Within-Category Storage Advantage in Visual Working Memory

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Abstract

How conceptual regularities, such as categorical relationships among memory items, affect visual working memory capacity is a controversial issue. Regarding this issue, there exist two hypotheses with completely different predictions in the academic community: (1) the mixed-category advantage hypothesis, (2) the same-category advantage hypothesis. A review of the literature reveals that such studies have all used real objects with detailed features as experimental materials; therefore, the mixed-category advantage effect or same-category advantage effect found in previous research must be confounded with the influence of low-level perceptual features. Therefore, this study adopts animal silhouettes with detailed information removed as memory materials to exclude the influence of the aforementioned factors, aiming to clarify the above two hypotheses, and employs contralateral delay activity as a neural indicator to further investigate the internal mechanism by which conceptual regularities influence working memory capacity. Two behavioral experiments found that, regardless of whether memory items were presented simultaneously or sequentially, a same-category memory advantage effect was present. The EEG experimental results revealed that, compared to remembering different-category objects, remembering the same number of same-category objects evoked contralateral delay activity with smaller amplitude. These results consistently demonstrate that visual working memory can organize same-category objects through conceptual means, thereby effectively expanding visual working memory capacity, supporting the same-category advantage hypothesis.

The Same-Category Storage Advantage in Visual Working Memory

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Abstract

How conceptual regularities such as categorical relationships among memory items influence visual working memory (VWM) capacity remains a controversial issue. Two competing hypotheses make divergent predictions: (1) the mixed-category advantage hypothesis and (2) the same-category advantage hypothesis. A review of the literature reveals that previous studies have exclusively used real objects with detailed features as experimental materials. Consequently, the mixed-category advantage or same-category advantage effects reported in prior research are inevitably confounded by low-level perceptual features. To address this limitation, the present study employed animal silhouettes devoid of detailed information as memory materials to isolate the influence of categorical relationships. Additionally, we utilized contralateral delay activity (CDA) as a neural index to investigate the underlying mechanisms through which conceptual regularities affect VWM capacity. Two behavioral experiments demonstrated a consistent same-category memory advantage, regardless of whether memory items were presented simultaneously or sequentially. The ERP experiment further revealed that maintaining an equivalent number of same-category objects elicited smaller CDA amplitudes compared to maintaining different-category objects. These convergent findings indicate that VWM can organize same-category objects conceptually, thereby effectively expanding VWM capacity and supporting the same-category advantage hypothesis.

Keywords: visual working memory, category information, contralateral delay activity
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Visual working memory (VWM) is a capacity-limited cognitive system that can temporarily store only three to four items for current cognitive processing (Cowan, 2001; Luck & Vogel, 1997). Although VWM capacity is limited, numerous studies have shown that this limit is not fixed. For instance, stimulus complexity can modulate VWM capacity (Alvarez & Cavanagh, 2004; Brady & Alvarez, 2015; Brady et al., 2016; Song & Jiang, 2006; but see Awh et al., 2007 for a different view), with more complex stimuli generally resulting in lower VWM capacity (Alvarez & Cavanagh, 2004; Song & Jiang, 2006). Paradoxically, despite being more complex than simple stimuli, real-world objects with detailed features are stored in greater numbers in VWM (Brady et al., 2016). Furthermore, relationships among memory items—such as statistical regularities (Brady et al., 2009), real-world spatial regularities (Kaiser et al., 2014, 2015), and semantic and functional relationships (O' donnell et al., 2018; Rudner et al., 2016)—all influence VWM capacity. However, how higher-order conceptual regularities such as categorical relationships among memory items affect VWM capacity remains a contentious issue.

Theoretically, there are two possibilities regarding how object categories might influence VWM capacity: a mixed-category advantage and a same-category advantage. The mixed-category advantage aligns with predictions from neural resource theory, which posits that the ability to simultaneously process multiple objects is limited by the degree of overlap in their neural representations. Specifically, greater overlap in neural representations leads to decreased ability to process multiple objects simultaneously due to competition for shared neural resources (Cohen et al., 2014). Because objects from the same category are more likely to have overlapping neural representations, mixed-category objects should exhibit a processing advantage. Previous research has provided substantial evidence supporting this theory. Cohen et al. (2014) asked participants to remember four items from either the same category (e.g., four faces) or different categories (e.g., two faces and two scenes) while using functional magnetic resonance imaging (fMRI) to measure cortical overlap among the neural representations of the four items. The results showed superior memory performance for different-category items, indicating a mixed-category advantage. Moreover, the fMRI results demonstrated that the degree of cortical overlap among the four items predicted the magnitude of this advantage: smaller cortical overlap was associated with a larger mixed-category advantage (Cohen et al., 2014). Subsequently, Jiang and Lee et al. (2016) reanalyzed the mixed-category advantage for faces and scenes to investigate how neural resources constrain VWM capacity. Their experiment replicated Cohen et al.' s (2014) findings, showing that remembering two faces and two scenes yielded better performance than remembering four faces or four scenes. However, this mixed-category advantage was specific to "face" stimuli: when faces were presented with scenes, memory for faces was better than when faces were presented with other faces, whereas memory for scenes was not better when presented with other scenes. Furthermore, this face-specific mixed-category advantage also emerged when faces were paired with houses, butterflies, or bodies, but disappeared when only man-made objects served as memory items (Wong et al., 2008).

