller overall magnitude of

errors for meaningful than for meaningless items. As can be seen in Figure

4b, depicting the mixture-model parameters, only the Swap parameter was

affected by meaning, as trials containing meaningful items had fewer swap

errors.

Experiment 1

Three participants were excluded from the analysis (2 for large

MAE > 80°, 1 participant's data did not converge). The removal of

these data did not affect any of the conclusions.

First, to ensure that meaning influenced memory performance we compared

the MAE

magnitude between meaningful-items and meaningless-items trials. A two-

sided paired samples t-test revealed a significant difference between the two

conditions, $t(31) = 4.18$, $p < .001$, $d = .73$, and a substantial Bayes factor of

$BF_{10} = 125$ was in accord with the stopping rule. Next, we

compared each of the three model's parameters, between meaningful and

meaningless trials. Only the swap error parameter (B) was significantly

different between the conditions, $t(31) = 4.4$, $p < .001$, $d = .79$, $BF_{10} = 274$.

We did not observe a significant difference in the SD parameter, $t(31) = 1.1$,

$p = .242$, $d = .21$, $BF_{01} = 2.77$, or in the guess rate parameter, $t(31) = 0.5$,

$p = .613$, $d = .09$, $BF_{01} = 4.69$.

Experiment 2

Two participants were excluded from the analysis (MAE > 80) and

the removal of these data did not affect any of the conclusions.

Overall performance was indeed worse in Experiment 2 than in

Experiment 1 as seen in the MAE (independent samples, $M = 52\mathring{}$

vs $39\mathring{}$, $t(52) = 3.43$, $p = .001$, $d = .95$). Importantly, once again,

there was an effect of meaning on the MAE, $t(21) = 3.75$, $p =$

$.001$, $d = .8$, and the Bayes factor of $BF_{10} = 31$ was in accord with

the stopping rule. Comparing the model parameters, we observed

the same results as in Experiment 1. The swap error parameter (B)

was significantly different between the conditions, $t(21) = 3.76$, p

$= .001$, $d = .8$, $BF_{10} = 31$. We did not observe a statistically

significant difference in the SD parameter, $t(21) = .7$, $p = .468$, d

$= .15$, $BF_{01} = 3.5$, nor in the guess rate parameter, $t(21) = 0.4$, p

$= .639$, $d = .1$, $BF_{01} = 4.04$. 21

Experiment 3

Two participants were excluded from the analysis (1 participant's data did

not converge

and 1 participant's SD estimate was inflated (SD > 89°)). The removal of

these data did not affect any of the conclusions.

Increasing memory set size had a large effect on the overall memory performance

compared to Experiment 1, as evident in the MAE (nonparametric independent samples Welch, $M = 5$ vs 3, $t(48.6) = 6.2$, $p < .001$, $d = 1.6$). Nevertheless, we observed the same pattern of results as in our previous experiments. The overall effect of meaning was significant, as evident in the MAE magnitude, $t(22) = 3.09$, $p = .005$, $d = .64$, and the Bayes factor of $BF_{10} = 8.3$ was in accord with the stoppage rule. Still, once again, the same pattern emerged: a significant difference for the swap error parameter, $t(22) = 3.14$, $p = .005$, $d = .655$, $BF_{10} = 9.2$, but not for the SD parameter, $t(22) = .18$, $p = .852$, $d = .03$, $BF_{01} = 4.4$, nor the guess rate, $t(22) = .79$, $p = .435$, $d = .16$, $BF_{01} = 3.4$.

Location memory precision

Given the idea that spatial location has a special status, in this analysis, we focused on the

potential difference (or lack of) between experiments in the precision of location memory. An

across-experiment analysis with the SD parameter as the dependent variable (Repeated Measures ANOVA: Meaningful/Meaningless as a within-subject factor, and Experiment as a between-

subjects factor), did not show statistically significant differences in the precision of spatial location by the item meaning, $F(1,74) = .01$, $p = .917$, nor by its interaction with the experiment, $F(2,74) = .75$, $p = .473$. Bayesian

RMANOVA, with the same factors, corroborated that the precision parameter was unaffected by stimulus meaning ($BF_{01} = 8.4$), and did not interact with experimental conditions ($BF_{01} = 8.9$), noting an overall high degree of precision ($M = 13.\mathring{7}$). Thus, semantic meaning does not affect precision, which seems high to begin with.

General Discussion

The present study examined how items' conceptual meaning affects VWM performance.

While traditional VWM research used simple stimuli to reduce LTM involvement, we manipulated the conceptual meaning of visually complex items, to directly examine LTM involvement in VWM. Specifically, we asked which aspect of memory is improved by conceptual meaning and whether meaning allows observers to better retain an arbitrary visual property of the stimuli, such as its spatial location. In three experiments, we compared two types of stimuli: Meaningful real-world items, and scrambled, meaningless items. The scrambling procedure preserved most of the visual statistics of the stimuli while stripping them of their semantic meaning (Brady & Störmer, 2022; Chung et al., 2023a; Sahar et al., 2020; Shoval & Makovski, 2022; Shoval et el., 2023; Starr et al., 2020), thus, the two stimulus sets mainly differed in their conceptual distinctiveness (but see reservation below). Consequently, when observers were exposed to the scrambled, meaningless items, they could not readily access the items' conceptual information, instead *primarily* relying on their visual features.

Experiment 1 revealed a large overall benefit in the location memory of

meaningful items.

