Semantic partitioning facilitates memory for object location through category-partition cueing

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This version of the article may not completely replicate the final authoritative version published: https://doi.org/10.1080/09658211.2024.2319363. ***It is not the version of record and is therefore not suitable for citation.***

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Abstract

In our lived environments, objects are often semantically organized (e.g., cookware and cutlery are placed close together in the kitchen). Across four experiments, we examined how semantic partitions (that group same-category objects in space) influenced memory for object locations. Participants learned the locations of items in a semantically partitioned display (where each partition contained objects from a single category) as well as a purely visually partitioned display (where each partition contained a scrambled assortment of objects from different categories). Semantic partitions significantly improved location memory accuracy compared to the scrambled display. However, when the correct partition was cued (highlighted) to participants during recall, performance on the semantically partitioned display was similar to the scrambled display. These results suggest that semantic partitions largely benefit memory for location by enhancing the ability to use the given category as a cue for a visually partitioned area (e.g., toys—top left). Our results demonstrate that semantically structured spaces help location memory across partitions, but not items within a partition, providing new insights into the interaction between meaning and memory.

Keywords: spatial memory, semantic memory, category membership, spatial organization

We share a complex relationship with the physical spaces we occupy. On one hand, physical environments can influence the way we behave (Koneya, 1976; Mateo et al., 2013; Norman, 1988; Zhu & Risko, 2016), process information (Kirsh, 1995; Radvansky & Copeland, 2006; Radvansky & Zacks, 2017; Solman & Kingstone, 2017a, 2017b), and experience emotions (Galea et al., 2005; Joye, 2007; Joye & Dewitte, 2016). On the other hand, we are also capable of exerting a significant amount of control over our physical spaces; in fact, our ability to shape, alter, and construct physical spaces has been argued to provide our species with unique evolutionary advantages (Laland & Brown, 2006). One way we exert control over our space is via spatial organization, or the ability to configure objects in our physical environment, which can help individuals to more easily navigate and perform everyday tasks (Kirsh, 1995, 1996; Solman & Kingstone, 2017b; Zhu & Risko, 2016). By rearranging objects in a physical space, certain choices or actions can be made more apparent, which can, in turn, reduce cognitive or physical demands during task performance (Kirsh, 1995; Risko & Gilbert, 2016). For example, organizing a file drawer in alphabetical order could reduce the amount of time required to locate a particular folder, and grouping functionally similar objects together in space (e.g., in a tool shed) could constrain an individual's search through memory for the location of a needed item.

According to the category adjustment model of location estimation (Huttenlocher et al., 1991), the organization or configuration of objects in space can influence our memory. When trying to remember a previously learned location, we make estimates based on our memory of an object's distance or direction from an edge (e.g., a physical boundary). However, we adjust our initial distance- and/or edge-based location estimates based on pre-existing notions of "categories". As defined in the model, a category can be delineated by either visible boundaries (Huttenlocher et al., 1994) or mentally imposed ones (such as cluster of related objects; Plumert

& Hund, 2001). Both types of categories have been shown to lead to systematic distortions in location estimation and memory; for example, participants underestimate distances between pairs of items within a perceptual boundary (Allen, 1981; Hirtle & Jonides, 1985; McNamara & LeSueur, 1989), recall same-category objects as being closer together in space (Hund et al., 2002; Hund & Plumert, 2003), and recall object locations as biased towards the center of their associated region clusters (Tompary & Thompson-Schill, 2021). However, only a handful of studies have investigated how the visual and/or semantic partitioning of objects in space can influence our location memory accuracy. We review two such studies below.

Visual and Semantic Partitioning

One strategy that we use to organize our environments is through *visual partitioning,* where we place objects into delineated spaces (like a room or drawer). There is evidence that visual partitioning can influence both search behaviour and location memory. For example, Solman and Kingstone (2017a) asked participants to search for target items (in a grid of items) via a series of repeated visual search tasks and then recall the item locations in a later memory task. For half of the study, participants performed the search task with visual partitions that divided the task space into four quadrants; in the other half, they performed the search task in an open display without any partitions. After completing each series of search tasks, participants completed a location memory task where they were asked to identify the location of each target item in the grid (where the items had been replaced by identical grey patches). The authors found that having visible partitions resulted in more systematic search behaviours, reducing inefficiencies such as re-inspection of the same areas in a space. Participants also had better memory for object locations when the task space was partitioned than when there were no partitions, which was reflected in a reduction in "near-misses" (i.e., errors occurring within one

unit of space from the target location) rather than "far-misses." Solman and Kingstone (2017a) concluded that the visual partitions had resulted in more precise location memory for objects. They speculated that both the increased search efficiency as well as memory improvement stemmed from participants using the visual partition lines as landmarks to define their visual search space and memory retrieval space.

Besides simple visual partitioning, we also organize objects according to their semantic and/or functional properties (i.e., *semantic partitioning*)[1]. There is evidence that the semantic clustering of objects in space can influence location memory. For example, Tompary and Thompson-Schill (2021) had participants learn where items were located in a display by dragging each item to its designated location one by one (the full display of objects was not visible during encoding). Critically, items in the display were distributed across eight regions, such that each region was composed mostly of items within the same category (e.g., birds), though items from other categories could be present as well (e.g., household items). After the encoding phase, participants completed a memory task by attempting to drag each item to its location as precisely as possible. The authors found that location memory accuracy (as measured by the distance from the chosen location to the item's actual location) was greater for same-category items that were clustered in the same region, compared to same-category items located in a different region. For example, "robin" would be located with greater accuracy if it had originally been near animals, rather than if it had been near household items. The authors hypothesized that, since same-category objects tended to be clustered near each other,

[1] A real-life example would be placement of cookware and cutlery in the kitchen, and clothing items in bedroom closets; these rooms are semantic partitions because they tend to contain items from the same semantic or functional category. While these semantic partitions are certainly also visible in space, throughout this article we reserve the term *visual partitioning* for those partitions delineated by visible lines (as in Solman & Kingstone, 2017a).

participants were able to pick up on this spatial cluster-category association and use the category label as a cue to retrieve the region associated with a particular object's category.

Semantic Effects in Memory Encoding and Retrieval

The category-as-cue proposal accords with traditional models of long-term memory that conceptualize retrieval as a search of memory in response to cues at test (e.g., Kimball et al., 2007; Raaijmakers & Shiffrin, 1981). Traditional free recall tasks have helped to illuminate important principles of memory search, such as temporal contiguity (items that were experienced close together in time tend to be recalled contiguously; Kahana, 1996), and semantic proximity (items that are semantically related tend to be recalled together; Bousfield et al., 1954; Howard & Kahana, 2002; Romney et al., 1993). Thus, memory for semantically blocked lists of words is better compared to randomized lists of words (Lewis, 1971; Puff, 1970), as the categorical information that can be extracted from such a list serves as a powerful cue to access information during retrieval (Mandler, 1967; Tulving & Pearlstone, 1966).

However, while semantic category-based cueing facilitates the retrieval of items that follow a common semantic or categorical theme, it can also increase interference between these items. At a more general level, semantic relatedness is a form of inter-item similarity, which can lead to improved or impaired memory depending on the situation (Kahana et al., 2022; Nelson et al., 2013). That is, similarity can benefit memory retrieval when it unifies the target items and renders them distinct from distractors, but this same mechanism also increases interference between similar items, which can be detrimental for certain kinds of memory (Kahana et al., 2022). For example, in the free recall of a semantically homogeneous list, the shared semantic theme facilitates the retrieval of matching target items on the list, and memory is thus improved. This can be further observed in the tendency for people to make recall transitions among

semantically related items during output (Bousfield et al., 1954; Romney et al., 1993), even with a list lacking obvious semantic structure (Howard & Kahana, 2002). In contrast to free recall, in a serial reconstruction task, the presented items are provided at test and correct performance requires reconstructing their presentation order. For a semantically related list, while relatedness would continue to cue the retrieval of matching items, only one of these is the 'correct' item that matches a given temporal position. In this task, semantic similarity between non-adjacent items can serve as a source of interference. Relatedness has therefore been found to improve item recall but increase the likelihood of making order errors (e.g., Baddeley, 1966; Murdock & Vom Saal, 1967; Saint-Aubin et al., 2005; Tse et al., 2009; Tse et al., 2011), though some studies have found a null effect of relatedness on order memory (e.g., Neale & Tehan, 2007; Neath et al., 2022; Saint-Aubin & Poirier, 1999; see also Ishiguro & Saito, 2021).

The "double-edged sword" of semantic similarity is illustrated within the same task in a series of studies by Guerin and Miller (2008). The experimenters had participants study both semantically blocked lists and randomly shuffled lists of words, then perform either a recall task or a recognition task (where the lures were from the same categories as the presented words). They found that the semantically blocked lists were associated with both increased hits and false alarm rates; that is, semantic relatedness induced false memories of unpresented yet thematically consistent information (see also Lu et al., 2021; Roediger & McDermott, 1995). Furthermore, while participants' recall outputs contained more categories of words for the semantically blocked lists, the mean number of items recalled per category decreased. The authors argued that the semantically blocked lists facilitated the use of a categorical/thematic cue to drive retrieval, which enabled the recall of more distinct categories, but also increased interference between

individual items in each category; that is, each item became less distinct within its category and less likely to be recalled (Brainerd et al., 2003).