The same-category advantage is consistent with predictions derived from rate-distortion theory, which holds that the performance of any capacity-limited communication system is subject to theoretical constraints (Sims et al., 2012). Based on this theory, the ideal observer hypothesis posits that memory precision decreases as feature variability in the environment increases (Sims et al., 2012, p. 812). Sims et al. (2012) confirmed this hypothesis through an orientation experiment and a line length experiment, demonstrating better memory for low-variability arrow orientations and line lengths compared to high-variability ones.

Additional studies have also supported this theoretical prediction. For example, memory for colors from the same category (e.g., light red, rose red, purplish red) was better than for colors from different categories (e.g., red, green, blue; Lin & Luck, 2009), and memory for average faces generated from same-identity faces was more precise than for average faces generated from different-identity faces (Jiang, Lee, et al., 2016). Although these studies attributed the same-category processing advantage to perceptual similarity, category information may have also played a significant role. In summary, we propose that the same-category advantage predicted by the ideal observer model may arise from two factors: first, same-category objects typically exhibit less variability in low-level perceptual features than mixed-category objects; second, same-category objects also show less variability in high-level conceptual features.

In conclusion, although neural resource theory predicts a mixed-category advantage, nearly all existing supporting evidence is limited to faces (Jiang, Lee, et al., 2016; Wong et al., 2008), thus restricting the theory’ s generalizability. Conversely, while the same-category advantage aligns with ideal-observer predictions, direct evidence supporting the extension of this hypothesis from low-level perceptual features to high-level conceptual features is lacking. Moreover, stimulus material selection is crucial for investigating category effects on VWM capacity. A review of previous studies reveals that research on category effects has exclusively used real objects with detailed information. The contradictory findings regarding mixed-category advantage (e.g., face-specific mixed-category advantage; Jiang, Remington, et al., 2016; Wong et al., 2008) and same-category advantage effects (Quinlan & Cohen, 2016) may primarily stem from differences in stimulus materials. This is because the expression of category information depends on certain key perceptual attributes of the stimuli, and irrelevant perceptual attributes should be controlled or eliminated as much as possible. Otherwise, the mixed-category or same-category advantage effects found in previous studies may be attributable to certain low-level perceptual properties of the objects rather than to high-level categorical relationships. Therefore, the current study employed animal silhouettes without detailed information as memory materials. Additionally, numerous studies have found that stimulus similarity affects VWM capacity. Increased similarity among memory items improves VWM performance (Lin & Luck, 2009; Peterson et al., 2015), and similarity also promotes holistic encoding of memory items, thereby reducing memory load and increasing information capacity (Mate & Baqués, 2009; Zhang et al., 2015). Consequently, the current study also controlled for posture similarity across same-category and different-category animal silhouettes to minimize or eliminate potential effects of perceptual similarity. For example, the basic category “cat” included 12 silhouette images, six with high-similarity postures and six with low-similarity postures (see Figure 1 [Figure 1: see original paper]).

The present research first designed two behavioral experiments to investigate whether category information can influence VWM capacity. If the results support neural resource theory, a mixed-category advantage should emerge, with better memory performance for different-category silhouettes, manifested as larger memory capacity in the mixed-category condition. Conversely, if the results support the ideal observer model, a same-category advantage should appear, with larger memory capacity for same-category silhouettes.

Figure 1 shows an example of 12 animal silhouettes from a single basic category. These animal silhouettes were sourced from the open-access website Pixabay (https://pixabay.com) and are used for illustrative purposes only.

Working memory tasks typically involve three distinct cognitive processing stages: encoding, maintenance, and retrieval. If category information can influence VWM capacity, at which stage might this category effect occur? Behavioral experiments cannot easily answer this question, whereas electrophysiological measures such as event-related potentials (ERPs) are particularly useful because they can help differentiate the possible stages at which effects may occur. Therefore, this study also designed an ERP experiment using the electrophysiological index contralateral delay activity (CDA) to further investigate the cognitive and neural mechanisms underlying how category information influences VWM capacity. CDA is a negative slow wave that appears in the hemisphere contralateral to the location where memory items were presented, typically maximal over parietal and parieto-occipital regions, and its amplitude is related to the number of objects maintained in VWM (Luria et al., 2016; McCollough et al., 2007; Vogel & Machizawa, 2004). CDA amplitude increases as the number of items maintained in VWM increases (Vogel & Machizawa, 2004) and decreases as the number of items maintained in VWM decreases (Vogel et al., 2005; Williams & Woodman, 2012). Therefore, recording CDA can help determine whether category effects occur during the maintenance stage of working memory. CDA also serves an important function in revealing the cognitive mechanisms underlying category effects. If a same-category memory advantage exists—that is, if category information can enhance VWM capacity—there are theoretically two possibilities: (1) Category information acts similarly to Gestalt organization, grouping same-category information into a larger chunk to enhance VWM capacity. This hypothesis predicts that CDA amplitude should be reduced in the same-category condition compared to the different-category condition. (2) Category information allows more information to be stored in VWM without forming chunks. This hypothesis predicts that CDA amplitude should be increased in the same-category condition compared to the different-category condition.

Experiment 1

Experiment 1 examined whether category information of simultaneously presented memory items affects VWM capacity. We predicted that Cowan’ s K would differ significantly between same-category and different-category conditions. To avoid underestimating VWM capacity, the duration of memory items was set according to the number of animal silhouettes (250 ms × number of animal silhouettes). Additionally, a concurrent articulatory suppression task was included to inhibit potential verbal encoding during memory for animal silhouettes (Curby & Gauthier, 2007; Vogel et al., 2001).