When the memory performance was decomposed into parameters using a

mixture-modeling

analysis (Bays et al., 2009), we observed that the benefit was driven only by

fewer swap errors,

not by better precision or by a smaller guess rate. That is, the advantage of

meaningful items

resulted from the fact that observers were more frequently correct about the

item's location *given*

its known identity (i.e., the memory probe). The results also revealed a high

precision in reporting the target's location along with a low guess rate that

might have concealed an effect in these parameters. Therefore, in

Experiment 2, we shortened the encoding duration and masked each item.

Despite an increase in the overall magnitude of errors, we observed again a

large location memory benefit for meaningful items and the same pattern of

results when decomposing the findings to the model parameters: Fewer

swap errors for meaningful stimuli, along with no difference for both the SD

and the guess-rate parameters. Experiment 3 used a larger set size, 6

items instead of 4 items. Once again, although this time smaller in

magnitude, we observed an

advantage for meaningful items. Consistently, as in the previous

experiments, fewer swap errors

were found for meaningful stimuli, and no effect was observed for the SD and
the guess-rate

parameters. Collectively, we showed that the semantic meaning

benefit was driven by fewer swap errors for meaningful stimuli,

rather than by improved precision or fewer location guesses.

Three main conclusions can be drawn from this study. First, overall memory
performance, as measured by the model-free Mean Absolute Error
magnitude (MAE), clearly showed that meaning improved memory
performance, specifically for spatial memory of an arbitrary location. This
result extends past findings demonstrating a role for conceptual meaning in
VWM (Asp et al., 2021; Conci et al., 2021; Overcott & Souza, 2023; Sahar et
al., 2020; Shoval & Makovski, 2022; Starr et al., 2020; Störmer & Brady,
2022). Furthermore, our findings demonstrate that memory not only
enhances stimulus aspects related to core identity, but also to an arbitrary
feature, such as location or color (Chung et al., 2023a). The findings that
semantic meaning dramatically improves VWM performance may challenge
the external validity of numerous findings from previous studies using
'simple' (meaningless) stimuli.

Second, a deeper examination of performance reveals that the main factor
affected by semantic meaning is feature binding, as participants made fewer
location-identity (or, location-shape) swap errors with meaningful than
meaningless items. This finding suggests that the enhancement of retention
capacity by semantic meaning might specifically relate to stimulus feature-

bindings, as suggested by Oberauer (2019). Our results are analogous to the findings of Markov and Utochkin (2022), who used a similar location reproduction task and analysis. In contrast to the current study, these authors used only real-world items (i.e., meaningful stimuli), for which they varied the conceptual distinctiveness in the memory array. That is, they contrasted same-category item trials (e.g., all apples, characterized by a low distinctiveness) with different-category item trials (e.g., an apple, a mug, and a rabbit, characterized by a high distinctiveness).

Most relevant to the current results, Markov and Utochkin (2022) consistently found that categorical similarity did *not* affect correct recognition rates of the item's identity, and did not affect the overall precision or guess rate for spatial locations. Similarly to the present findings, more swap errors were observed under the low-distinctiveness (i.e., high similarity) than the high-distinctiveness (low similarity) condition. That is, observers frequently swapped the location of items within the same category, suggesting that conceptual similarity creates interference between items. Notably, however, items from the same conceptual category also shared a high degree of visual similarity, whereas, in the present study the meaningless items varied in their perceptual features (albeit the scrambling procedure may have somewhat reduced their visual distinctiveness, relative to the meaningful objects). Nevertheless, despite these differences, the conclusions of both studies converge on each other: observers tend to rely on conceptual meaning in reducing item-to-item interference when

maintaining and retrieving stimuli's locations in VWM. Note that similar results were obtained when examining the effects of conceptual meaning on memory for an arbitrary color, that is, an enhanced item-color binding for the meaningful objects (Chung et al., 2023a, 2023b).

Lastly, the semantic meaning of the items did not affect the degree of location memory precision, which remained relatively high across all three experiments. Though speculative, this high precision might reflect the special status of spatial location. A similar high precision was observed by Markov and Utochkin (2022), using a within- vs. between-category manipulation. Furthermore, recent findings demonstrated that the recall of stimulus location (on a continuous report scale) yielded the highest precision and accuracy rates, compared to orientation, color, and shape (Tomić & Bays, 2022). Thus, the inherently high accuracy and precision of spatial locations in this, as well as other studies, might have obscured a potential effect with the precision parameter. Alternatively, the absence of a semantic effect on spatial location memory may suggest that spatial location *per-se* ('where') is processed independently of semantic meaning ('what'), and therefore, the latter exerts little direct impact on it. However, such a segregated view may oversimplify matters, as findings have shown that semantics and real-world items improved the accuracy in spatial working memory change-detection tasks (Hu & Jacobs, 2021).

Despite clear behavioral evidence that conceptual meaning improved item-feature binding, the current study cannot provide a definitive underlying