Of course, prior semantic knowledge can also exert influences at the encoding stage. In a series of classic studies, Bransford and Johnson (1972) had participants listen to prose passages describing a series of events that were confusing and difficult to comprehend. Participants who were given relevant knowledge before listening to the passages (e.g., this passage is about washing clothes) showed improved comprehension and better recall. Bransford and Johnson (1972) argued that participants who were given the relevant context information were able to integrate the new information into an existing knowledge schema. This suggests that prior knowledge can facilitate comprehension and memory for new information. However, schema use can also result in the incorporation of inaccurate (yet schema-consistent) information into memories (Bartlett, 1932). Similarly, the presence of semantic category information during learning can influence how each item is encoded. In the context of learning new items, the salience of the semantic categories may encourage relational encoding (Hunt & Einstein, 1981; Hunt & McDaniel, 1993), which occurs when participants focus on characteristics shared among list items. Relational encoding can be contrasted with item-specific encoding, which occurs when participants focus on the unique characteristics of individual list items. Compared to item-specific encoding, relational encoding is associated with increased rates of false memory in the study of categorized word lists (McCabe et al., 2004).

In sum, semantic organization can have both memorial benefits and costs operating at memory encoding and retrieval. It can encourage relational encoding, which improves memory for shared characteristics or relations between items, at the possible expense of item-specific information or details. In the same vein, it also facilitates the retrieval of items following a

common semantic or categorical theme, at the cost of increased interference between these items (both at encoding and retrieval).

The Current Investigation

The current experiments investigated the effects of semantically partitioning objects in space. As with semantically blocked lists, semantic partitioning (that groups together items belonging to the same category) may have the effect of increasing distinctiveness *between* partitions, but also increasing the similarity of items within a partition, thus increasing interference between the locations of the same-partition items. Therefore, in a space containing multiple partitions—as is the case in most physical environments we occupy—the influence of having each partition consist of semantically themed items (versus a scrambled assortment of different categories) on location memory should be considered at two levels: (1) whether it influences accuracy overall (i.e., across the entire space) and (2) whether it influences accuracy within each partition. In terms of overall location accuracy, we might expect to find a benefit of semantic partitioning if semantic category labels can serve as effective cues for the correct partition (e.g., toys—top left partition), thereby reducing the functional search space from the items within the entire space to the items within a smaller partition. That is, the semantic clustering of objects in space may improve memory for location in a similar fashion to semantically blocked word lists, because participants are able to use the category labels as cues to retrieve the regions associated with specific categories (Tompary & Thompson-Schill, 2021). However, within a given partition, we might predict a cost, as the semantic relatedness between same-category items could increase interference between the items within a partition at encoding and/or retrieval (e.g., Guerin & Miller, 2008; Saint-Aubin et al., 2005; Tse et al., 2011).

In the present investigation we report four pre-registered experiments (Experiment 1a: https://osf.io/f5qp8; Experiment 1b: https://osf.io/26yzv; Experiment 2a: https://osf.io/2zgpd; Experiment 2b: https://osf.io/a78qx). Our experiments adapted the procedure used in Solman and Kingstone (2017a) wherein the task space was divided by visual partition lines into four different quadrants. Each experiment consisted of two blocks. In each block, participants completed a single round of visual search to familiarize themselves with the target items and, subsequently, performed an explicit location memory task where they were given each target object one by one and asked to choose its location. In each experiment, participants completed two blocks of the search-memory tasks, one in which the items within each visually partitioned quadrant belonged to the same semantic category (i.e., semantic partitions), and one in which each visually partitioned quadrant contained a random array of objects from different semantic categories (i.e., scrambled partitions).

Thus, the present experiments allow us to examine three questions: (1) whether semantic partitioning benefits overall location memory performance over and above visual partitioning, (2) whether semantic partitioning benefits *partition* memory performance, that is, in choosing the correct partition; (3) whether semantic partitioning benefits location memory performance for the items within a partition. We expect that semantic partitioning will benefit overall location memory performance and partition-level accuracy; that is, the category-partition association will serve as a reliable cue to retrieve the correct partition (Tompary & Thompson-Schill, 2021). It is less clear how semantic partitioning may affect memory performance for items *within* a given partition, if at all. One possibility is that semantic partitioning might impair memory performance by increasing interference, during encoding and/or retrieval, between items within a partition, as those items would all share common semantic features and hence retrieval cues

(Saint-Aubin et al., 2005; Tse et al., 2011). An alternative possibility is that semantic partitioning might benefit memory performance within a partition. If the category-partition association (e.g., *all toys are in the top left quadrant*) is efficiently encoded by the participant in the semantically partitioned display, this would save time and effort during encoding, compared to individually encoding this information for each item in the scrambled condition (e.g., top left quadrant, then second item from the right). This might allow for more resources to be devoted to encoding the specific location within the partition, which could in turn lead to better location memory within a partition (Solman & Kingstone, 2017a).

Experiments 1a & 1b

Methods

Experiments 1a and 1b are identical (1b was intended as a replication of 1a) and are described together.

Participants

In each experiment, data from 65 participants (Exp 1a: 58 women, 6 men, 1 unknown, M = 21.34 years, SD = 4.58; Exp 1b: 52 women, 13 men, M = 21.51 years, SD = 4.94) were analyzed. We pre-registered this sample size based on a power analysis estimating a conservative, small-medium effect size for within-subjects comparisons (d_z = .35, α = .05, two-tailed, within-subjects t-test) using G*Power (Faul et al., 2007). This effect size is a conservative estimate compared to previous, comparable experiments (e.g., Morris & Fritz, 2013; Tompary & Thompson-Schill, 2021). We further anticipated this sample size to be a conservative estimate with respect to the generally more powerful mixed effects models we used (Quené & van den Bergh, 2004). Participants were undergraduate students at the University of Waterloo

participating for course credit and provided informed consent. Ethics clearance was given through the University of Waterloo Research Ethics Board (#42214).

Materials

Stimuli were objects from the Bank of Standardized Stimuli (BOSS) database (Brodeur et al., 2014). Eight categories of household objects were chosen, each consisting of nine exemplars. This was subdivided into two groups of four categories that formed the two grids of object images. One grid consisted of toiletries, sporting goods, instruments, office supplies; the other grid consisted of wearables, tools, toys, and kitchen supplies. For each participant, one of the two grids was randomly chosen to be semantically partitioned (each quadrant contained objects from a single category), and the other grid was scrambled (each quadrant contained different-category objects). The order of the semantic/scrambled grids was also randomized across subjects. Examples of the two grids are shown in Figure 1.



Figure 1. Semantic (left) and scrambled (right) object grids.

Procedure

Participants were given a brief overview of the experiment that briefly described both the search task and location memory task. Each participant then performed two blocks, each containing both the visual search task (i.e., location encoding) wherein participants learned the locations of the objects, and the location memory task (examples shown in Figure 2). These tasks are described below.

Visual Search Task. On each trial, participants were presented with a grid of objects on the left, and a target object on the right. They were instructed to find the object in the grid and click on it. If the participant clicked the correct object, then the "Correct" feedback screen appeared, and they advanced to the next trial. If they clicked on the wrong object, then the "Wrong! Try again" feedback screen appeared, and that trial was immediately restarted. Therefore, if a participant made no errors in the visual search task, there were 36 trials (one for each object, presented in a random order) for a single grid.

Location Memory Task. On each trial, participants were presented with the grid from the visual search task to the left, except that the objects were replaced by identical blurred grey patches. The target object was shown on the right. They were instructed to click on the patch that corresponded to the original location of the target object. There were 36 trials for a single grid (one for each object, presented in random order) and no feedback was given.

After participants completed the visual search task and location memory task for both blocks (semantic and scrambled), they were given a post-task questionnaire on self-reported everyday spatial ability and the subjective difficulty of the task (see Supplemental Material). Finally, participants were asked to provide their age in years as well as their self-identified gender, and given an opportunity to declare if they were paying attention to and giving effort during the experiment.

