Unpacking similarity effects in visual memory search: categorical, semantic, and visual contributions

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Abstract

Visual memory search involves comparing a probe item against multiple memorized items. Previous work has shown that distractor probes from a different object category than the objects in the memory set are rejected more quickly than distractor probes from the same category. Because objects belonging to the same category usually share both visual and semantic features compared with objects of different categories, it is unclear whether the category effects reported in previous studies reflected category-level selection, visual similarity, and/or semantic target-distractor similarity. Here, we employed old/new recognition tasks to examine the role of categorical, semantic, and visual similarity in short- and long-term memory search. Participants (N=64) performed visual long-term memory (LTM) or short-term memory (STM) search tasks involving animate and inanimate objects. Trial-wise RT variability to distractor probes in LTM and STM search was modelled using regression analyses that included predictors capturing categorical target-distractor similarity (same or different category), semantic target-distractor similarity (from a distributional semantic model), and visual target-distractor similarity (from a deep neural network). We found that for both memory tasks, categorical, semantic, and visual similarity all explained unique variance in trial-wise memory search performance. However, their respective contributions varied with memory set size and task, with STM performance being relatively more strongly influenced by visual and categorical similarity and LTM performance being relatively more strongly influenced by semantic similarity. These results clarify the nature of the representations used in memory search and reveal both similarities and differences between search in STM and LTM.

Keywords: object category, visual similarity, semantic similarity, categorical similarity, memory search

Introduction

When going to a supermarket to buy beverages for dinner, you need to compare the beverage in front of you with your shopping list in long-term memory (LTM). This example of probe-recognition memory illustrates how we frequently need to recognize whether an object in view (the probe) is one we memorized previously. Interestingly, previous work has shown that visual memory search is easier for some probe objects than others. For example, when the memory set consists of objects that all belong to one category (e.g., milk, beer, fruit juice – all beverages), participants are slow to decide that an object from the same category (e.g., cola) is not on the memory list relative to an object from another category (e.g., a plant; Gronau et al., 2024; Shang et al., 2024; Williams et al., 2024; Cunningham & Wolfe, 2012, 2014; Drew & Wolfe, 2014). In the current study, we investigated what drives this category effect, considering three factors that could contribute to the category effect: visual similarity, semantic similarity, and target category-level selection.

First, the category effect could reflect differences in the visual similarity between items within versus between categories: a milk bottle and a cola bottle are visually more similar than a milk bottle and a plant. Visual similarity is known to strongly influence attentional selection in visual search tasks (Duncan & Humphreys, 1989). Considering the close relationship between attention and memory (Sherman & Turk-Browne, 2024), visual similarity could also influence memory search, such that visually distinct items are more quickly rejected during memory search. Furthermore, recent studies showed that precise details of large numbers of memorized images can still be recognized (Brady et al., 2008; Vogt & Magnussen, 2007), suggesting that recognition memory may include a visual component.

Second, the category effect could reflect differences in the semantic similarity between items within versus between categories: a milk bottle and a cola bottle are

semantically more closely related than a milk bottle and a plant. Indeed, the limitless capacity of LTM may be supported by conceptual structure rather than visual features (Konkle et al., 2010a, 2010b). In line with a role for semantic similarity, memory search is often compared to a dynamic "foraging-like" search (Davelaar, 2015; Hills et al., 2012, 2015; Hills & Pachur, 2012), such that items related to the probe stimulus are concurrently activated in memory based on semantic similarity to generate search patches and facilitate memory search (Collins & Loftus, 1975; Collins & Quillian, 1969).

Finally, the category effect could additionally reflect a binary task-related categorical selection before memory search, which could be an efficient strategy when the memory items are all from one category. For example, while searching for the three beverages, participants may first decide whether an object belongs to the target category – whether it is a beverage or not – before commencing memory search. It should be noted that deciding whether an object is from the target category or not may itself be influenced by the object's visual and semantic similarity to the target category, but categorical similarity in this case is binary (target vs non-target category) and therefore not identical to visual and/or semantic similarity, which are continuous (e.g., objects within a category vary in terms of their visual and semantical similarity). Furthermore, target category selection is flexible and task-dependent and can, in principle, exist independently of general visual and semantic similarity. For example, when searching for the three beverages, an observer may set a pre-determined criteria independent of visual and semantic similarity, such as the budget, and use that criteria to categorically reject all beverages that are outside of their budget. The first aim of the current study was to examine the distinct contributions of visual and semantic similarity, as well as categorical selection, to memory search performance.

Our second aim was to compare these contributions across LTM and short-term memory (STM). Contrary to LTM, most studies on STM agree that there is a close

relationship between visual STM and visual representations (Hollingworth, 2004; Lin & Luck, 2009). For example, Lin and Luck (2009) reported that visual similarity improved the performance on visual STM, suggesting that participants classified the stimuli with similar appearance (i.e., colours) into the same category, and thus that visual features play an important role in visual STM. In addition, Hollingworth (2004) found that, although visual LTM and visual STM representations shared a similar format and content, visual STM could capture relatively more precise details. In addition, visual cortex representations are activated ("held online") during visual STM but not LTM (see Sreenivasan et al., 2014 for a review). This suggests that the role of the visual cortex in visual STM and visual LTM maintenance are different, with STM representations being stored in a more visual code than LTM representations. These considerations predict that STM is more strongly influenced by visual similarity than LTM and, conversely, that LTM is more strongly influenced by semantic similarity than STM.

To investigate distinct contributions to memory search performance, participants (N=64) performed visual long-term memory (LTM) or short-term memory (STM) search tasks involving animate and inanimate objects. To measure the category effect, the items in the memory set always came from one category (animate or inanimate) while the probe objects came from both categories. Our analyses focused on reaction times (RTs) to distractor objects, such that the response ("no") was the same for all objects included in the analyses. Specifically, we modelled trial-wise RT variability to distractor probes using regression analyses that included predictors capturing categorical target-distractor similarity (same or different category), semantic target-distractor similarity (from a distributional semantic model), and visual target-distractor similarity (from a deep neural network). This approach allowed us to investigate: 1) whether the category effects reported in previous studies remain when regressing out visual and semantic similarity, 2) whether visual and semantic similarity

independently contribute to memory search performance, and 3) whether the contributions of categorical selection, and semantic and visual similarity to memory search performance differ between LTM and STM search.