2.1.1 Participants

Twenty undergraduate students (13 females, aged 19–32 years, mean age = 24 years) participated in Experiment 1. Participants were recruited from Shandong Normal University and participated voluntarily, receiving course credit or monetary compensation. All participants had normal or corrected-to-normal vision. Participants were unaware of the study’ s purpose and provided informed consent before the experiment. The procedure complied with the ethical standards of the World Medical Association (Declaration of Helsinki) and was approved by the Research Ethics Committee of Shandong Normal University.

To ensure adequate statistical power, sample size was determined through power analysis using PANGEA (Westfall, 2015) based on the expected effect size. Drawing on previous behavioral studies (Jiang, Lee, et al., 2016; Jiang, Remington, et al., 2016), to achieve a large effect size (Cohen’ s d = 0.80) with alpha set at 0.05 and power at 85%, the calculated sample size was approximately 17 participants. Therefore, the 20 participants recruited in this study ensured sufficient statistical power.

2.1.2 Stimuli

Visual stimuli were controlled by a program written in PsychoPy (Peirce, 2007) and presented on a linearized CRT monitor (21-inch Sony G520; resolution: 1024 × 768 pixels; refresh rate: 100 Hz). Participants viewed the screen from a distance of approximately 70 cm. Stimuli were presented on a gray background with a mean luminance of 17.5 cd/m^2.

The experiment used 192 animal silhouette images belonging to 16 basic categories under four superordinate categories (carnivores, primates, ungulates, and birds): cat, dog, fox, lion; monkey, baboon, gorilla, human; cow, sheep, deer, horse; chicken, duck, peacock, pigeon. These images were selected from Google Images and remade using GIMP (version 2.8.16, GIMP Development Team, 2016). Each basic category contained 12 silhouette figures (2° × 2°), six with high-similarity postures (same head orientation and ground contact) and six with low-similarity postures (see Figure 1). We recruited 30 students (22 females, aged 19–27 years, mean age = 22 years) to rate the similarity of the animal silhouette images on a 5-point scale (1 = very dissimilar, 5 = very similar). Results showed that same-category high-similarity images received higher ratings (M = 4.21, SD = 0.65) than low-similarity images (M = 2.13, SD = 0.86), t(29) = 14, p < 0.001, Cohen’ s d = 2.56; different-category high-similarity images also received higher ratings (M = 3.79, SD = 0.81) than low-similarity images (M = 1.83, SD = 0.6), t(29) = 10.7, p < 0.001, Cohen’ s d = 1.95. Additionally, eight mask stimuli (2° × 2°) composed of a series of randomly generated achromatic circular outlines (size 0.1-0.36°, luminance values 0.3–74 cd/m^2) were created to eliminate afterimages of memory items.

2.1.3 Design and Procedure

Experiment 1 employed a 2 (memory load: 2, 4) × 2 (category: same, different) × 2 (posture: high similarity, low similarity) within-subjects design. Memory arrays consisted of either two or four animal silhouettes. In half of the trials, memory items belonged to the same basic category; in the other half, memory items belonged to two (or four) different basic categories but from the same superordinate category. In half of the trials, animal silhouettes had high-similarity postures, while in the other half they had low-similarity postures. All experiments used a single-probe detection task (a variant of the change detection paradigm). In this task, only one probe item was presented at the center of the screen during the test phase, and participants were required to judge whether the probe item had appeared in the memory array. In half of the trials, the probe item was identical to one of the memory items; in the other half, the probe item differed from all memory items. Changed probe items were randomly selected from four animal silhouettes within the same basic category as the corresponding memory item (excluding the studied silhouette, with two silhouettes having high-similarity postures and two having low-similarity postures). Experimental trials were presented in a mixed design, with each block containing all experimental conditions and equal numbers of each condition across blocks. Participants were informed of this arrangement in advance. Each participant completed 256 trials.

2.1.4 Procedure

The procedure for Experiment 1 is illustrated in Figure 2 [Figure 2: see original paper]. Each trial began with a 500 ms articulatory suppression sequence, in which two digits randomly selected from 1 to 9 were presented on either side of the screen center (separated by 4°). Participants were required to repeat these two digits aloud until they responded to the probe item. This was followed by a 500 ms fixation point, which remained visible throughout the experiment. Next, the memory array was presented for 500 ms or 1000 ms (depending on the number of items, to ensure equal encoding time per item: 250 ms/item) within two rectangular regions (4° × 12°). The distance between any two items was no less than 2.5°, and items were positioned 4° from the fixation point center. After the memory items disappeared, mask stimuli were presented for 100 ms at the same locations to eliminate afterimages. Following a 900 ms blank screen, a single probe item was presented at the screen center for 2000 ms or until participants responded. Participants were instructed to judge whether the probe item had appeared in the memory array, with emphasis on accuracy rather than response speed.

Figure 2 [Figure 2: see original paper] shows the trial procedure for Experiment 1 (with four memory items).

2.1.5 Data Analysis

VWM capacity was calculated based on Cowan’ s K (Cowan, 2001): K = (H - FA) × N, where H (hit rate) is the probability of responding “yes” when a change occurred, FA (false alarm rate) is the probability of responding “yes” when no change occurred, and N (set size) is the memory load. For correct-response trials, trials with reaction times less than 200 ms or exceeding three standard deviations were excluded (resulting in the exclusion of less than 1% of trials). We first conducted a three-way repeated-measures ANOVA on K with memory load (2, 4), category (same, different), and posture (high similarity, low similarity) as factors. Further analyses were conducted based on the results of this three-way ANOVA.