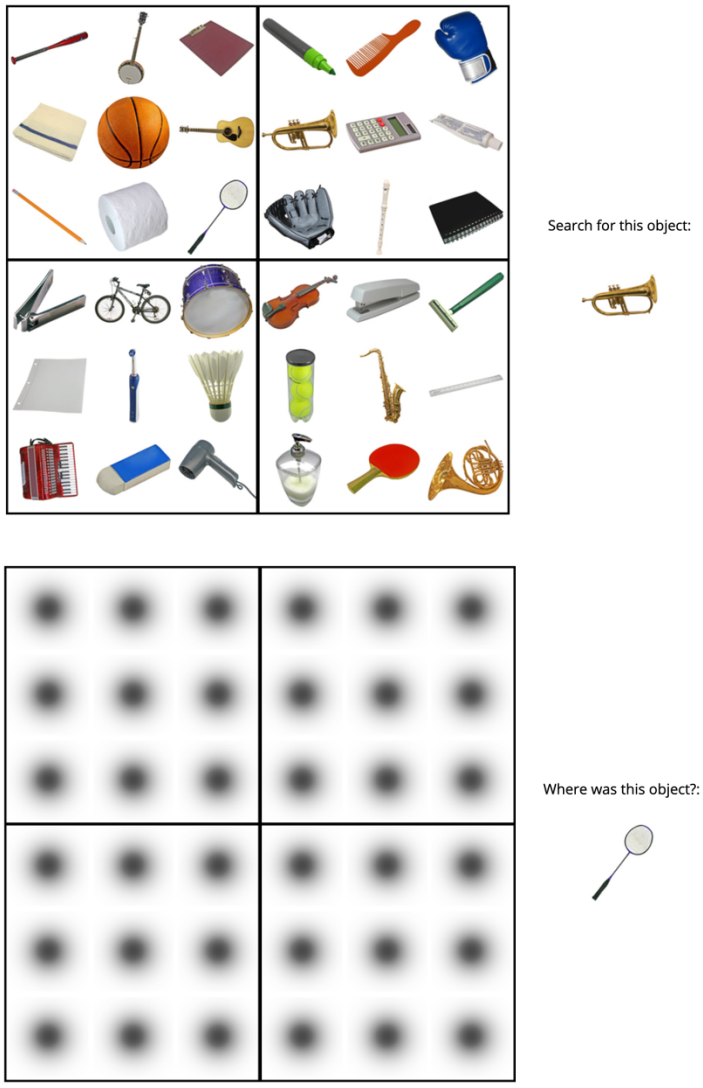


Figure 2. Visual search task (top) and location memory task (bottom).

Results

14 participants in Experiment 1a and 8 participants in Experiment 1b were excluded according to the following pre-registered criteria: (1) repeated more than 8 trials in the study phase, and/or (2) self-reported that they were not paying attention or did not give effort during the task. Excluded participants were removed and replaced. The analyses we report below were pre-registered unless stated otherwise. All analyses were conducted using R (R Core Team,

2019). Mixed-effect regressions were conducted using the *lme4* package (Bates et al., 2015). Unless otherwise specified, all linear and logistic mixed-effects models were run using the *bobyqa* optimizer. Given that degrees of freedom can be difficult to estimate accurately in mixed-effects models (Bates et al., 2015), approximate *p*-values using Wald tests are provided considering the relatively large number of observations in the current study. This was done using the *sjPlot* package (Lüdecke, 2018). We report Hedges' *g* using the *effsize* package (Torchiano, 2019) as a measure of effect size for two-group comparisons wherever appropriate. Additional exploratory analyses (exploring the variables of subjective difficulty, gender, presentation order, and individual differences in self-reported ability) can be found in the Supplemental Material. All data and analysis code are available at https://osf.io/68d2g/.

Mixed-Effect Model Specifications

Categorical predictors (e.g., semantic partitioning) were coded in our mixed-effect models using sum-contrasts. For the random effects structure, we began with a base model containing by-participant and by-stimuli random intercepts, as from a theoretical perspective, we expect some participants to perform better than others and some items to be more memorable than others. By-participant and by-stimuli random slopes for the effect of semantic/scrambled partitions were included only when doing so significantly improved the fit of the model (Bates et al., 2018; Matuschek et al., 2017). In order to decide whether to add by-participant and/or by-stimuli slopes, we compared the base model to the more complex models using likelihood ratio tests. If the by-participant slope model and the by-stimuli slope model were both significantly different from the base model, then we examined the BIC and AIC scores, prioritizing the model with the lowest BIC/AIC score. In the rare case that adding both by-participant and by-stimuli slopes represented a significant improvement in model fit, this was also confirmed using a

likelihood ratio test. In the event that the base model was singular, we chose to retain either the by-participant intercept only model or the by-stimuli intercept only model, prioritizing the model with the lowest BIC then AIC score if necessary. If both models were singular, then the simplest by-participant intercept only model was retained (this happened only once, as we note in a footnote).

Visual Search Task

Total Per-Item Search Time. While our focus was on performance in the recall task, we also conducted exploratory analyses of performance in the search task. In our experimental task, participants must correctly identify a target item in the search phase before moving on to search for the next item (e.g., Figure 2). If an individual identifies an incorrect item, the trial is repeated until the correct item is identified (this occurred on less than 1% of trials in both Experiment 1a and 1b). As such, we also accounted for the time that individuals spent on these erroneous trials by summing the total amount of time participants searched for each item (i.e., if a participant spent two trials searching for an item, the time spent on both trials is added together for that item). The total time spent on each item was then averaged per individual. We employed Wilcoxon signed-rank tests to examine whether median search time differed between the two displays, as search time was considerably positively skewed. Participants were faster at searching for target items in the semantic than the scrambled display in Experiment 1a, $V = 364$, $p < .001$; though, this result was not significant in Experiment 1b, $V = 850$, $p = .147$. We note that search times would not only reflect the time spent searching for an item, as participants could spend time studying the display if they wished. The displays did not differ in the number of errors made, i.e., there was no speed-accuracy tradeoff, Exp 1a: $V = 119$, $p = .361$; Exp 1b: $V = 137$, p

= .199. Table 1 presents mean and median search time and error rate by semantic/scrambled partitioning.

Table 1. Mean (median) search time and mean (median) number of errors by semantic/scrambled partitioning across Experiments 1a and 1b. Square brackets contain 95% bias-corrected and accelerated (Bca) bootstrap confidence intervals.

	Experiment 1a		**Experiment 1b**	
	Semantic	Scrambled	Semantic	Scrambled
Search Time Per Item (ms)	2562 (2348) [2391–2984]	2871 (2750) [2673–3354]	2615 (2413) [2410–2885]	2665 (2447) [2479–2910]
Number of Search Errors Per Grid	0.29 (0) [0.15–0.49]	0.37 (0) [0.20–0.60]	0.29 (0) [0.15–0.48]	0.45 (0) [0.26–0.69]

As our exploratory analyses suggested that search time could be a potential confounding factor, we conducted both our original pre-registered recall task analyses as well as those same analyses accounting for how long individuals spent looking for each item in the search phase. These analyses aimed to account for any potential differences in location accuracy due to search time. Given the considerable positive skew in the search time data, a log-transformation to the summed search time for each item was applied. Transformed search time per item was then entered as a covariate in mixed-effects models for each of the experiments. Whenever possible, the random effects structures of the original analyses were preserved, unless this led to model non-convergence or singularity. We found that including search time in the models did not influence any of the results; the full set of analyses is available at https://osf.io/68d2g/.

Overall Location Memory Performance

In order to examine whether semantic partitioning influenced overall location memory performance over and above visual partitioning, we looked at (1) absolute location accuracy, defined by whether participants chose the correct target square or not; (2) Euclidean distance from the chosen location to the correct location, on all trials; and (3) Euclidean distance on only incorrect trials (when participants chose a location square other than that containing the correct item).

Location Accuracy. We examined how location accuracy differed between the semantic and scrambled grids. As per our pre-registration, we conducted parallel *t*-tests and logistic regression. Paired sample *t*-tests revealed that individuals were able to correctly identify item locations significantly more often in the semantic than the scrambled conditions, Exp 1a: $t(64) = 3.31$, $p = .002$, $g_{rm} = 0.337$; Exp 1b: $t(64) = 6.45$, $p < .001$, $g_{rm} = 0.693$. A parallel mixed-effects logistic regression revealed similar results, Exp 1a: $b = 0.22$, 95% CI [0.10, 0.34], $z = 3.50$, $p < .001$; Exp 1b: $b = 0.39$, 95% CI [0.27, 0.51], $z = 6.46$, $p < .001$. (In all subsequent experiments, we opted to use pre-registered logistic regressions instead of *t*-tests.) When log-search time was included in the model as a covariate, there was no significant main effect on location accuracy, and the benefit of semantic partitioning remained significant even after accounting for log-search time. A combined analysis across Experiments 1a and 1b confirmed the significant main effect of condition on location accuracy, $b = 0.31$, 95% CI [0.22, 0.39], $z = 6.94$, $p < .001$. Figure 3A shows the mean location accuracy by condition.