mechanism for this pattern of results. However, at least two explanatory

models have nevertheless been suggested for the effects of conceptual

meaning on memory. First, Popov and Reder (2020) provided a

computational model that showed that contextual memory effects in word

lists (e.g., recency, primacy, etc.), can be explained by the frequency (i.e.,

familiarity) of the stimuli. Given a limited pool of resources, the authors

suggested that high-frequency words were better remembered due to their

consumption of less attentional resources for encoding than low-frequency

words. They concluded that the formation of a memory representation

requires the use of resources proportionally to the item's *memory strength*

(i.e., reflecting as a robust and accessible representation). In the present

study, one might consider meaningful items to be more 'strongly' encoded

due to their inherent familiarity, relative to the novel, scrambled items. Put

differently, meaningful items have a stronger memory signal since they are

heavily associated with prior knowledge. Consequently, they require less

resources for their encoding, sparing more resources for the encoding of

additional information, such as their location (see also Reder, 2013, Bellana

et al., 2021). This idea is closely related to the notion that activating an LTM

representation in VWM consists of prototypical information (like a common

label, shape, and surface features) that strongly defines the object. Such

information can increase the dimensionality of the representation while

reducing the information entropy (i.e., the cost of processing every bit of

visual information). Interestingly, consistent with the findings of our study,

Popov et al. (2022) showed that word familiarity (operationalized by high vs. low frequency) affected the probability of location swap errors, but not the precision memory of the target location. Again, the fact that feature-binding processes are long known to require attentional capacity (e.g., Treisman & Gelade, 1980) is highly consistent with the resource-based account (Popov & Reder, 2020; Popov et al., 2022).

A different model, emerging from a signal detection perspective ("Target Confusability Competition", TCC, Shurgin et al., 2020, see also Brady et al., 2024; Oberauer, 2023), suggests that swap errors occur due to a lower signal-to-noise ratio (i.e., lower d'). That is, visual similarity between items creates "confusability" between the target item and the foils. This is consistent with the current result as one may suggest that meaningful items have a stronger memory signal, on the account that they are more visually and a conceptually distinct. Although the scrambling manipulation maintained most low-level features and image statistics, the fact that local as well as global contours were largely blurred turned the meaningless items into somewhat less visually distinct from each other. Whether on a visual or a conceptual level, both types of distinctiveness (i.e., degree of similarity) can contribute to such pattern of errors (but see, Tomić & Bays, 2022). Further research is needed to examine, for example, if similar (conceptually) meaningful items that strongly differ in visual properties indeed support a stronger memory signal.

To conclude, our findings show that spatial location memory, as an arbitrary visual property, benefits from the item's conceptual meaning. This finding corroborates previous research, demonstrating how LTM involvement (long-term conceptual knowledge) enhances VWM performance (Asp et al., 2021; Chung et al., 2023a; Conci et al., 2021; Oberauer et al., 2017; Overcott & Souza, 2023; Sahar et al., 2020; Shoval & Makovski, 2022; Störmer & Brady, 2022). Critically, we show that meaning improves VWM for an item's location by specifically enhancing the binding between objects and their features similar to previous findings (Chung et al., 2023a; Markov & Utochkin, 2022; Oberauer, 2019), however, there was reliable evidence against the contribution of conceptual knowledge to VWM precision and/or the number of remembered locations. Nevertheless, meaningful semantics enhanced the capacity of information in VWM. Additional research is required to further uncover the nature of the interaction between LTM and VWM representations.

Declarations

Conflict of Interest The authors have no Conflict of Interest

Ethics This study was approved by the Ethics committee of the Open University of Israel (3366, 3247).

Consent to participate All participants signed consent prior to participation. The study was conducted according to the Helsinki Declaration.

Consent for publication All authors approved the final version of the manuscript and consented for publication.

Availability of data and materials Data and materials are available at https://osf.io/za3bm

Code Availability 'Not applicable'

Authors' contribution

Conceptualization: TS, NG, TM. Methodology: TS, NG, TM. Software: TS. Validation: TS, NG, TM. Formal analysis: TS. Investigation: TS, NG, TM. Resources: NG, TM. Data Curation: TS, NG, TM. Writing - Original Draft: TS. Writing - Review & Editing: TS, NG, TM. Visualization: TS. Supervision: NG, TM. Project administration: NG, TM. Funding acquisition: NG, TM.

Reference

Asp, I. E., Störmer, V. S., & Brady, T. F. (2021). Greater Visual Working Memory Capacity for Visually Matched Stimuli When They Are Perceived as Meaningful. *Journal of Cognitive Neuroscience*, 33(5), Article 5. https://doi.org/10.1162/jocn_a_01693

Bae, G.-Y., Olkkonen, M., Allred, S. R., & Flombaum, J. I. (2015). Why some colors appear more memorable than others: A model

combining categories and particulars in color working memory. *Journal of Experimental Psychology. General*, *144*(4), 744–763. https://doi.org/10.1037/xge0000076

Bays, P.M. (2016) Evaluating and excluding swap errors in analogue tests of working memory. *Nature - Scientific Report* 6, 19203. https://doi.org/10.1038/srep19203

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

Bellana, B., Mansour, R., Ladyka-Wojcik, N., Grady, C. L., & Moscovitch, M. (2021). The influence of prior knowledge on the formation of detailed and durable memories. *Journal of Memory and Language*, *121*, 104264. https://doi.org/10.1016/j.jml.2021.104264

Blalock, L. D. (2015). Stimulus familiarity improves consolidation of visual working memory representations. *Attention, Perception, & Psychophysics*, *77*(4). https://doi.org/10.3758/s13414-014-0823-z

Brady, T. F., & Alvarez, G. A. (2015). Contextual effects in visual working memory reveal hierarchically structured memory representations. *Journal of Vision*, 15(15). https://doi.org/10.1167/15.15.6

Brady, T. F., Alvarez, G. A., & Störmer, V. S. (2019). The Role of Meaning in Visual Memory: Face-Selective Brain Activity Predicts Memory for Ambiguous Face Stimuli. *Journal of Neuroscience*, 39(6), Article 6. https://doi.org/10.1523/JNEUROSCI.1693-18.2018

Brady, T. F., Konkle, T., & Alvarez, G. A. (2009). Compression in visual short-term memory: Using statistical regularities to form more efficient memory representations. *Journal of Experimental Psychology: General*, 138, 487–502. doi: 10.1037/a0016797