2.2 Results and Discussion

The K values for the eight conditions in Experiment 1 are presented in Table 1 . The three-way repeated-measures ANOVA on K revealed significant main effects of memory load, F(1, 19) = 79.34, $p < 0.001$, $p^2 = 0.81$, and category, F(1, 19) = 47.65, $p < 0.001$, $p^2 = 0.72$. The main effect of posture was not significant, F(1, 19) = 2.73, p = 0.115, $p^2 = 0.13$. Significant two-way interactions were found between memory load and category, F(1, 19) = 34.94, $p < 0.001$, $p^2 = 0.65$, between memory load and posture, F(1, 19) = 9.57, p = 0.006, $p^2 = 0.34$, and between category and posture, F(1, 19) = 14.51, p = 0.001, $p^2 = 0.43$. The three-way interaction was not significant, F(1, 19) = 1.19, p = 0.289, $p^2 = 0.06$.

Simple effects analysis of the significant memory load × category interaction (collapsing across posture levels, as shown in Figure 3a [Figure 3: see original paper]) indicated that when memory load was 2, K was significantly larger for same-category trials (M = 1.61, SD = 0.21) than for different-category trials (M = 1.47, SD = 0.10), t(19) = 3.36, p = 0.003, Cohen’ s d = 0.75. When memory load was 4, the same-category advantage was also observed [same category: M = 2.79, SD = 0.53; different category: M = 1.81, SD = 0.53; t(19) = 6.69, $p < 0.001$, Cohen’ s d = 1.50]. Furthermore, we calculated the same-category advantage effect size by subtracting K values for different-category trials from those for same-category trials at each memory load. A t-test on these effect sizes revealed that the same-category advantage was significantly larger at memory load 4 (M = 0.98, SD = 0.66) than at memory load 2 (M = 0.14, SD = 0.19), t(19) = 5.91, $p < 0.001$, Cohen’ s d = 1.32. These results indicate that a same-category advantage emerged at both memory loads, but was substantially larger when memory load was 4.

Simple effects analysis of the significant category × posture interaction (collapsing across memory load levels, as shown in Figure 3b [Figure 3: see original paper]) showed that when animal silhouettes had high-similarity postures, K was significantly larger for same-category trials (M = 2.36, SD = 0.30) than for different-category trials (M = 1.58, SD = 0.35), t(19) = 9.18, $p < 0.001$, Cohen’ s d = 2.05. The same category effect was observed for low-similarity postures [same category: M = 2.05, SD = 0.43; different category: M = 1.70, SD = 0.31; t(19) = 3.15, p = 0.005, Cohen' s d = 0.70]. Additionally, we calculated the same-category advantage effect size for both high- and low-similarity postures and found that the effect size was significantly larger for high-similarity postures (M = 0.78, SD = 0.38) than for low-similarity postures (M = 0.35, SD = 0.50), t(19) = 3.81, $p < 0.001$, Cohen' s d = 0.85. To further rule out the possibility that posture similarity drove the same-category advantage, we compared K values between low-similarity same-category and high-similarity different-category conditions. K was still significantly larger in the low-similarity same-category condition (M = 2.05, SD = 0.43) than in the high-similarity different-category condition (M = 1.58, SD = 0.35), t(19) = 3.82, p = 0.001, Cohen' s d = 0.85. These results demonstrate that the same-category advantage emerged regardless of posture similarity and was indeed caused by category information rather than perceptual similarity.

Simple effects analysis of the significant memory load × posture interaction (collapsing across category levels, as shown in Figure 3c [Figure 3: see original paper]) revealed that when memory load was 2, K was significantly smaller for high-similarity posture trials (M = 1.48, SD = 0.13) than for low-similarity posture trials (M = 1.59, SD = 0.19), t(19) = -2.82, p = 0.011, Cohen' s d = -0.63. When memory load was 4, K was significantly larger for high-similarity posture trials (M = 2.46, SD = 0.47) than for low-similarity posture trials (M = 2.15, SD = 0.51), t(19) = 2.55, p = 0.020, Cohen' s d = 0.57. These results indicate that posture similarity affects VWM capacity and that this effect is modulated by memory load.

Overall, we found that category information can influence VWM capacity, producing a same-category advantage effect.

Experiment 2: Effects of Category Information on VWM Capacity with Sequential Presentation of Memory Items

In Experiment 1, we found that memory capacity was larger in the same-category condition when memory items were presented simultaneously. In working memory research, memory items are typically presented in either simultaneous or sequential formats. Previous studies have shown multiple differences between these two presentation formats (Allen et al., 2006; Atkinson et al., 2018; Ding et al., 2015; Gao et al., 2016). First, the two formats involve different processing during the encoding stage: sequential presentation requires content updating, whereas simultaneous presentation does not (Allen et al., 2006). Second, the two formats yield different estimates of working memory capacity. For instance, sequential presentation may underestimate working memory capacity due to proactive and retroactive interference (Allen et al., 2006; Atkinson et al., 2018). Given these differences, Experiment 2 aimed to investigate whether the same-category advantage persists when memory items are presented sequentially.

3.1.2 Design and Procedure

Memory items were presented sequentially at randomly selected locations, each for 250 ms. Otherwise, the design and procedure were identical to those of Experiment 1.