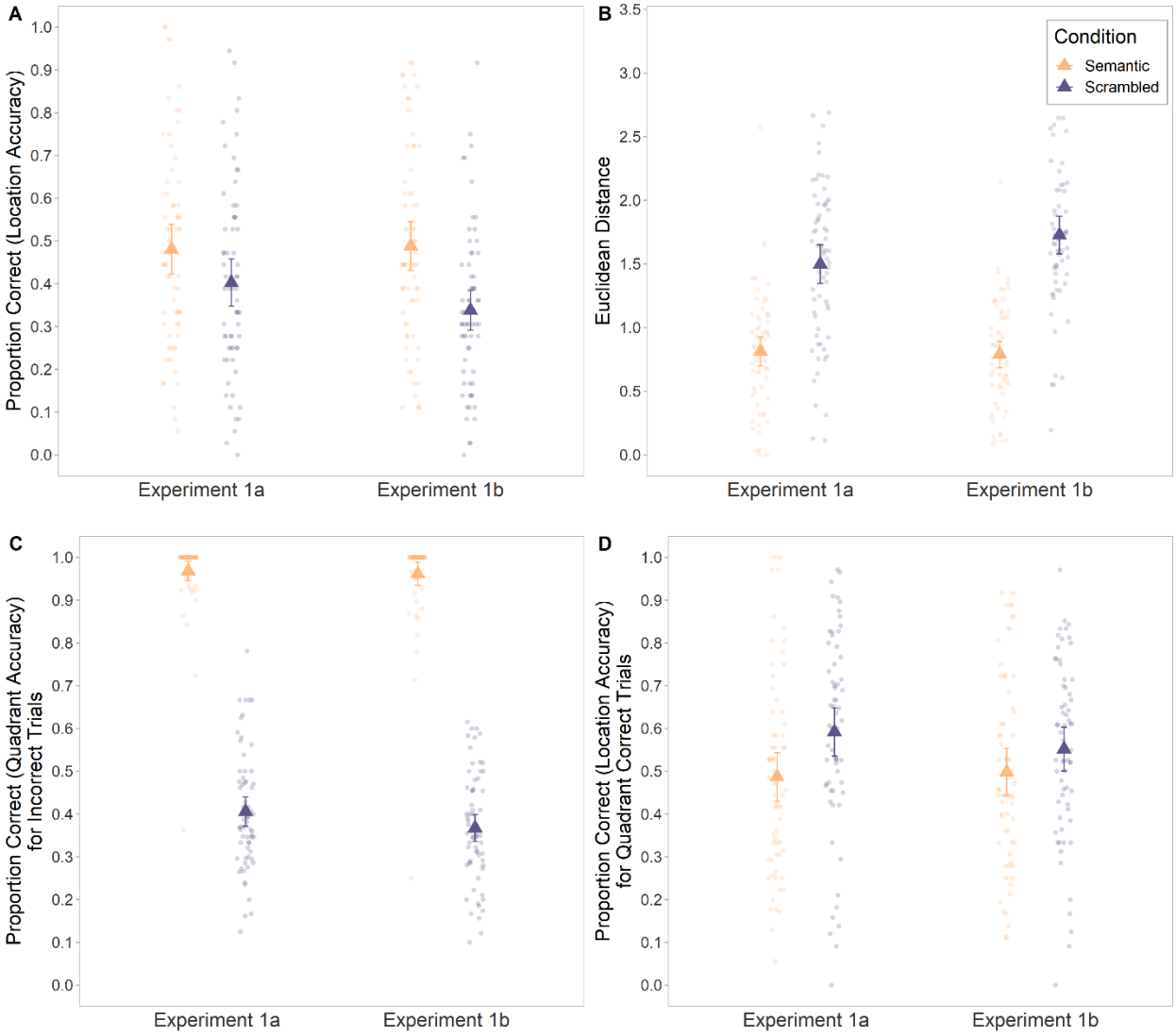


Figure 3. Mean (A) location accuracy, (B) Euclidean distance from the correct location, (C) quadrant-level accuracy on incorrect trials, and (D) location accuracy (for trials where the correct quadrant was chosen) by condition (semantic vs. scrambled partitioning) in Experiments 1a and 1b. Error bars represent 95% confidence intervals. Circles in the background represent each participant's average performance per condition.

Euclidean Distance. We used mixed-effects linear regression models to compare the Euclidean distance between the chosen location and the actual location across conditions.

Distances were smaller in the semantic than the scrambled conditions, Exp 1a: b = -0.34, 95% CI [-0.40, -0.28], t = 11.54, p < .001; Exp 1b: b = -0.47, 95% CI [-0.53, -0.41], t = 15.88, p < .001. When log-search time was included in the model as a covariate, greater log-search times predicted greater Euclidean distances in Exp 1a, b = 0.11, 95% CI [0.03, 0.19], t = 2.67, p = .008; this result was not significant in Exp 1b, 0.03, 95% CI [-0.05, 0.12], t = 0.79, p = .429. Importantly, the benefit of semantic partitioning remained significant even after accounting for log-search time. A combined analysis across Experiments 1a and 1b confirmed the significant main effect of condition on distance, b = -0.41, 95% CI [-0.45, -0.37], z = 18.87, p < .001. Figure 3B shows the mean distance by condition.

Euclidean Distance (Incorrect Trials). As the Euclidean distance measure would be strongly influenced by the proportion of correct trials (corresponding to a distance of zero), we repeated the Euclidean distance analysis on just the subset of incorrect trials (see Table 2). We used mixed-effects linear regression models to compare Euclidean distance across conditions for incorrect trials. Within incorrect trials, Euclidean distances were smaller in the semantic than the scrambled conditions, Exp 1a: b = -0.47, 95% CI [-0.53, -0.42], t = 17.45, p < .001; Exp 1b: b = -0.54, 95% CI [-0.58, -0.49], t = 25.06, p < .001. When log-search time was included in the model as a covariate, the effect of log-search time on distance was significant in Exp 1a: b = 0.13, 95% CI [0.04, 0.23], t = 2.72, p = .007, but not in Exp 1b, b = 0.02, 95% CI [-0.08, 0.11], t = 0.35, p = .728. Again, the benefit of semantic partitioning remained significant even after accounting for log-search time. A combined analysis across Experiments 1a and 1b confirmed the significant main effect of condition, b = -0.50, 95% CI [-0.54, -0.47], z = 28.28, p < .001.

Table 2. Number of trials (total, incorrect, quadrant-correct, and incorrect quadrant-correct) by condition in Experiments 1a and 1b.

	Experiment 1a		Experiment 1b	
	Semantic	Scrambled	Semantic	Scrambled
Total Trials	2340	2340	2340	2340
Incorrect Trials	1215	1398	1198	1549
Quadrant Correct Trials	2283	1498	2277	1344
Incorrect but Quadrant Correct Trials	1158	556	1135	553

Quadrant-Level Memory Performance

Quadrant Accuracy. In order to examine whether semantic partitioning influenced quadrant-level memory performance, we first examined quadrant accuracy between the semantic and scrambled displays, defined by whether participants chose a location that was within the correct quadrant. We found that quadrant accuracy was higher in the semantic than scrambled condition, Exp 1a: $b = 2.88$, 95% CI [2.17, 3.60], $z = 7.94$, $p < .001$; Exp 1b: $b = 2.77$, 95% CI [2.16, 3.39], $z = 8.80$, $p < .001$. When log-search time was included in the model as a covariate, there was no significant main effect on quadrant accuracy; importantly, the effect of semantic partitioning remained significant even after accounting for log-search time.

Quadrant Accuracy for incorrect trials only. Next, we examined quadrant accuracy only for the incorrect trials. As overall quadrant accuracy is heavily influenced by the number of

correct trials, restricting the analysis to the inaccurate trials allows us to examine how likely participants were to choose the correct quadrant even when the precise location was wrong. We used mixed-effects logistic regression models to compare quadrant accuracy across conditions for incorrect trials. Within incorrect trials, quadrant accuracy was again higher in the semantic than the scrambled condition, Exp 1a: $b = 2.67$, 95% CI [2.09, 3.25], $z = 9.06$, $p < .001$; Exp 1b: $b = 1.91$, 95% CI [1.76, 2.07], $z = 23.84$, $p < .001$. There was no significant main effect of log-search time when it was included in the model as a covariate, and the effect of semantic partitioning remained significant even after accounting for log-search time. Figure 3C shows mean quadrant accuracy by condition for incorrect trials only.

Within-Quadrant Memory Performance

In order to examine whether semantic partitioning influenced location memory performance for the items within a quadrant, we looked at (1) location accuracy on trials where the correct quadrant was chosen (see Table 3), (2) Euclidean distance from chosen to correct location on all trials where the correct quadrant was chosen, and (3) Euclidean distance on incorrect trials where the correct quadrant was chosen.

Location Accuracy on quadrant-correct trials. In Experiment 1a (exploratory), location accuracy was lower in the semantic than the scrambled condition when conditioned on the quadrant being correct, $b = -0.24$, 95% CI [-0.37, -0.11], $z = 3.68$, $p < .001$. A similar result emerged in Experiment 1b (pre-registered), though not significant, $b = -0.12$, 95% CI [-0.24, 0.00], $z = 1.92$, $p = .055$. There was no significant main effect of log-search time when it was included in the model as a covariate, and we found the same pattern of a semantic partitioning

cost after accounting for log-search time. Figure 3D shows the mean location accuracy on quadrant correct trials by condition.

Euclidean Distance on quadrant-correct trials. In an exploratory analysis, we found that the distance between the chosen and correct location was larger in the semantic than the scrambled condition when conditioned on the quadrant being correct, Exp 1a: $b = 0.09$, 95% CI [0.05, 0.13], $t = 4.44$, $p < .001$; Exp 1b: $b = 0.05$, 95% CI [0.01, 0.09], $t = 2.55$, $p = .011$. When log-search time was included in the model as a covariate, there was no significant main effect on Euclidean distance, and the semantic partitioning cost remained significant even after accounting for log-search time.