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), https://doi.org/10.1167/11.5.4

Brady, T. F., Konkle, T., Alvarez, G. A., & Oliva, A. (2008). Visual long-term memory has a massive storage capacity for object details. *Proceedings of the National Academy of Sciences*, 105(38), https://doi.org/10.1073/pnas.0803390105

Brady, T. F., Robinson, M. M., & Williams, J. R. (2024). Noisy and

hierarchical visual memory across timescales. *Nature Reviews Psychology*,

1-17. https://doi.org/10.1038/s44159-024-00276-2

Brady, T. F., & Störmer, V. S. (2022). The role of meaning in visual working

memory: Real world objects, but not simple features, benefit from deeper

processing. *Journal of Experimental Psychology: Learning, Memory, and

Cognition*, 48(7). https://doi.org/10.1037/xlm0001014

Brady, T. F., Störmer, V. S., & Alvarez, G. A. (2016). Working

memory is not fixed-capacity: More active storage capacity for

real-world objects than for simple stimuli. *Proceedings of the

National Academy of Sciences*, *113*(27),

https://doi.org/10.1073/pnas.1520027113

Chung, Y. H., Brady, T. F., & Störmer, V. S. (2023a). No Fixed

Limit for Storing Simple Visual Features: Realistic Objects

Provide an Efficient Scaffold for Holding Features in Mind.

Psychological Science, *34*(7),

https://doi.org/10.1177/09567976231171339

Chung, Y. H., Brady, T. F., & Störmer, V. S. (2023b). Sequential encoding aids working memory for meaningful objects' identities but not for their colors. *Memory & Cognition*. https://doi.org/10.3758/s13421-023-01486-4

Conci, M., Kreyenmeier, P., Kröll, L., Spiech, C., & Müller, H. J. (2021). The nationality benefit: Long-term memory associations enhance visual working memory for color-shape conjunctions. *Psychonomic Bulletin & Review*, *28*(6), Article 6. https://doi.org/10.3758/s13423-021-01957-2

Conci, M., Busch, N., Rozek, R. P., & Müller, H. J. (2023). Learning-Induced Plasticity Enhances the Capacity of Visual Working Memory. *Psychological Science, 34(10),* 10871100.

Cowan, N. (2010). The Magical Mystery Four: How is Working Memory Capacity Limited, and Why? *Current Directions in Psychological Science*, *19*(1), 51–57. https://doi.org/10.1177/0963721409359277

Gasparri, L., & Marconi, D. (2021). Word Meaning. In E. N. Zalta (Ed.), *The Stanford Encyclopedia of Philosophy* (Spring 2021). Metaphysics Research Lab, Stanford University.

https://plato.stanford.edu/archives/spr2021/entries/word-

meaning/

Golomb, J. D., Kupitz, C. N., & Thiemann, C. T. (2014). The influence of

object location on

identity: A "spatial congruency bias." *Journal of Experimental Psychology:*

General,

143(6), Article 6. https://doi.org/10.1037/xge0000017

Hu, R., & Jacobs, R. A. (2021). Semantic influence on visual working

memory of object identity and location. *Cognition*, *217*, 104891.

https://doi.org/10.1016/j.cognition.2021.104891

Konkle, T., Brady, T. F., Alvarez, G. A., & Oliva, A. (2010a).

Conceptual distinctiveness supports detailed visual long-term

memory for real-world objects. *Journal of Experimental*

Psychology: General, *139*(3),

https://doi.org/10.1037/a0019165

Konkle, T., Brady, T. F., Alvarez, G. A., & Oliva, A. (2010b). Scene Memory

Is More Detailed Than You Think: The Role of Categories in Visual Long-

Term Memory. *Psychological*

Science, *21*(11), 1551–1556. https://doi.org/10.1177/0956797610385359

Kouststaal, W., Reddy, C., Jackson, E. M., Prince, S., Cendan, D. L., &

Schacter, D. L. (2003).

False recognition of abstract versus common objects in older and younger

adults: Testing the semantic categorization account. *Journal of*

Experimental Psychology: Learning, Memory, and Cognition, *29*(4), Article

4. https://doi.org/10.1037/0278-7393.29.4.499

Kramer, M. A., Hebart, M. N., Baker, C. I., & Bainbridge, W. A.

(2023). The features underlying the memorability of objects.

Science advances, *9*(17), https://doi.org/10.1126/sciadv.add2981.

Lamy, D., & Tsal, Y. (2001). On the status of location in visual attention.

European Journal of Cognitive Psychology, *13*(3), Article 3.

https://doi.org/10.1080/09541440042000016

Li, A. Y., Fukuda, K., & Barense, M. D. (2022). Independent features form

integrated objects:

Using a novel shape-color "conjunction task" to reconstruct memory

resolution for multiple

object features simultaneously. *Cognition*, *223*, 105024.

https://doi.org/10.1016/j.cognition.2022.105024

Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for

features and conjunctions. *Nature*, *390*(6657), Article 6657.