3.2 Results and Discussion

The K values for the eight conditions in Experiment 2 are presented in Table 2 . A three-way repeated-measures ANOVA on K with memory load (2, 4), category (same, different), and posture (high similarity, low similarity) as factors revealed significant main effects of memory load, $F(1, 19) = 60.11$, $p < 0.001$, $p^2 = 0.76$, and category, $F(1, 19) = 82.06$, $p < 0.001$, $p^2 = 0.81$. The memory load × category interaction was significant, $F(1, 19) = 61.37$, $p < 0.001$, $p^2 = 0.76$, as was the memory load × posture interaction, $F(1, 19) = 7.50$, $p = 0.013$, $p^2 = 0.28$. However, the main effect of posture [$F(1, 19) = 1.62$, $p = 0.219$, $p^2 = 0.08$], the category × posture interaction [$F(1, 19) = 0.55$, $p = 0.467$, $p^2 = 0.03$], and the three-way interaction [$F(1, 19) = 0.14$, $p = 0.710$, $p^2 = 0.01$] were all non-significant.

Simple effects analysis of the significant memory load × category interaction (collapsing across posture levels, as shown in Figure 4a [Figure 4: see original paper]) showed that when memory load was 2, K was significantly larger for same-category trials ($M = 1.52$, $SD = 0.22$) than for different-category trials ($M = 1.38$, $SD = 0.26$), $t(19) = 2.50$, $p = 0.022$, Cohen's $d = 0.56$. When memory load was 4, the same-category advantage was also observed [same category: $M = 2.63$, $SD = 0.33$; different category: $M = 1.58$, $SD = 0.45$; $t(19) = 9.52$, $p < 0.001$, Cohen' s $d = 2.13$]. Furthermore, we calculated the same-category advantage effect size at each memory load and found that the effect size was significantly larger at memory load 4 ($M = 1.04$, $SD = 0.49$) than at memory load 2 ($M = 0.14$, $SD = 0.25$), $t(19) = 7.83$, $p < 0.001$, Cohen' s $d = 1.75$. These results indicate that a same-category advantage emerged at both memory loads, but was substantially larger when memory load was 4.

Although the category × posture interaction was not significant, planned comparisons based on Experiment 1' s results (collapsing across memory load levels, as shown in Figure 4b [Figure 4: see original paper]) revealed that when animal silhouettes had high-similarity postures, K was significantly larger for same-category trials ($M = 2.15$, $SD = 0.28$) than for different-category trials ($M = 1.50$, $SD = 0.34$), $t(19) = 7.59$, $p < 0.001$, Cohen' s $d = 1.70$. The same pattern was observed for low-similarity postures [same category: $M = 2.00$, $SD = 0.25$; different category: $M = 1.46$, $SD = 0.43$; $t(19) = 4.88$, $p < 0.001$, Cohen' s $d = 1.09$]. These results indicate that a same-category advantage emerged regardless of posture similarity. To further rule out the possibility that posture similarity drove the same-category advantage, we compared K values between low-similarity same-category and high-similarity different-category conditions. K was significantly larger in the low-similarity same-category condition (M =

2.00, SD = 0.25) than in the high-similarity different-category condition (M = 1.50, SD = 0.34), t(19) = 6.17, p < 0.001, Cohen’ s d = 1.38. These results again demonstrate that the same-category advantage was caused by category information rather than perceptual similarity.

Simple effects analysis of the significant memory load × posture interaction (collapsing across category levels, as shown in Figure 4c [Figure 4: see original paper]) revealed that when memory load was 2, K was significantly smaller for high-similarity trials (M = 1.42, SD = 0.21) than for low-similarity trials (M = 1.49, SD = 0.24), t(19) = -2.11, p = 0.049, Cohen’ s d = -0.47. When memory load was 4, the difference between high-similarity (M = 2.24, SD = 0.41) and low-similarity (M = 1.97, SD = 0.44) trials was marginally significant, t(19) = 2.01, p = 0.059, Cohen’ s d = 0.45. These results indicate that posture similarity affects VWM capacity, with an inhibitory effect at low memory loads and a facilitative effect at high memory loads.

Overall, the results of Experiment 2 replicated those of Experiment 1, confirming that the same-category advantage persists even when memory items are presented sequentially.

Experiment 3: ERP Study on the Effects of Category Information on VWM Capacity with Simultaneous Presentation

In Experiments 1 and 2, we consistently found a same-category advantage in VWM capacity. In Experiment 3, in addition to measuring the behavioral index Cowan’ s K, we also measured the electrophysiological index CDA to further investigate the cognitive and neural mechanisms underlying the same-category advantage. If same-category information simply increases the number of VWM units, then CDA amplitude should be larger in the same-category condition than in the different-category condition. If same-category information enhances the information capacity of individual VWM units through conceptual organization, then CDA amplitude should be smaller in the same-category condition than in the different-category condition. Because Experiments 1 and 2 found a same-category advantage regardless of posture similarity, Experiment 3 used only low-similarity posture materials, with all other aspects identical to Experiment 1.

4.1.1 Participants

Based on previous CDA research (Brady et al., 2016), the sample size for this experiment was set at 18. A new group of 20 participants (9 females, aged 19–21 years, mean age = 19 years) participated in Experiment 3. Two participants were excluded from analysis due to excessive eye movements and other artifacts.

4.1.2 Design and Procedure

Experiment 3 employed a 2 (memory load: 2, 4) × 2 (category: same, different) within-subjects design. To measure CDA, memory items were presented on the cued side of the fixation point. Control items were selected according to the same rules and presented on the side opposite to the memory items, such that when memory items were from the same (or different) category, control items were also from the same (or different) category. Additionally, to reduce EEG artifacts, the articulatory suppression task was not used in this experiment. Each participant completed 800 trials. All other aspects were identical to Experiment 1.