Euclidean Distance for incorrect trials on quadrant-correct trials. We found that the Euclidean distances (on incorrect but quadrant-correct trials only: see Table 2) were larger in the semantic than the scrambled condition, Exp 1a: $b = 0.03$, 95% CI [0.01, 0.06], $t = 2.36$, $p = .018$; Exp 1b: $b = 0.03$, 95% CI [0.00, 0.06], $t = 2.29$, $p = .022$. When log-search time was included in the model as a covariate, there was no significant effect on distance, and the semantic partitioning cost remained significant even after accounting for log-search time.

Discussion

As outlined in the Introduction, we examined (1) whether semantic partitioning benefits overall location memory performance over and above visual partitioning, (2) whether semantic partitioning benefits *partition* memory performance, that is, in choosing the correct partition; (3) whether semantic partitioning benefits location memory performance for the items within a partition.

With respect to (1), whether semantic partitioning benefits overall location memory performance over and above visual partitioning: Across Experiments 1a and 1b, individuals indeed performed better in a location memory task when presented with a semantically partitioned display than a partitioned display where items within the partitions were scrambled. Specifically, we found that overall absolute location accuracy increased when partitions contained semantically related items compared to a scrambled set of items from different categories. Relatedly, the average distance between a chosen location and the target location was smaller in the semantically partitioned condition compared to the scrambled condition, both overall as well as on incorrect trials. These results were confirmed in combined analyses across Experiments 1a and 1b. While semantic partitioning also reduced item search times, controlling for search time did not impact any of the recall task results. Interestingly, when there was a main effect of search time, it was such that longer search times predicted worse memory accuracy; this is addressed further in the General Discussion. Altogether, these results provide evidence that location memory performance for items shown in a semantically partitioned display is improved compared to items presented in a purely visually partitioned display.

With respect to (2), whether semantic partitioning benefits partition memory performance: When examining individuals' partition-level (i.e., quadrant) accuracy, we found that participants were able to identify the correct partition close to 100% of the time when items were semantically partitioned; this number remained close to 100% even when we examined only the subset of trials in which participants did not correctly identify an item's exact location. However, when participants were given the scrambled partition display, partition accuracy was only 60% and dropped to 40% when we examined only the incorrect trials. This suggests that when items are semantically partitioned, individuals are able to recall the partitions associated

with each of these categories at a high level of accuracy, at least with a relatively small number of categories (four here). It is also important to note that while partition accuracy was lower in the scrambled condition, it nevertheless remained well above chance (i.e., 25%) even on the incorrect trials.

Finally, with respect to (3), whether semantic partitioning benefits location memory performance for the items within a partition: As a measure of within-partition location memory accuracy, we examined just the subset of trials where the correct partition had already been chosen. We observed that the benefit of semantic partitioning was eliminated. Indeed, both accuracy and distance measures indicated a *cost* to within-partition memory accuracy in the semantically partitioned condition (where items within the partition were all from the same category) compared to the scrambled partition condition, rather than a benefit. However, this finding should be interpreted with caution. In the semantically partitioned condition, quadrant accuracy was near ceiling; this suggests that even if a participant was unable to retrieve any location memory information on a given trial, they were nevertheless highly likely to place their guesses within the correct partition by virtue of knowing the category-partition association alone. This potentially means that the quadrant-correct subset of trials would include more random guesses in the semantic condition. On the other hand, in the scrambled condition, a purely random guess, in the absence of any retrieval of location memory, would be unlikely to land in the correct quadrant. That is, in order to select the correct quadrant in the scrambled condition, they would likely have to have retained some information about the location of the target item (even if this information is imprecise). As a result, this would create an illusion of a cost in the semantic condition when examining performance on the quadrant-correct trials. This limitation is addressed in the following set of experiments.

Experiments 2a & 2b

The results of Experiments 1a and 1b suggest that semantic partitioning may benefit location memory accuracy by cueing participants to select an item's possible location within a smaller partition. However, they also suggest that accuracy within that partition might be impaired. That is, while there was a benefit of semantic partitioning overall, when we examined just the trials on which individuals identified the correct partition, location memory performance in the semantically partitioned condition was actually worse compared to the scrambled condition. While this observation is consistent with our hypothesis that the benefit of semantic partitioning on location memory performance is driven by partition-level accuracy, the exact effects on within-partition accuracy remain unclear. We address this further by introducing a cued-partition condition in Experiments 2a and 2b. Specifically, for half of the trials in the location memory task, the correct quadrant was highlighted to the participant at retrieval (i.e., cued trials). Importantly, participants could not choose target locations outside of the highlighted quadrant. For the other half of the trials, the correct quadrant was not highlighted (i.e., uncued trials), nor was there a restriction on participants' ability to select a given quadrant (i.e., identical to Experiments 1a and 1b).

By introducing an additional cued/uncued manipulation at retrieval, the semantic and scrambled conditions can be compared when the benefit of partition (quadrant) accuracy is controlled for (on the cued trials). That is, if the benefit on location memory performance in the semantically partitioned condition is indeed conferred by the category labels providing salient cues to the correct partitions (Tompary & Thompson-Schill, 2021), then introducing a quadrant cue in the randomized display should reduce the gap in performance across the semantic and scrambled displays. Moreover, this design allows us to better assess whether memory

performance for *specific* object locations in a semantically partitioned display would be reduced relative to a scrambled display. Since individuals could only choose locations within the highlighted quadrant on cued trials, distance measures across the two conditions will be more comparable. Therefore, if semantic partitioning is associated with poorer memory for specific object locations, then we would expect a greater average distance from the chosen location to the target location compared to when participants are presented with a scrambled display (on the cued trials). As an additional measure of within-partition accuracy, we also planned to compare the proportion of "near-misses" (defined as one square away from the target, either adjacent or diagonal) on the cued trials (as in Solman & Kingstone, 2017a). A lower proportion of near-misses (corresponding to higher proportion of far-misses) would presumably reflect poorer memory for specific object locations.

Methods

Experiments 2a and 2b are identical (2b was intended as a replication of 2a) and are described together.

Participants

In each experiment, data from 65 participants (Exp 2a: 46 women, 18 men, 1 other, M = 21.06 years, SD = 2.07; Exp 2b: 51 women, 14 men, M = 19.83 years, SD = 1.67) were analyzed. We pre-registered the same sample sizes as in Experiments 1a and 1b, anticipating that effects of interest (i.e., difference between two conditions for within-subjects comparison) would be at least a small-medium size. Participants were undergraduate students at the University of Waterloo participating for course credit and provided informed consent.

Materials and Procedure

Stimuli and procedure were identical to Experiments 1a and 1b except for the location memory task. Participants were told that on some of the location memory task trials, the border of the correct quadrant would be colored in orange (i.e., cued trials). Importantly, selecting a location outside of the orange bordered quadrant was disabled on the cued trials; in other words, clicking on those regions did not advance the experiment. Of the 36 total trials, half of the trials were *cued* and half were *uncued*. On *cued* trials, therefore, the correct quadrant was highlighted, while there was no highlighting in the *uncued* trials (i.e., they were identical to the trials in Experiments 1a and 1b).

Results

Nine participants in Experiment 2a and twelve participants in Experiment 2b were excluded according to the following pre-registered criteria: (1) repeated more than 8 trials in the study phase, and/or (2) self-reported that they were not paying attention or did not give effort during the task. Excluded participants were removed and replaced. As in Experiments 1a and 1b, we also report exploratory analyses on whether search time differed between the semantic versus scrambled displays. For the recall task, we conducted a mixed-effects regression for each variable of interest (logistic for location accuracy and linear for distance) with partitioning (semantic/scrambled) and cue (cued/uncued) as fixed effects. We followed up each omnibus analysis with separate mixed-effects regressions for cued and uncued trials, which allowed us to examine (1) whether semantic partitioning benefits overall location memory in the uncued trials; (2) whether semantic partitioning benefits within-quadrant accuracy in the cued trials, as quadrant-level accuracy is controlled for. Quadrant-level accuracy was examined using mixed-effects logistic regressions for the uncued trials only (since participants could only select the correct quadrant on cued trials). We also repeated these analyses while accounting for search

time and found the same pattern of results. In addition, we conducted Bayesian *t*-tests on participant mean-level data using JASP (JASP Team, 2022). The prior for the standardized effect size δ was assigned the default Cauchy prior distribution centered at zero with scale parameter set to $\sqrt{1/2}$. Additional exploratory analyses (exploring the variables of subjective difficulty, gender, presentation order, and individual differences in self-reported ability) can be found in the Supplemental Material.

Visual Search Task

Total Per-Item Search Time. Participants were faster at searching for target items in the categorized than randomized display, Exp 2a: $V = 3174$, $p = .012$; Exp 2b: $V = 3210$, $p = .015$. The displays did not differ in the number of errors made, Exp 2a: $V = 68$, $p = 1$; Exp 2b: $V = 48.5$, $p = .517$ (i.e., there was no speed-accuracy tradeoff). Again, repeated trials due to errors occurred on less than 1% of trials in both Experiment 2a and 2b. Table 3 presents mean and median search time and error rate by semantic/scrambled partitioning.

Table 3. Mean (median) search time and mean (median) number of errors by semantic/scrambled partitioning across Experiments 2a and 2b. Square brackets contain 95% bias-corrected and accelerated (Bca) bootstrap confidence intervals.