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

Makovski, T. (2016). What is the context of contextual cueing? *Psychonomic

Bulletin &

Review*, *23*(6), https://doi.org/10.3758/s13423-016-1058-x

Makovski, T. (2018). Meaning in learning: Contextual cueing relies on

objects' visual features

and not on objects' meaning. *Memory & Cognition*, *46*(1).

https://doi.org/10.3758/s13421-017-0745-9

Markov, Y. A., & Utochkin, I. S. (2022). Effects of item distinctiveness on the

retrieval of

objects and object-location bindings from visual working memory. *Attention, Perception,*

& Psychophysics, *84*(7), https://doi.org/10.3758/s13414-022-02451-0

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 3.

https://doi.org/10.1167/jov.21.3.18

Oberauer K. (2023). Measurement models for visual working memory-A factorial model

comparison. *Psychological review*, 130(3), 841–852. https://doi.org/10.1037/rev0000328

Oberauer K. (2019). Working Memory Capacity Limits Memory for Bindings. *Journal of*

Cognition, 2(1), 40. https://doi.org/10.5334/joc.86

Oberauer, K., Awh, E., & Sutterer, D. W. (2017). The role of long-term memory in a test of

visual working memory: Proactive facilitation but no proactive interference. *Journal of Experimental Psychology: Learning,*

Memory, and Cognition, *43*(1), Article

1.https://doi.org/10.1037/xlm0000302

Oberauer, K., Farrell, S., Jarrold, C., & Lewandowsky, S. (2016). What limits

working memory capacity? *Psychological Bulletin*, *142*(7), 758–799.

https://doi.org/10.1037/bul0000046

Oberauer, K., & Lin, H.-Y. (2017). An interference model of visual working

memory.

Psychological Review, *124*(1), https://doi.org/10.1037/rev0000044

Olsson, H., & Poom, L. (2005). Visual memory needs categories.

Proceedings of the National Academy of Sciences, 102(24), 8776-

8780. https://doi.org/10.1073/pnas.0500810102

Overkott, C., & Souza, A. S. (2022). Verbal descriptions improve

visual working memory buthave limited impact on visual long-

term memory. *Journal of Experimental Psychology: General*, *151*,

321–347. https://doi.org/10.1037/xge0001084

Overkott, C., & Souza, A. S. (2023). The fate of labeled and

nonlabeled visual features in working memory. *Journal of*

Experimental Psychology: Human Perception and Performance,

49, 384–407. https://doi.org/10.1037/xhp0001089

Peirce, J., Gray, J. R., Simpson, S., MacAskill, M., Höchenberger, R., Sogo,

H., Kastman, E., & Lindeløv, J. K. (2019). PsychoPy2: Experiments in

behavior made easy. *Behavior*

Research Methods, *51*(1), https://doi.org/10.3758/s13428-018-01193-y

Pertzov, Y., & Husain, M. (2014). The privileged role of location in visual

working memory.

Attention, Perception & Psychophysics, *76*(7),

https://doi.org/10.3758/s13414-

013-0541-y

Phillips, W. A. (1974). Distinction between sensory storage and short-term

visual

memory. *Perception and Psychophysics, 16(2),* 283–290.

Popov, V., & Reder, L. M. (2020). Frequency effects on memory: A resource-

limited theory.

Psychological Review, *127*(1), Article 1. https://doi.org/10.1037/rev0000161

Popov, V., So, M., & Reder, L. M. (2022). Memory resources recover

gradually over time: The

effects of word frequency, presentation rate, and list composition on binding

errors and

mnemonic precision in source memory. *Journal of Experimental Psychology:*

Learning,

Memory, and Cognition, *48*(9), 1263–1280.

https://doi.org/10.1037/xlm0001072

Reder, L. M., Victoria, L. W., Manelis, A., Oates, J. M., Dutcher, J.

M., Bates, J. T., Cook, S.,Aizenstein, H. J., Quinlan, J., & Gyulai, F.

(2013). Why it's easier to remember seeing a face we already

know than one we don't: Preexisting memory representations

facilitate memory formation. *Psychological Science*, *24*(3).

https://doi.org/10.1177/0956797612457396

Rosch, E. (1975). Cognitive representations of semantic categories. *Journal*

of Experimental

Psychology: General, *104*(3), 192–233. https://doi.org/10.1037/0096-

3445.104.3.192

Sahar, T., Gronau, N., & Makovski, T. (2024, February 15).

Semantic Meaning Enhances Feature-Binding but not

Quantity or Precision of Locations in Visual Working Memory.

Retrieved from osf.io/za3bm

Sahar, T., Sidi, Y., & Makovski, T. (2020). A Metacognitive Perspective of

Visual Working

Memory With Rich Complex Objects. *Frontiers in Psychology*, *11*.

https://www.frontiersin.org/articles/10.3389/fpsyg.2020.00179

Schneegans, S., & Bays, P. M. (2017). Neural Architecture for Feature

Binding in Visual

Working Memory. *Journal of Neuroscience*, *37*(14).

https://doi.org/10.1523/JNEUROSCI.3493-16.2017

Schurgin, M. W., Wixted, J. T., & Brady, T. F. (2020). Psychophysical scaling

reveals a unified theory of visual memory strength. *Nature human*

behaviour, *4*(11), 1156-1172.

https://doi.org/10.1038/s41562-020-00938-0

Schönbrodt, F. D., & Wagenmakers, E.-J. (2018). Bayes factor design

analysis: Planning for

compelling evidence. *Psychonomic Bulletin & Review*, *25*(1).

https://doi.org/10.3758/s13423-017-1230-y

Shepard, R. N. (1967). Recognition memory for words, sentences, and pictures. *Journal of Verbal Learning and Verbal Behavior*, *6*(1), 156–163. https://doi.org/10.1016/S0022-5371(67)80067-7

Shoham, A., Kliger, L., & Yovel, G. (2022). Learning faces as concepts improves face

recognition by engaging the social brain network. *Social Cognitive and Affective*

Neuroscience, *17*(3), https://doi.org/10.1093/scan/nsab096

Shoval, R., Gronau, N., Sidi, Y., & Makovski, T. (2023a). Objects' perceived meaningfulness

predicts both subjective memorability judgments and actual memory performance. *Visual*

Cognition, *31(6),* 1-13.