Method

Participants

In total, sixty-four participants were recruited from the online platform Prolific and signed an online informed consent form. Thirty-one participants (18 male and 13 female) between 20 and 35 years of age (M = 23.80, SD = 2.92) participated in the LTM task while the other thirty-three new participants (25 male and 8 female) between 18 and 35 years old (M = 23.76, SD = 3.08) were recruited for the STM task. In total, one participant in the LTM task and three participants in the STM task were excluded because of low accuracy in the set size 8 conditions (below 3 SD of the group mean), preventing accurate estimation of reaction times (our main dependent measure). All participants received 6 euro per hour after the experiment.

Stimuli and design

A total of 1020 full-colour images including 30 animate categories and 30 inanimate object categories were selected from Google Images and from Brady et al. (2008), respectively. Each category contained 17 exemplar images. Each image was used only once in each task. The current study followed a 2 (LTM/STM task; between-subjects) × 2 (within/between category; within-subjects) × 4 (memory set size (MSS) 1/2/4/8; within-subjects) mixed design. For each task, all participants were tested on both categories over all four MSS. Both tasks were programmed with PsychoPy v2020.2.3 (Peirce et al., 2019) and were hosted on Pavlovia. Before each task, 20 practice trials were conducted to ensure that the participants were familiar with the experimental instructions and procedure.

Procedure

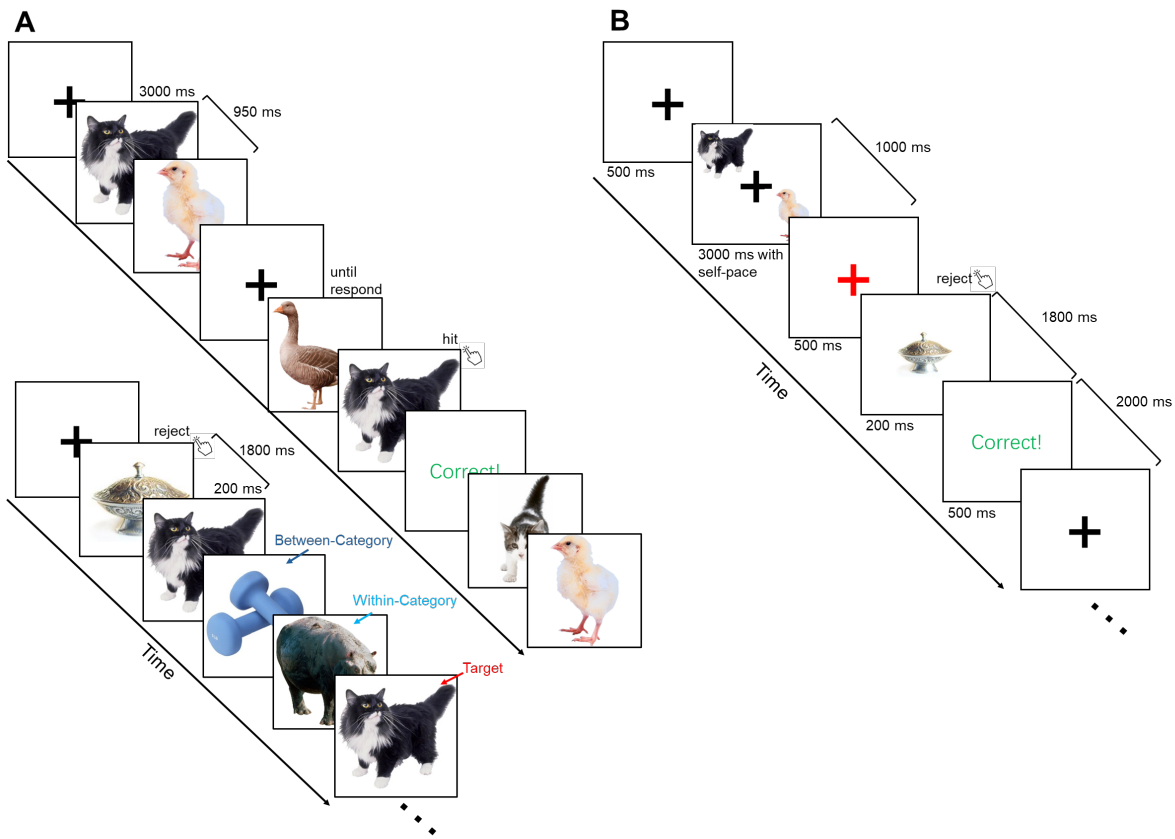
LTM task

The LTM task was an old/new recognition task with 50% target-absent trials. The experiment was structured in blocks in which one MSS was used. Each block consisted of a study phase, a memory test phase, and the main experiment phase. In the study phase, a central fixation cross appeared for 0.5 sec as a prompt indicating the beginning of the block, followed by 1, 2, 4, or 8 targets from either animate or inanimate category presented in the centre of the screen on a white background, one at a time, for 3 sec with an inter-stimulus interval of 0.95 sec (Figure 1A). Participants were instructed to memorize the objects. The subsequent memory test phase followed the same procedure except for the duration of the object display. In addition, when the test object was presented, participants needed to decide whether it was part of the memory set (target) or not, and the display terminated upon response. Only participants with >80% accuracy twice consecutively were allowed to continue to the next and main phase.

The main experiment phase consisted of eight blocks of 60 trials each (30 targets and 30 distractors (15 animate and 15 inanimate). A central fixation cross appeared for 0.5 sec, followed by a target or a distractor object presented in the centre of the screen on a white background for 0.2 sec with an inter-trial interval of 1.8 sec. Participants were required to decide whether the object presented on the screen was a target or not within 2 sec. All distractors were only shown once in the experiment. All targets were only used in one block, but the targets could repeat within a block. Trial order was randomized.

Figure 1

Illustrations of the procedures of (A) LTM and (B) STM Tasks



Note. The example presents an animate block with two targets (i.e., MSS 2). (A) The participants in the LTM task first memorized two objects from the same category (animal category in this example). Once they memorized the objects, they continued with the main experiment, deciding if a probe object was a target or not (old/new recognition task). Distractor objects could come from the same category (within-category distractor) or from the other category (between-category distractor). All analyses focused on reaction time to the distractor objects. (B) As in the LTM task, the participants in the STM task also memorized two objects, and then decided if the probe object was the target or not after 1-sec retention.

STM task

For the visual STM task, the stimuli were randomly selected from the same stimulus pool as used in the LTM task, and were equally divided into 7 blocks. Each block consisted of 32

trials (16 targets and 16 distractors (8 animate and 8 inanimate). Participants could take a brief break at the end of each block.