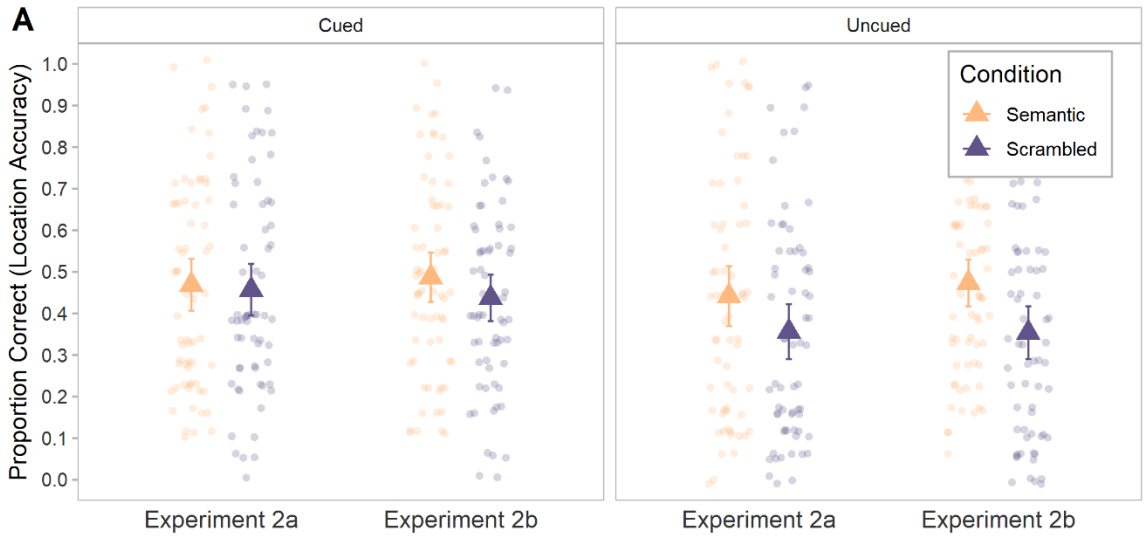
	Experiment 2a		**Experiment 2b**	
	Semantic	Scrambled	Semantic	Scrambled
Search Time Per Item (ms)	3099 (2757) [2854–3499]	3513 (2933) [3114–4204]	2749 (2443) [2494–3168]	3038 (2663) [2762–3525]
Number of Search Errors Per Grid	0.20 (0) [0.09–0.31]	0.20 (0) [0.11–0.31]	0.22 (0) [0.09–0.38]	0.28 (0) [0.14–0.45]

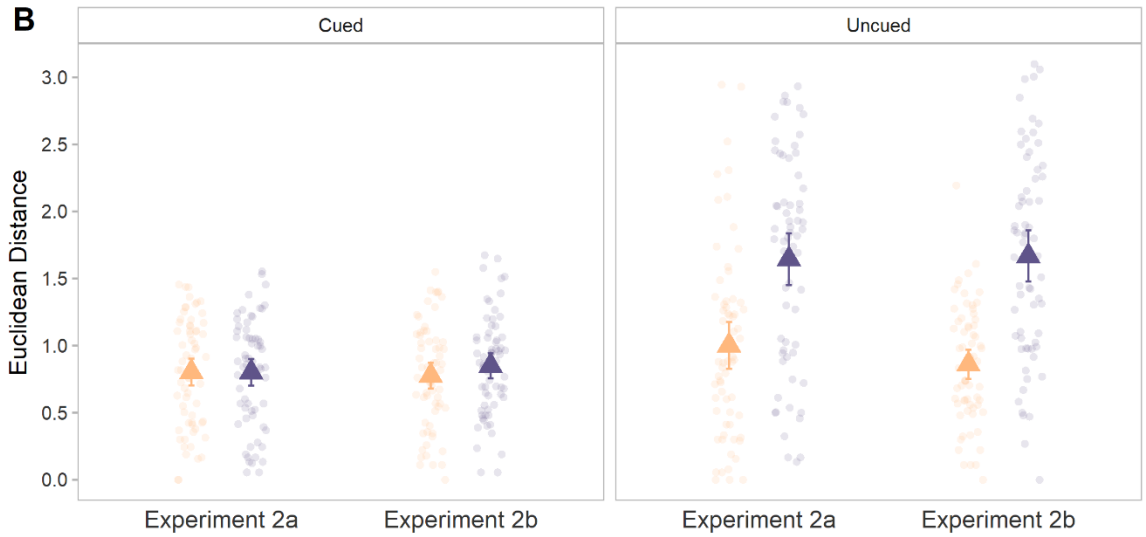
Location Memory

Location Accuracy. A mixed-effects logistic regression revealed that there was a significant interaction between semantic partitioning and cue, Exp 2a: $b = -0.11$, 95% CI [-0.17, -0.04], $z = 3.09$, $p = .002$; Exp 2b: $b = -0.09$, 95% CI [-0.15, -0.02], $z = 2.64$, $p = .008$. There was a main effect of semantic partitioning, Exp 2a: $b = 0.14$, 95% CI [0.03, 0.26], $z = 2.40$, $p = .016$; Exp 2b: $b = 0.23$, 95% CI [0.11, 0.35], $z = 3.76$, $p < .001$. There was also a main effect of cue, Exp 2a: $b = 0.17$, 95% CI [0.11, 0.24], $z = 5.06$, $p < .001$; Exp 2b: $b = 0.13$, 95% CI [0.06, 0.19], $z = 3.87$, $p < .001$. For the cued trials, the effect of semantic partitioning on location accuracy was not significant in Exp 2a: $b = 0.03$, 95% CI [-0.10, 0.16], $z = 0.44$, $p = .658$, nor in Exp 2b: $b = 0.13$, 95% CI [0.00, 0.27, $z = 1.92$, $p = .055$; for the uncued trials, the effect of semantic partitioning was significant, such that there was higher accuracy in the semantically partitioned than scrambled condition, Exp 2a: $b = 0.25$, 95% CI [0.11, 0.40], $z = 3.39$, $p = .001$; Exp 2b: $b = 0.35$, 95% CI [0.20, 0.51], $z = 4.53$, $p < .001$. Figure 4A shows the effect of semantic partitioning on location accuracy for cued and uncued trials. There was no significant main effect of log-search time when it was included in the model as a covariate, and the patterns reported above were unaffected.

We confirmed the significant interaction between semantic partitioning and cue in a combined analysis across Experiments 2a and 2b, $b = -0.10$, 95% CI [-0.15, -0.05], $z = 4.15$, $p < .001$. While the effect of semantic partitioning on location accuracy was not significant on cued trials, $b = 0.08$, 95% CI [-0.01, 0.18], $z = 1.72$, $p = .086$, it significantly increased accuracy on uncued trials, $b = 0.31$, 95% CI [0.20, 0.41], $z = 5.78$, $p < .001$. We also analyzed the participant mean-level data on cued trials using Bayesian *t*-tests. The alternative hypothesis was that the semantic condition was not equal to the scrambled condition, and the null hypothesis was

that the two conditions were equal. The Bayes factor indicated anecdotal evidence for the null hypothesis, $BF_{01} = 3.00$, error percentage = 0.061. Figure 5A shows the Bayes factor robustness plot, which shows the Bayes factor for a wide range of prior distributions, demonstrating anecdotal evidence in favour of the null hypothesis across a range of different plausible prior distributions.


A
Cued
Uncued
Condition
Semantic
Scrambled
Proportion Correct (Location Accuracy)
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Experiment 2a
Experiment 2b
Experiment 2a
Experiment 2b


B
Cued
Uncued
Euclidean Distance
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Experiment 2a
Experiment 2b
Experiment 2a
Experiment 2b

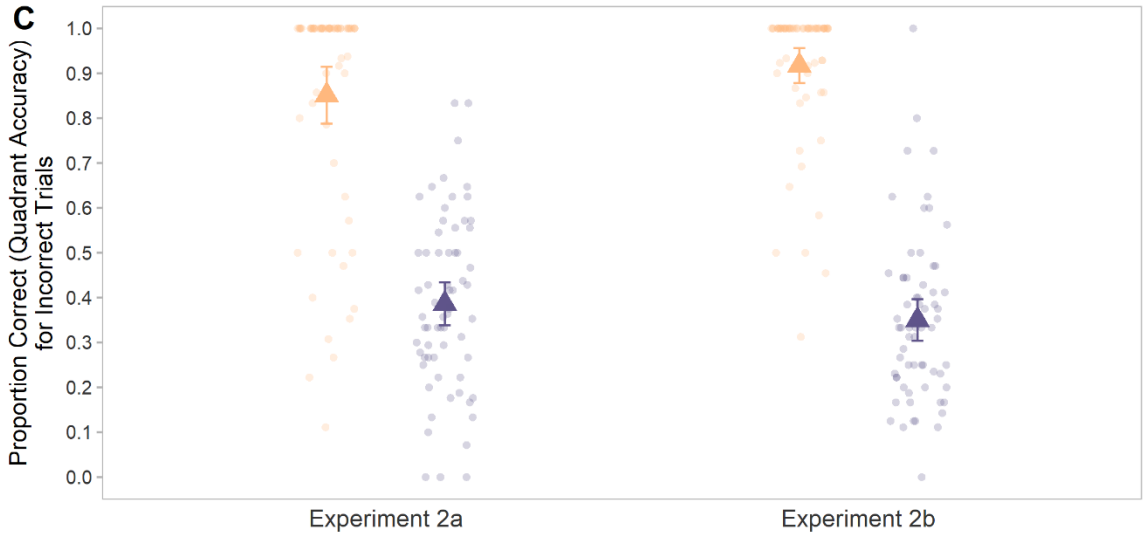

C
Proportion Correct (Quadrant Accuracy) for Incorrect Trials
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Experiment 2a
Experiment 2b

Figure 4. Mean (A) location accuracy, (B) Euclidean distance, and (C) quadrant-level accuracy by semantic/scrambled partitioning and presence or absence of quadrant cues in Experiment 2a and 2b. Error bars represent 95% confidence intervals. Circles in the background represent each participant's average performance per condition.