4.1.3 Procedure

The procedure for Experiment 3 is illustrated in Figure 5 [Figure 5: see original paper]. At the beginning of each trial, two arrows pointing in the same direction were displayed for 200 ms to cue left or right, followed by a random delay of 300–400 ms during which only a fixation point was visible. Next, two memory arrays (memory items or control items) were presented for 500 or 1000 ms (depending on the number of items: 2 or 4, 250 ms/item) within two rectangular regions (visual angle: 4° × 12°, 4° from center). This was followed by a 1000 ms blank screen with only the fixation point, after which two probe items were presented at the centers of the rectangular regions for 2000 ms or until participants responded. Participants were required to judge whether the probe item on the cued side had appeared in the memory array on the same side, with emphasis on accuracy rather than response speed.

4.1.4 EEG Recording

EEG was recorded using a NeuroScan CURRY 7 system with a 64-channel electrode cap based on the international 10–20 system extended montage. FPz served as the ground electrode. Horizontal electrooculogram (EOG) was recorded from electrodes placed approximately 1.5 cm lateral to the outer canthi of both eyes, and vertical EOG was recorded from electrodes placed approximately 1 cm above and below the left eye. The left mastoid served as the reference electrode, which was later converted to the average of both mastoids during offline analysis. The bandpass filter was 0.05–100 Hz, and the sampling rate was 500 Hz. Impedance for each electrode was maintained below 5 kΩ.

4.1.5 EEG Preprocessing

EEG data from correct-response trials (excluding 29% error trials) were processed offline using EEGLAB software (Delorme & Makeig, 2004) with the ERPLAB plugin (Lopez-Calderon & Luck, 2014). A 0.1–30 Hz zero-phase Butterworth filter (48 dB/oct slope) was applied. Epochs were extracted from 200 ms before to 1500 ms after memory item onset for memory load 2, or 2000 ms for memory load 4, with the 200 ms pre-stimulus interval serving as the baseline.

The simple voltage threshold function in the ERPLAB plugin was used to reject epochs with amplitudes exceeding $±$75 V at any electrode, and the step function was used to reject epochs with vertical EOG exceeding $±$100 V or horizontal EOG exceeding $±$32 V. Observers with more than 10% of trials rejected due to eye movements or motion artifacts were excluded from analysis (two participants were excluded).

4.1.6 EEG Analysis

Contralateral difference waves were obtained by subtracting ipsilateral activity from contralateral activity relative to the cue side. A time window of 400–1000 ms after memory array offset was selected to measure the contralateral-minus-ipsilateral difference wave, based on previous research (Brady et al., 2016; Kang & Woodman, 2014). Representative electrode sites over parietal (P8/P7, P6/P5, P4/P3) and parieto-occipital (PO8/PO7, PO6/PO5, PO4/PO3) regions were selected for further analysis, following previous studies using CDA as an index of VWM capacity (Gao et al., 2011; Qi et al., 2014). For each electrode pair, the CDA index was obtained by averaging the amplitude differences between contralateral and ipsilateral electrode sites. A two-way repeated-measures ANOVA on mean CDA amplitudes within the time window was conducted with memory load (2, 4) and category (same, different) as factors.

4.2 Results

4.2.1 Behavioral Results The K values for the four conditions in Experiment 3 are presented in Table 3 . A two-way repeated-measures ANOVA on K with load (2, 4) and category (same, different) as factors revealed significant main effects of memory load, F(1, 17) = 134.98, $p < 0.001$, $p^2 = 0.46$, and category, F(1, 17) = 95.54, $p < 0.001$, $p^2 = 0.37$. The memory load × category interaction was also significant, F(1, 17) = 52.70, $p < 0.001$, $p^2 = 0.26$. Simple effects analysis showed that when memory load was 2, K was significantly larger for same-category trials (M = 0.97, SD = 0.23) than for different-category trials (M = 0.86, SD = 0.24), t(17) = 3.62, p = 0.002, Cohen' s d = 0.85. When memory load was 4, the same same-category advantage was observed [same category: M = 1.95, SD = 0.41; different category: M = 1.08, SD = 0.40; t(17) = 8.90, $p < 0.001$, Cohen' s d = 2.10]. Furthermore, the same-category advantage effect size was significantly larger at memory load 4 (M = 0.88, SD = 0.42) than at memory load 2 (M = 0.11, SD = 0.13), t(17) = 7.26, $p < 0.001$, Cohen' s d = 1.71. These results, consistent with Experiments 1 and 2, indicate that a same-category advantage emerged at both memory loads but was substantially larger when memory load was 4.

Figure 6 [Figure 6: see original paper] shows the behavioral results for Experiment 3, illustrating the effect of memory load on same-category and different-category trials. Error bars represent within-subject 95% confidence intervals. ** $p < 0.01$.

4.2.2 CDA Results A two-way repeated-measures ANOVA on CDA amplitudes with memory load (2, 4) and category (same, different) as factors revealed a significant main effect of category, F(1, 17) = 32.15, $p < 0.001$, $p^2 = 0.65$. The main effect of memory load was not significant, F(1, 17) = 0.43, p = 0.520, $p^2 = 0.03$, nor was the memory load × category interaction, F(1, 17) = 0.16, p = 0.697, $p^2 = 0.01$. Planned comparisons (Figure 7b [Figure 7: see original paper]) showed that when memory load was 2, mean CDA amplitude was significantly smaller for same-category trials (M = -0.72 μV, SD = 0.62) than for different-category trials (M = -0.90 μV, SD = 0.67), t(17) = 2.53, p = 0.022, Cohen' s d = 0.60. When memory load was 4, the same pattern was observed [same category: M = -0.64 μV, SD = 0.63; different category: M = -0.87 μV, SD = 0.62; t(17) = 3.43, p = 0.003, Cohen' s d = 0.81].