A black central fixation cross appeared for 0.5 sec as a prompt indicating the beginning of the trial, and then participants were required to memorize 1 to 8 targets from either animate or inanimate category. These targets were presented simultaneously for a maximum of 2, 3, 5, or 9 sec depending on the memory set size (1, 2, 4, 8 items, respectively). After a 1-sec interval, a probe object was presented for 0.2 sec, followed by a 1.8-sec response window (or until response). Participants had to respond within 2 sec or they would get negative feedback. The inter-trial interval was also 2 sec (Figure 1B).

Behavioural data analyses

For both tasks, the main analyses focused on RT of target-absent (i.e., distractor) trials. Only correct trials were included in RT analyses. For each set size and each category condition, RTs beyond 3 standard deviations (SD) of the mean were excluded as outliers. Under this criterion, 1.36% of data points in the LTM task and 1.14% of data points in the STM task were excluded from further analyses on RT.

Establishing visual and semantic similarity

Visual similarity

AlexNet (Krizhevsky et al., 2017) is a commonly used neural network model of human visual object processing, showing good alignment with visual cortex representations (Jozwik et al., 2018). We used AlexNet to establish the visual similarity between all pairs of objects. Specifically, we used Spearman correlation to correlate the flattened activation matrices of each pair of objects at each layer, and thereby obtained eight representational similarity matrices (one for each layer).

Next, we used these correlations to establish the visual target-distractor similarity at the single trial level, in order to relate this measure to behavioural performance across trials. In both tasks, however, in a given target-absent trial, the individually presented distractor object could be paired with multiple targets (when MSS>1). Thus, for each target-absent trial, we would obtain at least two correlation coefficients for each layer. Here, two approaches were employed to compute the visual similarity for each trial. The first approach was to average the similarity correlations of the multiple targets and the single distractor for each trial at each layer. The second approach was to select the maximum similarity correlation on a given trial, based on the idea that behavioural performance may be limited by the most similar item. However, we did not observe any statistical difference between these two approaches. Therefore, all reported results were based on the mean similarity correlation.

Semantic similarity

To compute semantic similarity, all object images were first given names at the basic category level (e.g., “cat”, “monkey”, “guitar”, “bag”). The semantic similarity of these names was then determined using Word2Vec (Mikolov et al., 2013; Řehůřek & Sojka, 2010), a method of natural language processing (NLP). Through modelling text within large corpora, Word2Vec uses word co-occurrence patterns to identify words with similar contexts and then maps them to vectors that can be considered in terms of their cosine similarity. Trial-wise semantic similarity was computed in the same way as described above for visual similarity. Also here, mean and max similarity gave highly similar results and only mean similarity results are reported.

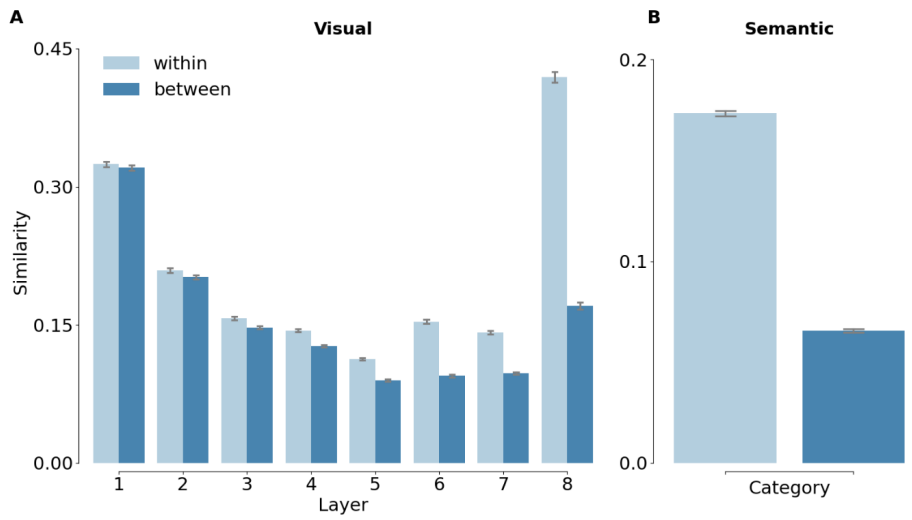
Mean similarity for within- and between-category pairs

Intuitively, objects of the same category are visually and semantically relatively similar. To test whether this was the case for the objects in our experiments, we employed AlexNet and

Word2Vec to compute the visual similarity and semantic similarity between 1020 objects, both for within-category (e.g., frog-rabbit, which are both animate) and between-category (e.g., frog-sofa, which are animate-inanimate) pairs. Duplicate and auto-correlated pairs were excluded. Because objects within a subcategory generally have the same or similar names, leading to similar semantic similarity values, for this analysis, we averaged the pairwise similarity values across the pairs in each subcategory (there were a total of 60 subcategories: 30 animate + 30 inanimate). This way, 1770 subcategory pairs were included (i.e., the number of unique elements in a symmetric 60x60 similarity matrix). The results (Figure 2) showed that from the 2nd layer, visual similarity was significantly higher for within- than between-category pairs for each layer (see Table 1 for statistical values). The mean semantic similarities for within- and between-category pairs also differed: 0.173 and 0.066, respectively (permutation $t = 19.932$, $p < 0.001$). Finally, visual and semantic similarity were moderately correlated across subcategories (this correlation ranged from 0.068 in Layer 1 to 0.432 in Layer 6). Importantly, however, visual and semantic similarity were not identical and could be dissociated. For example, Layer-6 visual similarity between “frog” and “rabbit” was low (0.07), while their semantic similarity was relatively high (0.40).

Figure 2

Visual similarity and semantic similarity between object images within and between animate/inanimate categories.



Note. (A) Visual similarity for the eight AlexNet layers and (B) Semantic similarity (from Word2Vec). For all figures, light blue bars indicate the within-category condition while the dark blue indicate the between-category condition. The error bars represent the standard error of the mean.

Table 1

Mean within- and between-category visual similarity for each DNN layer and the difference in the mean similarity between within- and between-category pairs.

Layer	Mean Visual Similarity		Difference	
	Within-Category	Between-Category	*permutation t*	*p*
1	0.325	0.321	0.919	0.179
2	0.209	0.202	2.038	0.026*
3	0.157	0.147	3.959	0.001***
4	0.144	0.127	7.91	0.001***
5	0.113	0.09	12.217	0.001***
6	0.153	0.095	19.809	0.001***
7	0.142	0.098	18.354	0.001***
8	0.419	0.171	27.181	0.001***

Note. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Relating visual and semantic similarity to behavioural performance

To reveal the unique contribution of visual similarity to behavioural performance, we regressed out effects of semantic similarity before estimating the effect of visual similarity, using two-step regression analyses. To additionally remove categorical effects (within- vs between-category), analyses were performed separately for within and between-category distractors and then averaged. The same method and steps were used to test for the unique contribution of semantic similarity to behavioural performance, now regressing out visual similarity. For each participant, each layer, and set size, all variables (including RT) were standardized using Z-score normalization. As a result, all the data were rescaled to have a mean of 0 and a standard deviation of 1.