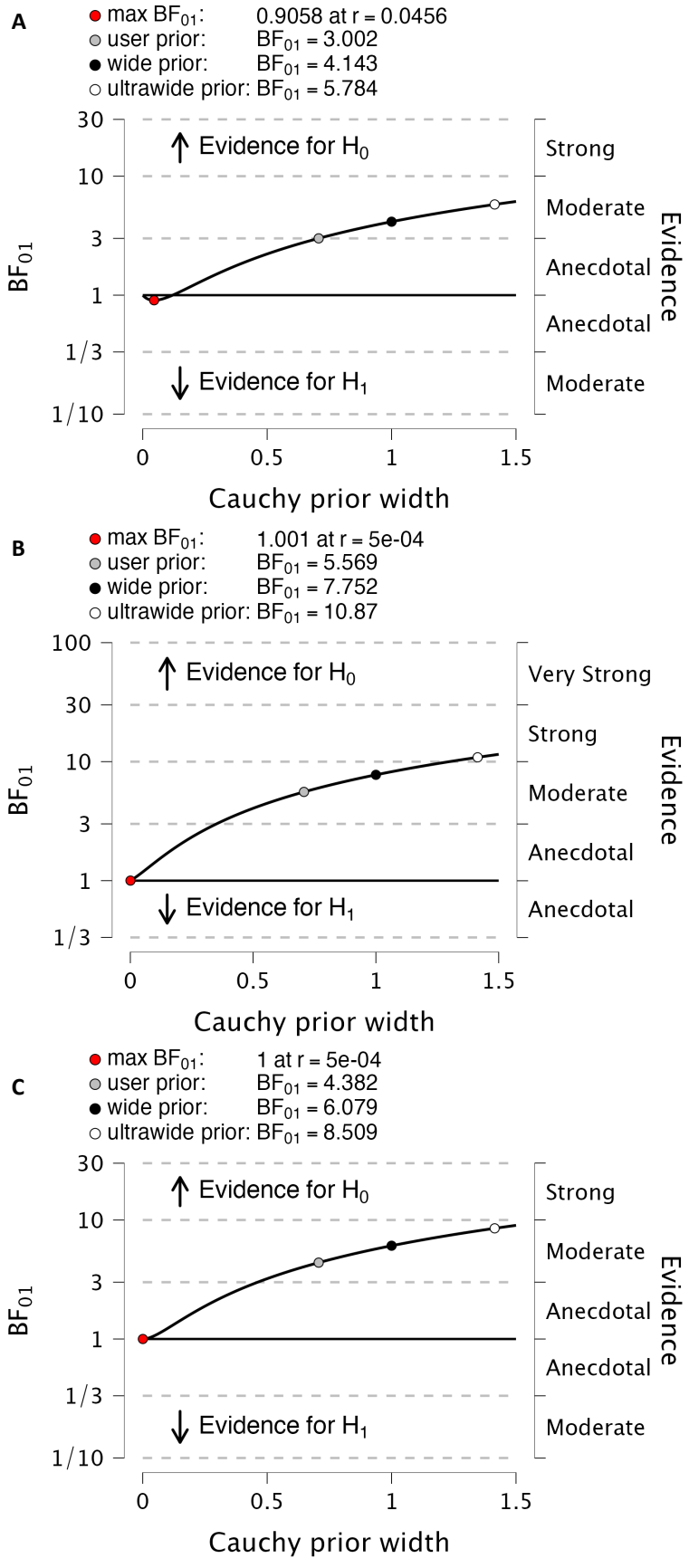

A
max BF01: 0.9058 at r = 0.0456
user prior: BF01 = 3.002
wide prior: BF01 = 4.143
ultrawide prior: BF01 = 5.784
Evidence for H0
Evidence for H1
BF01
30
10
3
1
1/3
1/10
Strong
Moderate
Anecdotal
Anecdotal
Moderate
Evidence
0
0.5
1
1.5
Cauchy prior width
B
max BF01: 1.001 at r = 5e-04
user prior: BF01 = 5.569
wide prior: BF01 = 7.752
ultrawide prior: BF01 = 10.87
Evidence for H0
Evidence for H1
BF01
100
30
10
3
1
1/3
Very Strong
Strong
Moderate
Anecdotal
Anecdotal
Evidence
0
0.5
1
1.5
Cauchy prior width
C
max BF01: 1 at r = 5e-04
user prior: BF01 = 4.382
wide prior: BF01 = 6.079
ultrawide prior: BF01 = 8.509
Evidence for H0
Evidence for H1
BF01
30
10
3
1
1/3
1/10
Strong
Moderate
Anecdotal
Anecdotal
Moderate
Evidence
0
0.5
1
1.5
Cauchy prior width

Figure 5. Robustness checks for Bayes factors for the null effect of semantic/scrambled partitioning on cued trials for (A) location accuracy, (B) Euclidean distance, and (C) Euclidean distance on incorrect trials.

Euclidean Distance. A mixed-effects linear regression revealed that there was a significant interaction between semantic partitioning and cue, Exp 2a: $b = 0.16$, 95% CI [0.13, 0.19], $t = 10.72$, $p < .001$; Exp 2b: $b = 0.18$, 95% CI [0.15, 0.21], $t = 11.91$, $p < .001$. There was a main effect of semantic partitioning, Exp 2a: $b = -0.16$, 95% CI [-0.21, -0.11], $t = 6.00$, $p < .001$; Exp 2b: $b = -0.22$, 95% CI [-0.27, -0.17], $t = 8.70$, $p < .001$. There was also a main effect of cue, Exp 2a: $b = -0.26$, 95% CI [-0.29, -0.23], $t = 17.23$, $p < .001$; Exp 2b: $b = -0.23$, 95% CI [-0.26, -0.20], $t = 15.03$, $p < .001$. For the cued trials, the effect of semantic partitioning on distance was not significant in Exp 2a: $b < 0.01$, 95% CI [-0.04, 0.05], $t = 0.10$, $p = .923$, or Exp 2b: $b = -0.04$, 95% CI [-0.08, 0.00], $t = 1.75$, $p = .080$; for the uncued trials, the effect of semantic partitioning was significant in that the distance between chosen and correct locations was smaller in the semantically partitioned than scrambled condition, Exp 2a: $b = -0.32$, 95% CI [-0.40, -0.24], $t = 7.95$, $p < .001$; Exp 2b: $b = -0.40$, 95% CI [-0.48, -0.32], $t = 9.97$, $p < .001$. Figure 4B shows the effect of semantic partitioning on Euclidean distance for cued and uncued trials. There was no significant main effect of log-search time when it was included in the model as a covariate, and the patterns reported above were unaffected.

We confirmed the significant interaction between semantic partitioning and cue in a combined analysis across Experiments 2a and 2b, $b = 0.17$, 95% CI [0.15, 0.19], $z = 16.19$, $p < .001$. While the effect of semantic partitioning was not significant on cued trials, $b = -0.02$, 95% CI [-0.05, 0.01], $z = 1.12$, $p = .262$, it significantly reduced the distance between chosen and correct locations on uncued trials, $b = -0.36$, 95% CI [-0.42, -0.31], $z = 12.62$, $p < .001$. A

Bayesian *t*-test on the participant mean-level data for the cued trials resulted in a Bayes factor indicating substantial evidence for the null hypothesis, $BF_{01} = 5.57$, error percentage = 0.104. Figure 5B shows the Bayes factor robustness plot demonstrating substantial evidence in favour of the null hypothesis across a range of different plausible prior distributions.