Shoval, R., Gronau, N., & Makovski, T. (2023b). Massive visual long-term memory is largely dependent on meaning. *Psychonomic Bulletin & Review*, *30*(2), 666–675.

https://doi.org/10.3758/s13423-022-02193-y

Shoval, R. & Makovski, T. (2021). The locus of proactive interference in visual working

memory. *Journal of Experimental Psychology; Human Perception & Performance, 47(5),*

704-715.

Shoval, R., & Makovski, T. (2022). Meaningful stimuli inflate the role of proactive interference in visual working memory. *Memory & Cognition*, *50*(6), Article 6. https://doi.org/10.3758/s13421-022-01338-7

Souza, A. S., Overkott, C., & Matyja, M. (2021). Categorical distinctiveness constrains the 50 labeling benefit in visual working memory. *Journal of Memory and Language*, *119*, 104242. https://doi.org/10.1016/j.jml.2021.104242

Souza, A. S., & Skóra, Z. (2017). The interplay of language and visual perception in working

memory. *Cognition*, *166*, 277–297.

https://doi.org/10.1016/j.cognition.2017.05.038

Standing, L. (1973). Learning 10000 pictures. *Quarterly Journal of Experimental Psychology*, *25*(2), 207–222. https://doi.org/10.1080/14640747308400340

Starr, A., Srinivasan, M., & Bunge, S. A. (2020). Semantic knowledge influences visual working memory in adults and children. *PLOS ONE*, *15*(11), Article 11. https://doi.org/10.1371/journal.pone.0241110

Stojanoski, B., & Cusack, R. (2014). Time to wave good-bye to phase scrambling: Creating controlled scrambled images using diffeomorphic transformations. *Journal of Vision*, *14*(12), Article 12. https://doi.org/10.1167/14.12.6

Suchow, J. W., Brady, T. F., Fougnie, D., & Alvarez, G. A. (2013). Modeling visual working memory with the MemToolbox. *Journal of Vision*, *13*(10), Article 10. https://doi.org/10.1167/13.10.9

Thibeault, A., Stojanoski, B., & Emrich, S. (2023). *Investigating the Effects of Perceptual Complexity Versus Conceptual Meaning on the Object Benefit in Visual Working Memory*. PsyArXiv. https://doi.org/10.31234/osf.io/3dmrq

Tomić, I., & Bays, P. M. (2022). Perceptual similarity judgments do not predict the distribution of errors in working memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*. Advance online publication. https://doi.org/10.1037/xlm0001172

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology*, *12*(1), 97–136. https://doi.org/10.1016/0010-0285(80)90005-5

Van den Berg, R., Shin, H., Chou, W.-C., George, R., & Ma, W. J. (2012).Variability in encoding precision accounts for visual short-term memory limitations. *Proceedings of the National Academy of Sciences*, *109*(22), Article 22. https://doi.org/10.1073/pnas.1117465109

Williams, J. R., Robinson, M. M., Schurgin, M. W., Wixted, J. T., & Brady, T. F. (2022). You cannot "count" how many items people remember in visual working memory: The importance of signal detection–based measures for understanding change detection

performance. *Journal of Experimental Psychology: Human Perception and Performance*, 48(12), 1390–1409. https://doi.org/10.1037/xhp0001055

Wyble, B., Swan, G., & Callahan-Flintoft, C. (2016). Measuring visual memory in its native format. *Trends in Cognitive Sciences*, *20*, 790–791. https://doi.org/10.1016/j.tics.2016.08.012

Xie, W., & Zhang, W. (2017). Familiarity speeds up visual short-term memory consolidation. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(6), Article 6. https://doi.org/10.1037/xhp0000355

Xie, W., & Zhang, W. (2018). Familiarity Speeds Up Visual Short-term Memory Consolidation: Electrophysiological Evidence from Contralateral Delay Activities. *Journal of Cognitive Neuroscience*, *30*(1), Article 1. https://doi.org/10.1162/jocn_a_01188

Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature*, *453*(7192), Article 7192. https://doi.org/10.1038/nature06860