Data availability

The data and scripts used to reproduce the findings of this study are openly available in the Open Science Framework at https://osf.io/9zbq4/

Results

Analyses on mean ACC and RT

In the first analysis, we aimed to test how category influences memory search performance across different memory set sizes, replicating the category effects in previous studies (Drew & Wolfe, 2014; Shang et al., 2024), and to compare category and memory set size influences between LTM and STM search. Figure 3 shows the mean data for target-absent trials of the two tasks, and Table 2 shows the results of the three-way mixed ANOVAs with one between- (LTM/STM task) and two within-subject factors (within-/between-category condition; MSS 1/2/4/8), using Greenhouse-Geisser correction. For both ACC and RT, all main effects and interactions were significant (Figure 3). Two-way ANOVAs for RT further revealed significant effects of MSS and category in both tasks (see Table 3). The results observed in

the LTM task replicated the findings of a previous study (Shang et al., 2024) and showed that LTM and STM shared a similar pattern of set-size related RT increases. The analysis on ACC in the STM task mirrored these findings, while the effects on ACC in the LTM task were not significant. This was expected, as participants were close to ceiling in all LTM conditions (Figure 3).

Table 2

Three-way mixed ANOVA for ACC and RT (in sec).

	Effect	DFn	DFd	*F*	η_P^2	*p*
ACC	Task	1	58	37.347	0.392	0.001***
	MSS	2.17	125.95	29.573	0.338	0.001***
	Category	1	58	70.643	0.549	0.001***
	Task × MSS	2.17	125.95	37.392	0.392	0.001***
	Task × Category	1	58	53.089	0.478	0.001***
	MSS × Category	2.23	129.58	23.244	0.286	0.001***
	Task × MSS × Category	2.23	129.58	22.135	0.276	0.001***
RT	Task	1	58	12.685	0.179	0.001***
	MSS	2.39	138.36	102.308	0.638	0.001***
	Category	1	58	140.139	0.707	0.001***
	Task × MSS	2.39	138.36	9.640	0.143	0.001***
	Task × Category	1	58	41.052	0.414	0.001***
	MSS × Category	3	174	20.945	0.265	0.001***
	Task × MSS × Category	3	174	6.792	0.105	0.001***

Note. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table 3

Two-way repeated ANOVA for ACC and RT (in sec), separately for LTM and STM tasks.

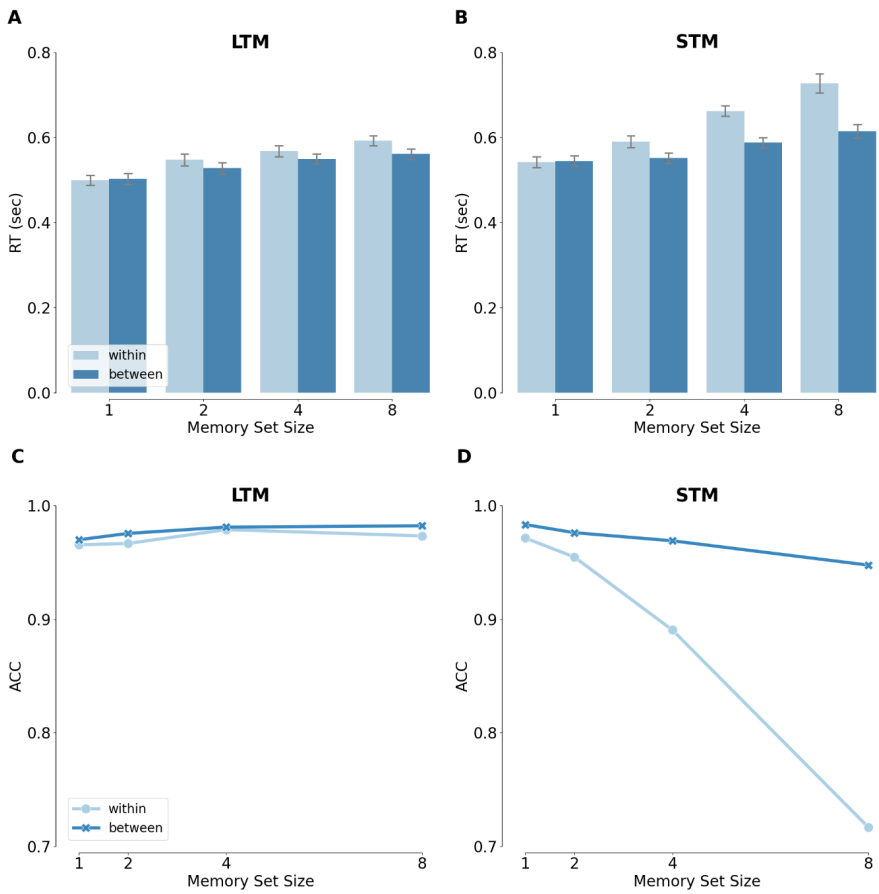
	Task	Effect	DFn	DFd	*F*	η_P^2	*p*
ACC	LTM	MSS	2.17	63.1	1.54	0.05	0.221
		Category	1	29	1.86	0.06	0.183
		MSS × Category	3	87	0.201	0.007	0.896
	STM	MSS	1.84	53.5	39.6	0.577	0.001***
		Category	1	29	74	0.719	0.001***
		MSS × Category	2.09	60.7	25.8	0.471	0.001***
RT	LTM	MSS	3	87	51.1	0.638	0.001***

	Category	1	29	54.2	0.652	0.001***
	MSS × Category	3	87	6.72	0.188	0.001***
	MSS	2.15	62.3	57.8	0.666	0.001***
STM	Category	1	29	96.3	0.769	0.001***
	MSS × Category	3	87	15.3	0.345	0.001***

Note. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Figure 3

Mean performance (ACC and RT (in sec)) of target-absent trials, separately for LTM and STM tasks.