Figure 7a [Figure 7: see original paper] shows contralateral-minus-ipsilateral waveforms at parietal (P8/P7, P6/P5, P4/P3) and parieto-occipital (PO8/PO7, PO6/PO5, PO4/PO3) regions for memory loads 2 and 4. The gray bar indicates the memory array presentation period, and the gray rectangle indicates the CDA time window. Figure 7b [Figure 7: see original paper] shows mean CDA amplitudes measured from 400 ms after memory array offset. Error bars represent 95% confidence intervals. * $p < 0.05$, ** $p < 0.01$.

The CDA results demonstrate that category information affected CDA amplitude regardless of memory load, with smaller mean CDA amplitudes for same-category than for different-category objects. Combined with the behavioral results, these findings indicate that category information can compress representations of same-category objects through conceptual organization, thereby expanding the overall information capacity of VWM.

General Discussion

The present study investigated how object category information affects VWM capacity. The results from two behavioral experiments showed that regardless of whether memory items were presented simultaneously or sequentially and whether animal silhouettes had high- or low-similarity postures, category information consistently influenced VWM capacity. Specifically, memory capacity for same-category objects was significantly larger than for different-category objects. The ERP data further revealed that same-category objects elicited smaller CDA amplitudes than different-category objects. These findings indicate that category information can serve as an organizational cue to compress representations of same-category objects, thereby expanding VWM capacity.

Our results are consistent with predictions from the ideal observer model, which posits that greater feature variability leads to poorer memory precision (Sims et al., 2012). Specifically, smaller variability in categorical relationships among memory items results in larger VWM capacity. In addition to categorical relationships among objects, recent research has shown that other semantic and functional relationships among objects also influence VWM capacity (O' donnell et al., 2018; Rudner et al., 2016). For example, memory performance for semantically related object pairs (e.g., golf club and golf ball, lighter and cigarette) was better than for semantically unrelated pairs (e.g., lighter and golf ball, golf club and cigarette). These findings suggest that ideal-observer predictions can be extended from low-level perceptual features (e.g., color and shape) to high-level conceptual features (e.g., categorical relationships).

Our findings are inconsistent with predictions from neural resource theory. According to this theory, different-category objects should have more non-overlapping neural resources and thus enhance rather than impair VWM capacity (Cohen et al., 2014). Two factors may account for this inconsistency. First, the applicability of neural resource theory may be limited. Multiple studies have shown that mixed-category advantages are restricted to face stimuli (Jiang, Lee, et al., 2016; Wong et al., 2008). Furthermore, when man-made objects with detailed information (e.g., furniture and musical instruments) served as memory items, no category effects on VWM were observed (Quinlan & Cohen, 2016). Second, the current study differed from research supporting neural resource theory (Cohen et al., 2014; Jiang, Lee, et al., 2016; Wong et al., 2008) in two key aspects: (1) we used silhouettes rather than real objects with detailed information as memory items, eliminating potential effects of detailed information on memory capacity; and (2) we did not use face stimuli, as faces represent a special class of objects with unique processing advantages in VWM (Curby & Gauthier, 2007). Of course, memory for detailed information is also an important aspect of working memory. The presence or absence of detailed information may modulate whether observers focus on global or detailed aspects of the memory task. For example, if memory items contain detailed information, observers may focus on details, producing a mixed-category advantage; if memory items lack detailed information, observers may focus on global aspects, producing a same-category advantage. Therefore, the generalizability of our conclusions may have certain limitations. Future research should continue to investigate how detailed information affects VWM capacity and category effects.

How does category information expand VWM capacity? The present study demonstrates that category information can serve as an organizational cue to integrate representations of same-category objects, thereby expanding VWM capacity. Limited capacity is a core feature of working memory (Bays & Husain, 2008; Cowan, 2001; Luck & Vogel, 2013). One solution to this limitation is to bind or organize multiple features into a holistic representation. Gestalt principles such as similarity (Gao et al., 2011; Peterson et al., 2015) and common fate (Luria & Vogel, 2014) can influence VWM capacity through organizational processes. Gao et al. (2011) found that four squares of the same color could be integrated into a single representation, resulting in no difference in CDA between four same-colored squares and a single square, with both showing lower CDA amplitudes than four uniquely colored squares. Regarding common fate, objects moving together are also organized into a holistic representation (Luria & Vogel, 2014). Additionally, other non-perceptual factors such as semantic and functional relationships among objects (O' donnell et al., 2018) and real-world regularities (Kaiser et al., 2014, 2015) can serve as organizational principles in VWM. Our findings indicate that categorical relationships among objects can also function as an organizational principle in VWM.