Zhang, W., & Luck, S. J. (2009). Sudden Death and Gradual Decay in Visual Working Memory. *Psychological Science*, *20*(4), Article 4. https://doi.org/10.1111/j.1467-9280.2009.02322.x
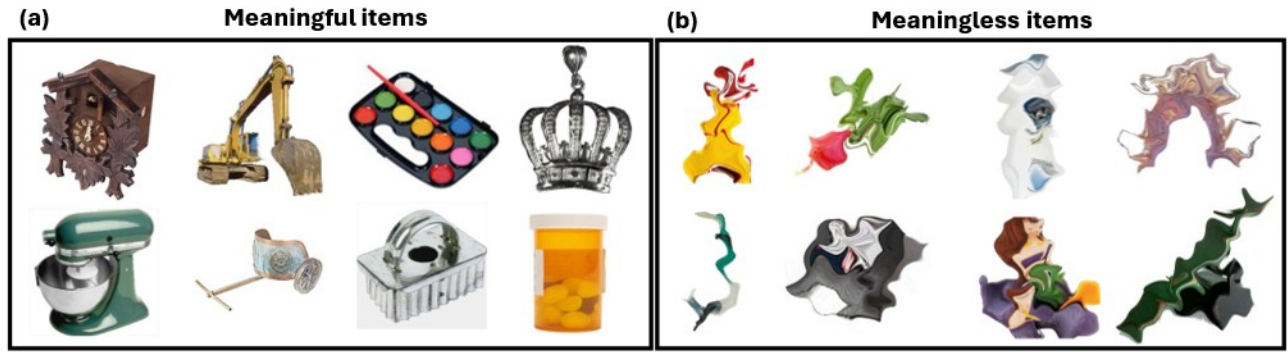
Figure 1. *Examples of stimuli from all experiments. (a) Examples of intact, meaningful items (b) Examples of distorted, meaningless items.*
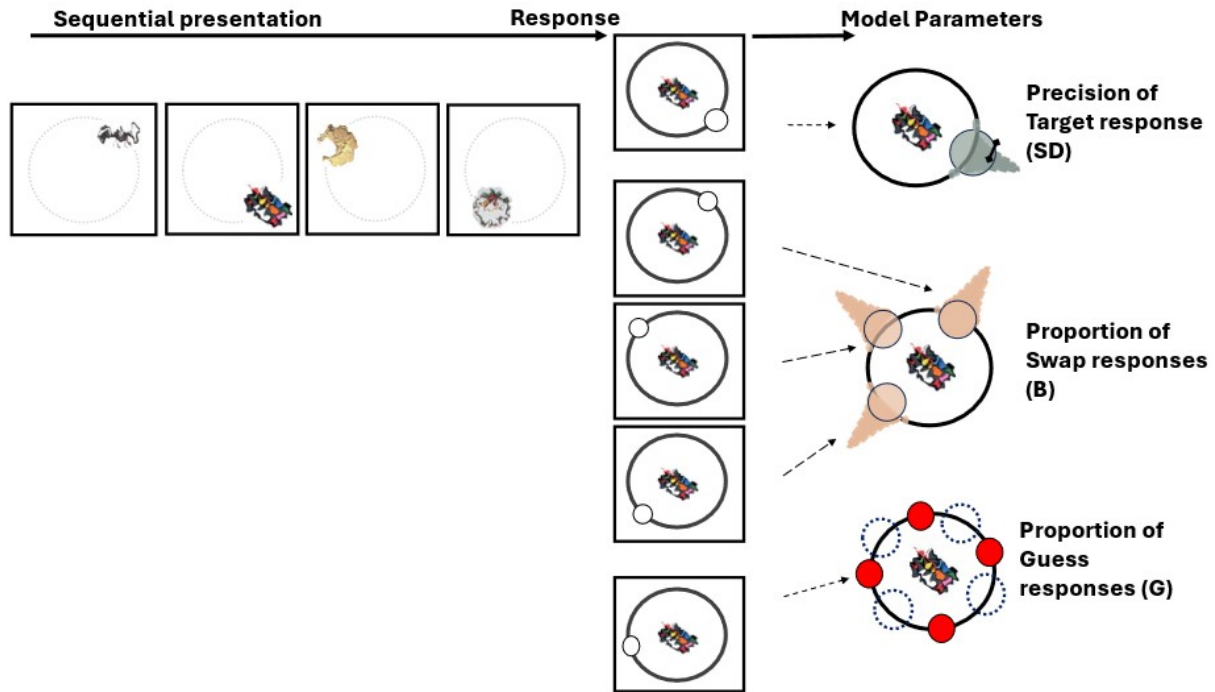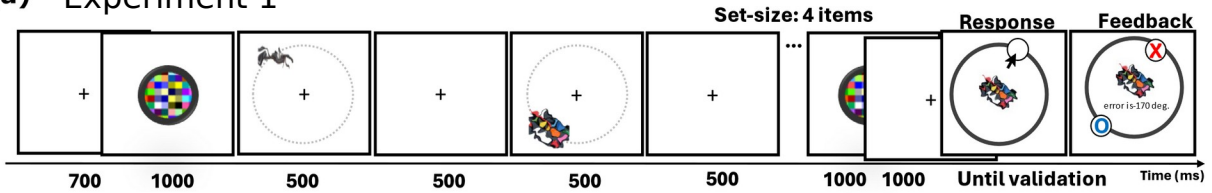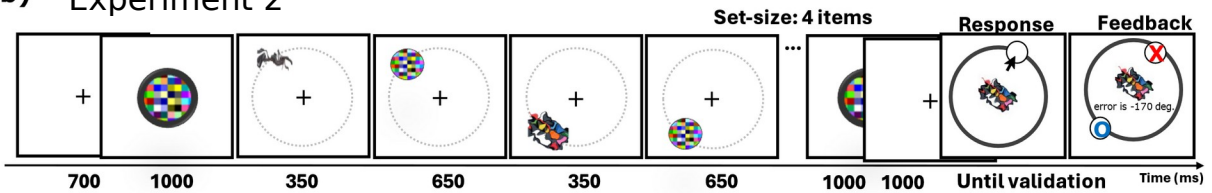
Figure 2 *Schematic illustration of a trial containing meaningless items and the mixture-modeling approach with the swap model (Bays et al., 2009): (Left)* **Presentation sequence**: *each trial consists of 4 items presented sequentially, each presented in a distinct location around the perimeter of a circle, see details below and Figure 3. (Middle)* **Response**: *In the response phase participants are asked to reproduce the target location (i.e., the location of the item appearing inside the circle) by continuously adjusting a probe (small white circle) to the target location on the perimeter of the outer circle. (Right)* **Correspondence of responses to the model parameters**: *Responses in the near vicinity of the correct target location are classified as Target*

responses (marked in gray); The Precision of response (SD) is estimated from the spread of responses. Responses at the location of non-target items (marked in orange) are classified as Swap responses. Unrelated responses (marked in red) are classified as guess responses.