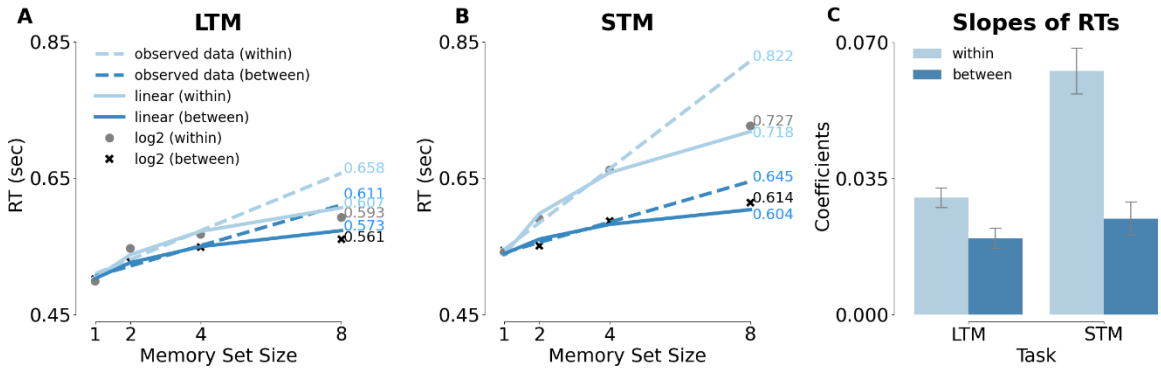
Note. (A) and (B) show the mean RTs in LTM and STM tasks, respectively. (C) and (D) show the mean ACCs in LTM and STM tasks, respectively. Light blue indicates the within-category condition while dark blue indicates the between-category condition. For all figures, the error bars represent the standard error of the mean.

To test whether RTs were log-linearly related to set size, following previous studies (e.g., Drew & Wolfe, 2014; Shang et al., 2024), the RTs from set size 1 to 4 were used to predict the performance on set size 8 (Figure 4A & B), For both tasks, the absolute error of the log-linear model was significantly smaller than the absolute error of the linear model, for both within-category, LTM: $t_{(29)} = -3.895$, $p = 0.001$, $d = 0.711$, STM: $t_{(29)} = -4.176$, $p < 0.001$, $d = 0.762$, and between-category conditions, LTM: $t_{(29)} = -4.703$, $p < 0.001$, $d = 0.859$, STM: $t_{(29)} = -3.735$, $p = 0.001$, $d = 0.682$.

Altogether, these results indicate that performance on the two tasks was similarly influenced by category and memory set size, although they differed in some aspects, as shown by two-way mixed ANOVAs on the log-linear slope coefficients. This analysis showed significant main effects of task and category condition, $F_{(1, 58)} = 16.065$, $p < 0.001$, $\eta^2 = 0.217$ and $F_{(1, 58)} = 54.494$, $p < 0.001$, $\eta^2 = 0.484$. There was also a significant interaction between task and category condition, $F_{(1, 58)} = 17.672$, $p < 0.001$, $\eta^2 = 0.234$, reflecting a stronger category effect in STM than in LTM (Figure 4C). Importantly, however, the simple main effects of category were significant in both tasks, LTM: $F_{(1, 29)} = 18.1$, $p < 0.001$, $\eta^2 = 0.384$ and STM: $F_{(1, 29)} = 39$, $p < 0.001$, $\eta^2 = 0.574$, with steeper slopes (less efficient memory search) for within-category distractors (Figure 4).

Figure 4

Linear vs log 2 model in target-absent trials



Note. (A) and (B) Linear vs log 2 model in target-absent trials of LTM and STM tasks. The light grey dots and dark grey crosses refer to the observed data in within-category and between-category conditions, respectively. The dashed lines represent linear regression models, while the solid lines represent log-linear models. For all the figures, the light blue always represents the within-category condition while the dark blue represents the between-category condition. (C) Log 2 slopes of the RTs in target-absent trials of LTM and STM tasks. The error bars represent the standard error of the mean.

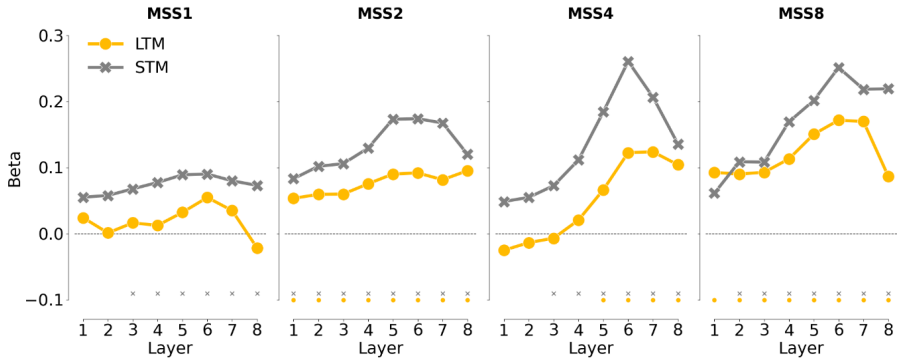
Analyses on visual similarity

Basic visual similarity

One of the main aims of the current study was to investigate whether category can explain the performance on memory recognition beyond visual similarity. To this end, we first tested if trial-wise RT variability in memory search could be explained by target-distractor visual similarity. The z-transformed visual similarity established using AlexNet (see Methods) was employed to predict the z-transformed reaction times of old/new recognition tasks using regression analysis, separately for each set size. The cluster-based permutation test showed that visual similarity could significantly predict RT in both tasks (cluster-based $p < 0.05$). For both tasks, visual similarity in the late AlexNet layers best predicted RT, with a peak in the 6th layer (Figure 5).