How does organization based on perceptual similarity differ from organization based on category information from long-term memory? Brady et al. (2011) proposed a hierarchical theory of working memory, suggesting that working memory representations exist at multiple levels, including low-level feature representations, object representations, and integrated representations. Moreover, these representations are influenced by information from long-term memory. Perceptual similarity represents a low-level organizational principle that affects the encoding stage of working memory. Similar objects can be integrated into a holistic representation during encoding, thereby facilitating memory representations (Brady & Tenenbaum, 2013). Research has shown that when the number of memory items increases, CDA amplitude increases for high-similarity objects but not for low-similarity objects; when the number of memory items is constant, CDA amplitude is lower for high-similarity than for low-similarity objects (Zhang et al., 2015). That is, individuals tend to integrate similar objects through organizational processes, reducing memory load and thereby expanding memory capacity. Furthermore, information stored in long-term memory can provide encoding models for current working memory representations. These encoding models consist of multiple feature dimensions, including perceptual features and category-specific conceptual features. When encoding same-category information, existing encoding models can facilitate the encoding of same-category objects (Brady et al., 2011). For example, recent research has shown that semantic and functional relationships from long-term memory can expand VWM capacity through organizational processes (O' donnell et al., 2018; Rudner et al., 2016). Our experimental results provide more explicit support for this category-encoding-model explanation. The behavioral results from all three experiments showed that category information can expand the capacity of information maintained in working memory, and the ERP results showed that same-category objects elicited lower CDA amplitudes than different-category objects, further suggesting that the same-category advantage is achieved through processes similar to perceptual organization. In summary, organization based on perceptual similarity and organization based on category information from long-term memory share many similarities in their cognitive and neural mechanisms, with the primary difference being whether long-term memory information is involved. The neural basis of how category information from long-term memory modulates VWM capacity warrants further investigation.

Memory load affected behavioral results across all three experiments but disappeared in the CDA results. This discrepancy may be because VWM capacity is reduced when complex objects such as animal silhouettes serve as memory items. Generally, when simple stimuli (e.g., circles and squares) are used as memory items, VWM capacity is approximately 3–4 items. However, numerous studies have shown that stimulus complexity reduces VWM capacity. Gao et al. (2009) used CDA amplitude as an index of VWM capacity and found that VWM capacity is not fixed but is affected by the complexity of memory items. When complex polygons were remembered, CDA amplitude did not increase as memory load increased from 2 to 4; however, when simple feature objects were remembered, CDA amplitude increased with memory load. Other researchers (Luria et al., 2010) found that VWM capacity became saturated with just two random polygons. Therefore, although animal silhouettes were simplified as much as possible compared to real animal pictures, they still represent complex objects rather than simple feature objects. Consequently, VWM capacity may become saturated with just two animal silhouettes. As shown in Figures 3 and 4, the memory load effects in Experiments 1 and 2 were primarily driven by larger VWM capacity at memory load 4 than at memory load 2 in the same-category condition (Experiment 1: memory load effect size was calculated by subtracting K at load 2 from K at load 4 for same-category and different-category conditions separately; a paired t-test showed that the memory load effect size was significantly larger in the same-category condition than in the different-category condition, $t(19) = 5.91$, $p < 0.001$, Cohen' s $d = 1.32$; Experiment 2: similarly, the memory load effect size was significantly larger in the same-category condition than in the different-category condition, $t(19) = 7.83$, $p < 0.001$, Cohen' s $d = 1.75$). However, as noted above, this capacity increase was primarily due to organization of same-category objects. The CDA results showed that the number of units stored in VWM was the same regardless of whether 2 or 4 items were presented, but more information was compressed within each unit when memory load was 4. This can explain the discrepancy between the presence of memory load effects in behavioral results and their absence in CDA results across all three experiments. Moreover, because animal silhouettes lack detailed information such as texture, spots, and color found in real objects, their storage capacity in working memory differs from previous findings that storage capacity for real objects with detailed information (Brady et al., 2016) is greater than for simple objects. That is, animal silhouettes did not show the same capacity enhancement as real objects with detailed information.

The behavioral results showed that memory load not only modulated the effect of category information on VWM capacity but also modulated the effect of posture similarity. Regarding the former, all three experiments showed that the same-category advantage was significantly larger at memory load 4 than at memory load 2. This may be because at memory load 2, working memory capacity was generally sufficient regardless of whether category-based organization occurred, resulting in a smaller same-category advantage. However, when memory load was 4, exceeding working memory capacity, only through category-based organization could the limited capacity be freed to store more memory items. That is, the category-based organizational effect was more evident when memory items exceeded working memory capacity before organization. Regarding the effect of memory load on posture similarity, Experiments 1 and 2 showed that at memory load 2, posture similarity had an inhibitory effect on capacity, whereas at memory load 4, it had a facilitative effect. This may be because when memory load was 2, working memory resources were sufficient. According to the hierarchical theory of working memory (Brady et al., 2011), individuals represent each item at both the object level and the feature level. Under high-similarity conditions, memory items consume capacity resources to process each item' s features in detail, and similar features interfere with each other, thereby reducing VWM capacity. Under low-similarity conditions, memory items have more distinct features that are easier to represent at the feature level, with less interference among them, resulting in higher VWM capacity relative to high-similarity conditions. Therefore, at memory load 2, posture similarity showed an overall inhibitory effect. When memory load was 4, working memory resources were insufficient for object-level representation of each item, and individuals tended to represent items holistically. Posture similarity can facilitate holistic representation (Son et al., 2020). Therefore, at memory load 4, posture similarity showed an overall facilitative effect on VWM capacity. The differential modulation of memory load on category effects and posture similarity effects also reflects differences in the mechanisms through which category information and perceptual similarity influence VWM capacity.

In summary, this study demonstrates a same-category advantage in VWM capacity, indicating that categorical relationships among objects can expand VWM capacity by enabling the grouping of same-category objects. This suggests that VWM capacity is not fixed but can vary flexibly depending on the type of information to be remembered. Furthermore, the study extends ideal-observer predictions from low-level perceptual features to high-level conceptual features.

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Note: Figure translations are in progress. See original paper for figures.