(a) Experiment 1
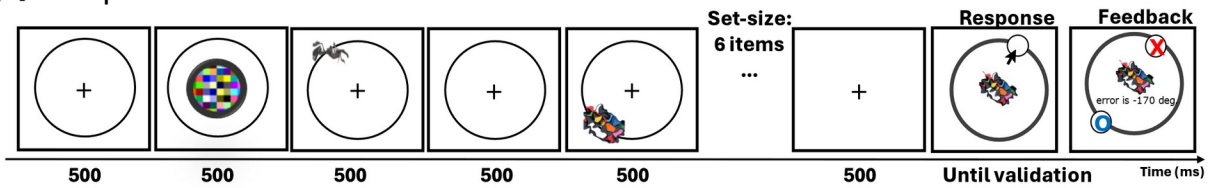

(b) Experiment 2

(c) Experiment 3

Figure 3. *Schematic illustration of the trial's sequence in Experiment 1 (a), 2 (b), and 3 (c). Note: items and displays are not scaled to their real size, Experiment 3 used smaller images (see below).*
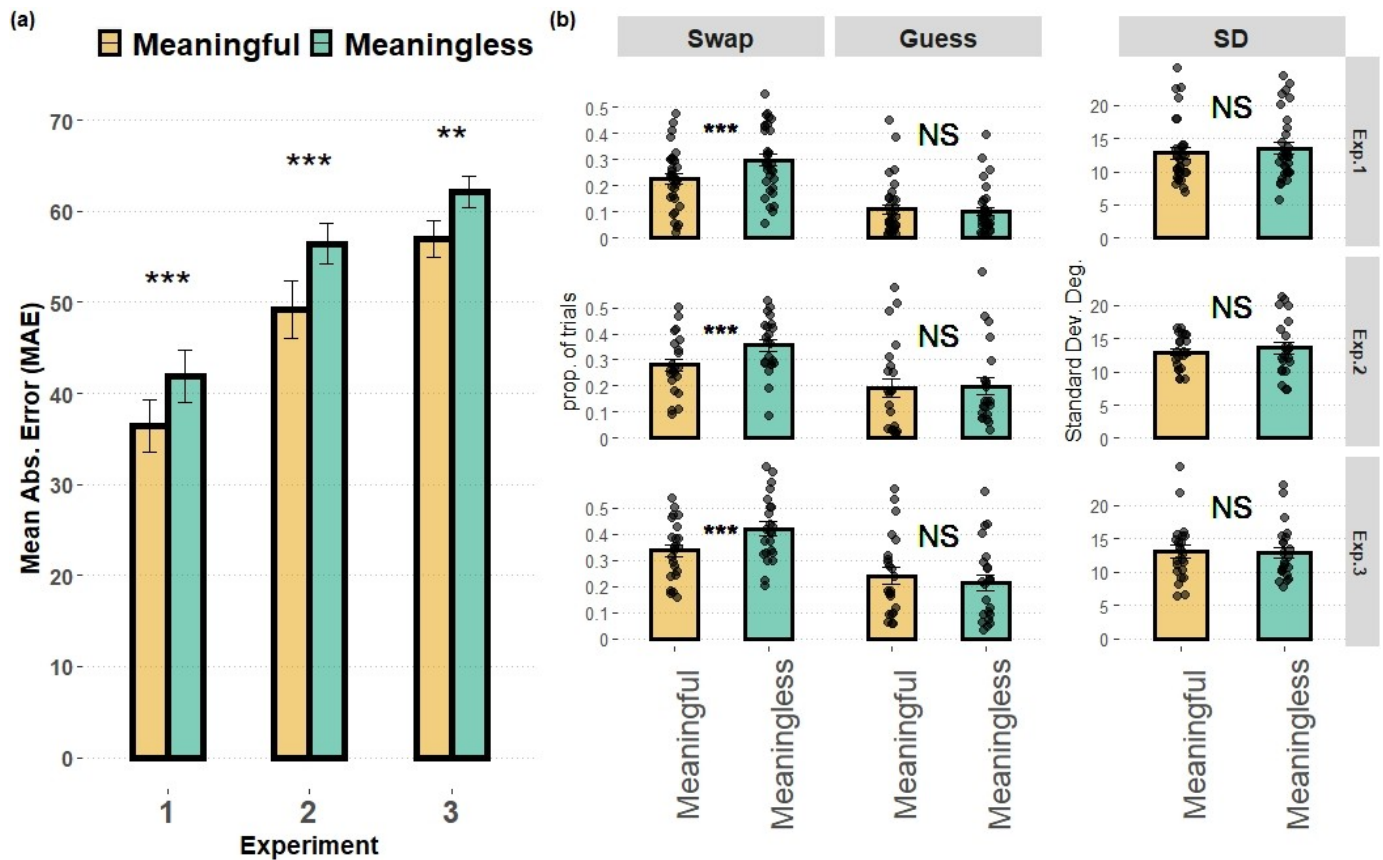
52

Figure 4. *Results in the three experiments. (a) Overall spatial memory performance: The Mean Absolute Error (MAE) as a function of stimulus condition and experiment (b) Model parameters: In rows, the results for each experiment. In columns, parameter values: proportion of Swap-rate, proportion of Guess-rate, and the Standard Deviation in degrees (SD) as a function of stimulus condition. Black circles represent individual data. Error bars denote 1 SEM, ** denotes p <.01, *** denotes p <.001, NS denotes p >.05.*