Figure 5

Results of regression analyses for visual target-distractor similarity

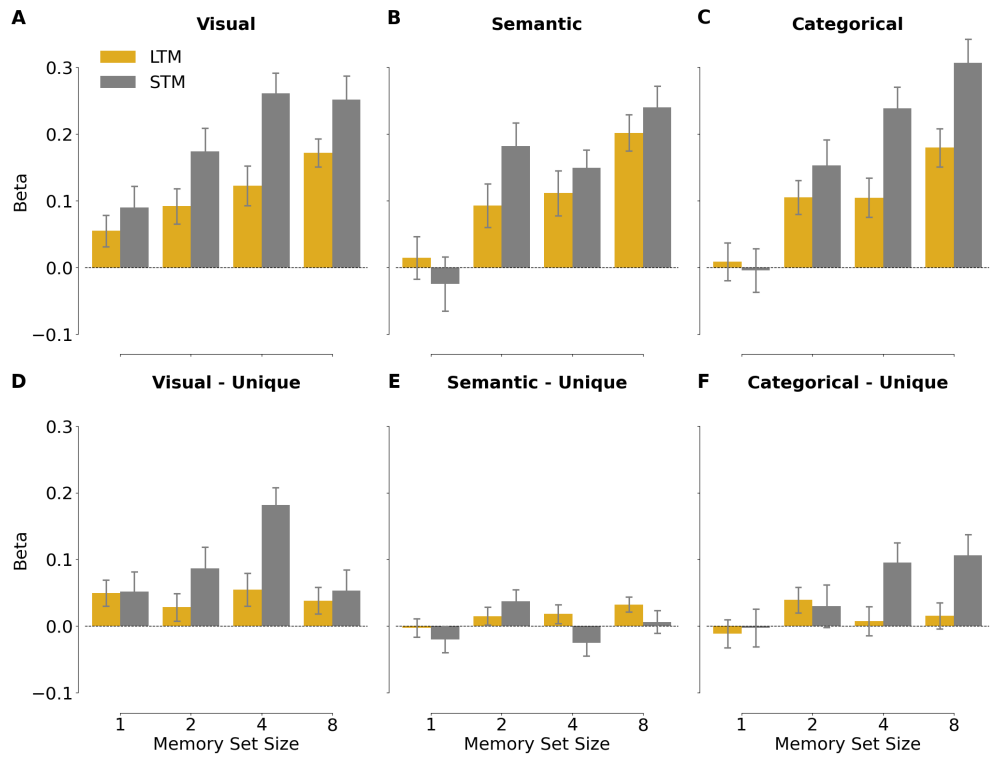


Note. Visual similarity (derived from the 8 layers of AlexNet) was used to predict trial-wise RTs for the two tasks and the four memory set sizes (MSS) separately. The orange lines represent results of the LTM task while the grey lines represent results of the STM task. Asterisks indicate significance based on the cluster-based permutation test (*$p < 0.05$).

Considering that Layer 6 best predicted RT across conditions, and was thus the most relevant measure of visual similarity (see also Yeh et al., 2024), we performed more detailed analyses using visual similarity established using this layer, comparing the visual similarity across the four set sizes and the two tasks. A two-way mixed ANOVA (LTM/STM task × MSS 1/2/4/8) showed significant main effects of task, $F_{(1, 58)} = 14.085$, $p < 0.001$, $\eta_P^2 = 0.195$, and MSS, $F_{(2.91, 168.7)} = 9.419$, $p < 0.001$, $\eta_P^2 = 0.140$, but no significant interaction, $F_{(2.91, 168.7)} = 1.057$, $p = 0.368$, $\eta_P^2 = 0.018$. These results indicate that visual similarity more strongly predicted RTs in the STM than the LTM task (Figure 6A). Furthermore, as memory set size increased, the contribution of visual similarity gradually became larger. Finally, the influence of visual similarity in LTM and STM tasks followed a similar set size pattern.

Figure 6

Results of regression analyses for Layer-6 target-distractor similarity



Note. Visual - Unique = visual similarity after regressing out categorical and semantic similarity; Semantic - Unique = semantic similarity after regressing out visual and categorical similarity. Categorical - Unique = categorical similarity after regressing out visual and semantic similarity. The orange bars represent results of the LTM task while the grey bars represent results of the STM task.

Unique contribution of visual similarity to trial-wise RT variability

In order to reveal the unique contribution of visual similarity (Layer 6) to trial-wise RT variability, semantic similarity was first used to predict RTs separately in the within- and between-category conditions. Then (still separately for the two categories), visual similarity was used to predict the residuals obtained in the first step to obtain visual similarity beta coefficients independent of semantic and categorical similarity. Finally, the visual similarity

beta coefficients were averaged across the two category analyses. This way, variability related to within- vs between-category differences could not contribute to the results.

A two-way mixed ANOVA (LTM/STM task × MSS 1/2/4/8) showed main effects of task, $F_{(1, 58)} = 7.711$, $p = 0.007$, $\eta_P^2 = 0.117$, and MSS, $F_{(2.9, 168.3)} = 3.355$, $p = 0.022$, $\eta_P^2 = 0.055$, while the interaction did not reach the significance level, $F_{(2.9, 168.3)} = 2.331$, $p = 0.078$, $\eta_P^2 = 0.039$. These findings again showed a stronger influence of visual similarity in predicting STM than LTM performance (Figure 6D).

Analyses on semantic similarity

Basic semantic similarity

In the second series of analyses, we asked whether the semantic similarity of target and distractor objects predicted trial-wise RT variability. A two-way mixed ANOVA showed a significant main effect of MSS, $F_{(2.74, 158.9)} = 15.506$, $p < 0.001$, $\eta_P^2 = 0.211$. The main effect of task, $F_{(1, 58)} = 2.18$, $p = 0.145$, $\eta_P^2 = 0.036$, and the interaction were not significant, $F_{(2.74, 158.9)} = 1.249$, $p = 0.294$, $\eta_P^2 = 0.021$. This result indicates that the influence of semantic similarity increases with set size but does so similarly for STM and LTM (Figure 6B).

Unique contribution of semantic similarity to trial-wise RT variability

In order to reveal the unique contribution of semantic similarity to trial-wise RT variability, visual similarity (Layer 6) was first used to predict RTs separately in the within- and between-category conditions. Then, semantic similarity was used to predict the residuals obtained in the first step, separately for the two categories. Finally, the semantic similarity beta coefficients were averaged across the two category analyses.

A two-way mixed ANOVAs showed no significant main effects or interaction, task: $F_{(1, 58)} = 1.954$, $p = 0.168$, $\eta_P^2 = 0.033$; MSS: $F_{(2.89, 167.3)} = 2.541$, $p = 0.06$, $\eta_P^2 = 0.042$, interaction: $F_{(2.89, 167.3)} = 1.511$, $p = 0.215$, $\eta_P^2 = 0.025$. The intercept was significant, $F_{(1, 58)} =$

128.056, $p < 0.001$, $\eta_P^2 = 0.688$. These results show that semantic similarity explained variance in RT over and above visual and categorical similarity, but this influence did not depend on either task or set size (Figure 6E).

Analyses on categorical similarity

Basic categorical similarity

In the final section, we turn to the question of whether category (as a binary variable, animate vs inanimate) explains the performance on memory recognition beyond visual and semantic similarity. When not regressing out visual similarity, categorical similarity was a good predictor of memory performance (Figure 6C). An ANOVA showed that there were significant differences in the category beta estimates between the two tasks, $F_{(1, 58)} = 14.686$, $p < 0.001$, $\eta_P^2 = 0.202$. The main effect of MSS was also significant, $F_{(2.91, 168.6)} = 19.174$, $p < 0.001$, $\eta_P^2 = 0.248$. However, the interaction was not significant, $F_{(2.91, 168.6)} = 2.289$, $p = 0.082$, $\eta_P^2 = 0.038$, suggesting a similar MSS-related increase in the two tasks.

Unique contribution of categorical similarity to trial-wise RT variability

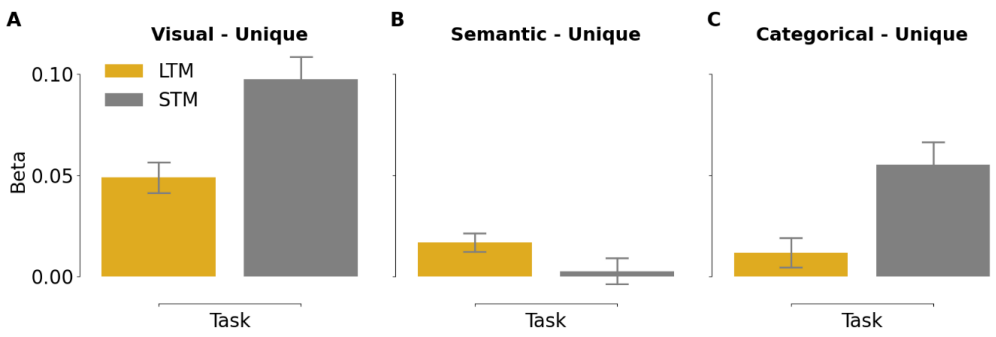
We repeated these analyses after regression out visual (Layer 6) and semantic similarity. In this case, only the main effect of task was significant, $F_{(1, 58)} = 7.113$, $p = 0.01$, $\eta_P^2 = 0.109$; MSS: $F_{(2.69, 155.9)} = 2.518$, $p = 0.067$, $\eta_P^2 = 0.042$, and interaction: $F_{(2.69, 155.9)} = 1.908$, $p = 0.137$, $\eta_P^2 = 0.032$. These results indicate that compared with LTM search, in which the contribution of superordinate category was relatively weak, STM search depended more on the binary categorical distinction (i.e., animacy), especially in large set size (Figure 6F).

Comparison of the contributions of visual, semantic, and categorical similarity between LTM and STM tasks

The previous sections showed no interactions between task and set size, indicating that the influence of visual, semantic, and categorical similarity similarly changed across set size for the two tasks. Therefore, in a final analysis, we averaged across the set size conditions to compare the unique influence of visual, semantic, and categorical similarity between the tasks. Figure 7 summarizes the contributions to performance in the two memory tasks of unique visual (regressing out categorical and semantic similarity), unique semantic (regressing out categorical and visual similarity), and unique categorical (regressing out visual and semantic similarity) similarity. Because betas cannot be directly compared across dimensions, two-sample t-tests were employed to compared the unique similarity influences across the two tasks. Results showed stronger influences on STM than LTM performance of visual similarity, $t_{(49.791)} = -2.777$, $p = 0.008$, $d = -0.192$, and categorical similarity, $t_{(47.876)} = -2.667$, $p = 0.010$, $d = -0.165$ (Figure 7A and C). By contrast, the influence of semantic similarity was numerically larger for LTM than STM (Figure 7B), although this difference was not significant, $t_{(45.343)} = 1.398$, $p = 0.169$, $d = 0.870$.

Figure 7

Comparison of the mean (averaged across set size) unique contributions of visual, categorical, and semantic similarity between the two tasks



Note. Visual - Unique = visual similarity after regressing out categorical and semantic similarity; Semantic - Unique = semantic similarity after regressing out visual and categorical

similarity. Categorical - Unique = categorical similarity after regressing out visual and semantic similarity. The orange bars represent results of the LTM task while the grey bars represent results of the STM task.

General discussion

In this study, we investigated the roles of visual, semantic, and categorical similarity in short- and long-term memory search. While these three factors are correlated, they are clearly not identical. Indeed, our results show that all factors predicted trial-wise variability in reaction times, even after the other factors were regressed out. The results answer the three questions outlined in the Introduction: First, results showed that the category effect in long-term memory search, as reported in previous studies (Gronau et al., 2024; Shang et al., 2024; Williams et al., 2024; Cunningham & Wolfe, 2012, 2014; Drew & Wolfe, 2014), remained significant even when visual and semantic similarity were regressed out. Second, we found that visual and semantic similarity also independently contributed to long-term memory search performance. Finally, we found that LTM and STM differed in the contributions of visual, semantic, and categorical similarities: STM was more strongly influenced by visual and categorical similarity than LTM was, while LTM was (numerically) more strongly influenced by semantic similarity than STM was, particularly for larger set sizes (Figure 7B). We will discuss each of these findings below.

Category effects in LTM search

Previous studies observed significant categorical influences on memory search performance that increased with increasing set size (Gronau et al., 2024; Shang et al., 2024; Williams et al., 2024; Cunningham & Wolfe, 2012, 2014; Drew & Wolfe, 2014), which we replicated here. However, none of these studies investigated what exactly contributed to this category effect, specifically, whether the category effects could be explained by object attributes (e.g.,

visual or semantic target-distractor similarity) other than the binary categorical target-distractor similarity. Therefore, in the current study, we used neural network and distributional semantic models to establish visual similarity and semantic similarity, respectively, in order to measure (and regress out) their influence on memory search performance. We observed that when the influences from visual and semantic similarity were regressed out, the superordinate category of the distractor still predicted long-term memory search performance, confirming the distinct contribution of categorical similarity.

Using category membership is an efficient strategy to quickly reject distractors when all targets are drawn from the same category. This could be achieved by directing attention to visual features that are diagnostic of the target category (e.g., curved shapes when all memory items are animals), such that objects from other categories can be filtered out before the memory search stage (Shang et al., 2024). This account predicts that reaction times scale with the degree to which an object matches the attentional template (Duncan & Humphreys, 1989). However, the features included in the template are not known. One possibility is that the template consists of the visual features that are common to the items in the memory set. In that case, rejecting distractor probe items that are visually relatively similar to the items in the memory set would be relatively slow. In the current experiment, this variability is captured by our model of the average visual similarity of the probe item to the items in the memory set, which was a good predictor of trial-wise RT variability (Figure 7). Indeed, regressing out high-level visual similarity reduced the category effect.

Interestingly, we observed a significant residual category effect when regressing out the contribution of visual and semantic similarity. This raises the possibility that participants formed a more abstract (or generic) categorical template, based on experience with that category (e.g., animals) across a lifetime. When forming an attentional template, it may be easier for participants to activate an overlearned categorical representation than to retrieve the

shared features of the items in the memory set, which vary from trial to trial (in STM) or from block to block (in LTM). In line with this interpretation, previous studies have provided evidence that attention can be directed at the level of object category for highly familiar categories (Peelen et al., 2014), including animals (Evans & Treisman, 2005; Stein & Peelen, 2017).

Visual and semantic similarity independently predict LTM search

In addition to category, memory search performance was also significantly and independently predicted by visual similarity across AlexNet layers, with a peak at the 6th layer (Figure 5). The strong performance of Layer 6 is in line with an earlier study that found that Layer 6 and Layer 7 representations were the best predictors of perceptual similarity, as established using same/different and oddball visual search tasks (Yeh et al., 2024). As discussed above, the influence of visual similarity on RTs in the current study could reflect the partial match of distractor items to the attentional template, with visually highly dissimilar distractors being rejected already before the memory search stage. Alternatively, it could reflect interference during the memory search itself, with visually similar distractors being more effective lures than visually dissimilar distractors.

When the influences of visual and categorical similarity were regressed out, semantic similarity also still predicted LTM search performance. This result is in line with previous work that emphasized the role of conceptual distinctiveness in memory recognition (Konkle et al., 2010b). Support from conceptual structure was shown to contribute to explaining the remarkable performance on visual memory tasks involving thousands of pictures (Konkle et al., 2010b). Our finding that visual and semantic similarity both contributed to memory task performance is also in line with other recent studies. For example, participants were shown to depend on both visual and semantic information to classify pictures, such that when pictures had similar semantics, participants took longer to classify them (Lotto et al., 1999). Other

studies showed that, compared with visual information, semantic information plays a greater role in memory tasks (Victoria et al., 2019; Shoham et al., 2024). Shoham et al. (2024) also reported that when participants recalled images from memory, they depended more on semantic information to reconstruct the visual features of the images. However, while these studies emphasized the important role of semantic information in memory, they also highlighted that through mental representations, visual and semantic information interactively influence perception and memory tasks.

Differences between LTM and STM

Previous studies found a log-linear set-size-RT increase in an STM task, similar to what we observed for LTM, but interpreted it as an effect of the study-test lag resulting from the serial presentation of stimuli (Nosofsky, Cao, et al., 2014; Nosofsky, Cox, et al., 2014). Because of the serial order, for target-present trials, the shorter the lag was, the stronger the memory strength was, and the faster the RTs were; while for target absent trials, the increase in memory set size also led to longer RTs, which might reflect that the new probe was compared with all the items in the memory set, which increased with memory set size (Nosofsky, Cao, et al., 2014; Nosofsky, Cox, et al., 2014). To test whether the categorical attentional template was also used in STM, the current study compared LTM and STM tasks. We focused on the differences in the contributions of categorical, semantic, and visual similarity between LTM and STM, different from most previous studies that focused on the double dissociation between LTM and STM in the dual-store memory model (Atkinson & Shiffrin, 1968; Sullivan & Sagar, 1991). Our findings showed that all three similarities significantly contributed to STM. In addition, the similarity contributions to LTM and STM followed rather similar patterns. However, LTM task performance depended more on semantic similarity, while STM task performance depended more on categorical similarity and visual similarity.

Averaged across set size, unique semantic similarity predicted LTM but not STM performance (Figure 7B), while, conversely, the influences of visual similarity and categorical similarity were greater for STM than LTM (Figure 7A and C). It should be noted that this does not mean that semantic information does not contribute to STM at all. For example, previous studies demonstrated that compared with meaningless stimuli, participants performed better on meaningful stimuli (Sahar et al., 2024; Shoval and Makovski, 2022) which could also influence the upper limit of working memory capacity (Asp et al., 2021). By contrast to these studies, our study focused on the influence of semantic target-distractor similarity on trial-wise RT, showing that semantically similar and dissimilar distractor probes are rejected equally fast, after the influence of visual and categorical similarity are regressed out.

The finding that the contribution of visual similarity was more important for STM than for LTM was expected and is in line with the studies reviewed in the Introduction, including the study of Hollingworth (2004), which showed that compared with visual LTM, visual STM contains more precise visual details even though LTM had greater capacity than STM. Nevertheless, the same study demonstrated that scene representations in visual LTM could include not only the gist, but also specific visual information. Brady et al. (2008) further confirmed that participants could visually distinguish different details belonging to the same exemplars. However, they also acknowledged that it was still unclear how the details were encoded and stored in LTM. Regarding this issue, previous studies on LTM emphasized the importance of conceptual structures in LTM (e.g., Konkle et al., 2010b). One possibility is that detailed representations in LTM require support from semantics. This account is in line with our finding that semantic similarity predicted LTM (but not STM) performance (Figure 7B).

Special cases

Set size 1 is a special case in our experiment, as for this set size, the task is effectively a single-target detection task rather than a memory search task. Participants can maintain a precise top-down attentional template for one item (Olivers et al., 2011) such that all distractor objects can be quickly rejected, irrespective of their semantic or categorical similarity to the target item. Accordingly, only visual similarity explained trial-wise RT variability (Figure 5). Nevertheless, when there is competition (e.g., when presenting multiple probe items), semantic and categorical similarity could still influence visual orienting later in time (De Groot et al., 2016; Yeh & Peelen, 2022).

Set size 8 is a special case for STM because the set size exceeds the normal capacity of visual STM (~4 items). In this case, categorical similarity had a particularly strong influence on RT (Figure 6 C&F). This may be because participants could only memorize the animacy of the target objects, and then rejected the between-category distractors primarily based on their category. This would also lead to high error rates for within-category distractors compared with between-category distractors, as confirmed by the accuracy data, $t_{(29)} = 7.602$, $p < 0.001$, $d = 1.388$, which was not observed for set size 8 of the LTM task, $t_{(29)} = 1.137$, $p = 0.265$, $d = 0.208$. This suggests that categorical strategies compress visual information (Cowan, 2001; Olsson & Poom, 2005). For example, Olsson and Poom (2005) demonstrated that when the stimuli belonged to different categories (e.g., discrete colour/shape), participants could remember nearly 3 stimuli, while when all the objects belonged to a single category, only one stimulus could be remembered because all the information was compressed into one category which impeded the recognition of target objects. This indicates that STM requires the support of categorical structures in LTM. Participants in the STM task may remember categories rather than objects. Thus, participants can quickly reject the distractor objects from different categories through categorial similarity.

Conclusion

In summary, the current study shows that memory search performance is determined by a combination of visual, semantic, and categorical target-distractor similarity. For both LTM and STM tasks, visual, semantic, and categorical similarity each independently contributed to predicting memory search performance, following similar patterns across set size in both tasks. However, visual and categorical influences (but not semantic influences) were stronger in STM than LTM search. These results clarify the nature of the representations used in STM and LTM search.

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