Euclidean Distance (Incorrect Trials). On incorrect trials (see Table 4), a mixed-effects linear regression revealed that there was a significant interaction between semantic partitioning and cue, Exp 2a: $b = 0.20$, 95% CI [0.17, 0.23], $t = 11.37$, $p < .001$; Exp 2b: $b = 0.24$, 95% CI [0.20, 0.27], $t = 13.74$, $p < .001$. There was a main effect of semantic partitioning, Exp 2a: $b = -0.19$, 95% CI [-0.23, -0.14], $t = 8.09$, $p < .001$; Exp 2b: $b = -0.24$, 95% CI [-0.27, -0.21], $t = 13.96$, $p < .001$. There was also a main effect of cue, Exp 2a: $b = -0.34$, 95% CI [-0.37, -0.30], $t = 19.28$, $p < .001$; Exp 2b: $b = -0.30$, 95% CI [-0.33, -0.26], $t = 17.35$, $p < .001$. In the cued condition, the effect of semantic partitioning on distance was not significant, Exp 2a: $b = 0.02$, 95% CI [-0.01, 0.05], $t = 1.17$, $p = .241$[2]; Exp 2b: $b = 0.00$, 95% CI [-0.03, 0.03], $t = 0.07$, $p = .944$, but was significant in the uncued condition, Exp 2a: $b = -0.38$, 95% CI [-0.44, -0.32], $t = 12.60$, $p < .001$; Exp 2b: $b = -0.47$, 95% CI [-0.53, -0.42], $t = 16.03$, $p < .001$, such that the distance was smaller in the semantically partitioned than scrambled condition. When log-search time was included in the model as a covariate, the patterns reported above were unaffected. In Exp 2a, greater log-search times predicted greater distances, $b = 0.09$, 95% CI [0.02, 0.15], $t = 2.52$, $p = .012$; this result was not significant in Exp 2b: $b = 0.04$, 95% CI [-0.03, 0.11], $t = 1.13$, $p = .257$.

[2] This model was singular even with the simplest random effects structure (intercepts for participants), which is equivalent to running a simple linear regression.

We confirmed the significant interaction between semantic partitioning and cue in a combined analysis across Experiments 2a and 2b, $b = 0.22$, 95% CI [0.19, 0.24], $z = 17.62$, $p < .001$. While the effect of semantic partitioning was not significant on cued trials, $b = 0.01$, 95% CI [-0.01, 0.03], $z = 0.80$, $p = .424$, it significantly reduced the distance between chosen and correct locations on uncued trials, $b = -0.43$, 95% CI [-0.47, -0.39], $z = 20.15$, $p < .001$. A Bayesian *t*-test on the participant mean-level data for the cued trials resulted in a Bayes factor indicating substantial evidence for the null hypothesis, $BF_{01} = 4.38$, error percentage = 0.084. Figure 5C shows the Bayes factor robustness plot demonstrating substantial evidence in favour of the null hypothesis across a range of different plausible prior distributions.

Table 4. Number of trials (total, incorrect) by condition in Experiments 1a and 1b.

	Experiment 1a		**Experiment 1b**	
	Semantic	Scrambled	Semantic	Scrambled
Total Trials	2340	2340	2340	2340
Incorrect Trials	1274	1388	1216	1414

Distribution of Euclidean Distances. We examined the Euclidean distance results further by plotting the distribution of distances, broken down by presence of cue (cued vs. uncued) and partitioning (semantic vs. scrambled), as shown in Figure 6. For a baseline, we simulated data that modeled random selection based on whether they were choosing randomly within a quadrant (i.e., from a 3x3 grid) as well as choosing randomly from the whole display (i.e., from a 6x6 grid). In the random simulations, the proportion of correct choices (i.e., a Euclidean distance of 0) corresponded to 1/9 (3x3 grid) and 1/36 (6x6 grid). Visual inspection of Figure 6 suggests that

on uncued trials (right), performance in the semantically partitioned condition was superior to the scrambled condition, whereas this difference was minimal on the cued trials (left).

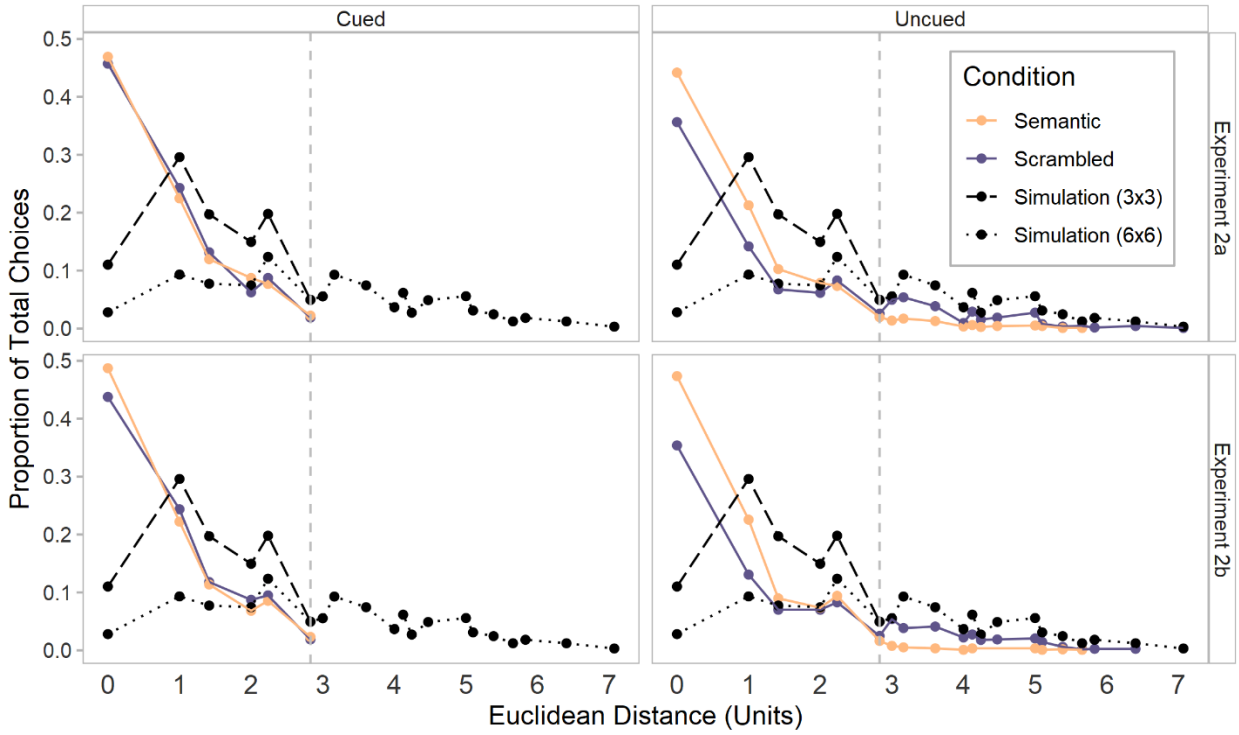


Figure 6. Distribution of Euclidean distances in the cued and uncued trials across semantic and scrambled partitioning for Experiments 2a and 2b. Data points in black reflect simulated results of random guessing with 10,000 replications. Simulation refers to: simulating random selection within a quadrant (3x3 squares); random selection within the whole grid (6x6 squares). Dotted vertical lines denote the maximum distance for choice distances within a 3x3 quadrant.

Distribution of Euclidean Distances (Error Trials Only). Figure 6 shows that participants' performance in both the semantically partitioned and scrambled conditions was superior to random guessing. The proportion of correct choices (i.e., a Euclidean distance of 0) clearly exceeded what would be expected from random guessing within either a 3x3 space or a 6x6 space. In order to compare the distributions of near and far errors without the contribution of

correct choices (as in Solman & Kingstone, 2017a), we also examined the error distance results further by plotting the distribution of the proportion of errors made at each distance (divided by the total errors), broken down by presence of cue (cued vs. uncued) and partitioning (semantic vs. scrambled), as shown in Figure 7A. While Figure 6 shows the average number of choices made at each distance divided by the number of total choices, Figure 7A shows the relative proportion of different errors (nearer or further from the correct location) as the correct choices have been excluded. Visual inspection of Figure 7A shows that, on uncued trials, the distribution of errors made in the scrambled condition tended to have a fatter tail (i.e., more far errors), and more closely resembled the 6x6 random simulation; whereas the distribution of errors made in the semantically partitioned condition was more positively skewed, and more closely resembled the 3x3 (restricted) random simulation. On the other hand, on cued trials there was little difference between the semantic and scrambled distributions.

Near-Misses on Cued Trials. To quantify any differences in the Euclidean distance distributions in Figures 6 and 7, we examined the proportion of "near-misses" made in the cued condition only; this analysis was exploratory in Experiment 2a and pre-registered in Experiment 2b. Near-misses were defined as occurring within one square, either adjacent (1 unit distance) or diagonal (~1.4 unit distance) away from the correct location (as in Solman & Kingstone, 2017a). For each participant, near-miss rate was obtained by dividing the number of near-misses by the total number of errors. A higher near-miss rate therefore represented greater memory precision (i.e., errors that tended to be close to the target location). Semantic partitioning was entered as a fixed predictor into a linear model using generalized estimating equations predicting the near-miss rate in the cued condition. In Experiment 2a, there was a lower near-miss rate in the semantically partitioned condition compared to scrambled, b = -0.04, 95% CI [-0.08, -0.01], t =

5.10, p = .024; this was not significant in Experiment 2b, b = 0.00, 95% CI [-0.04, 0.03], t = 0.08, p = 0.781. Figure 7B shows the effect of semantic partitioning on near and far errors for cued and uncued conditions.

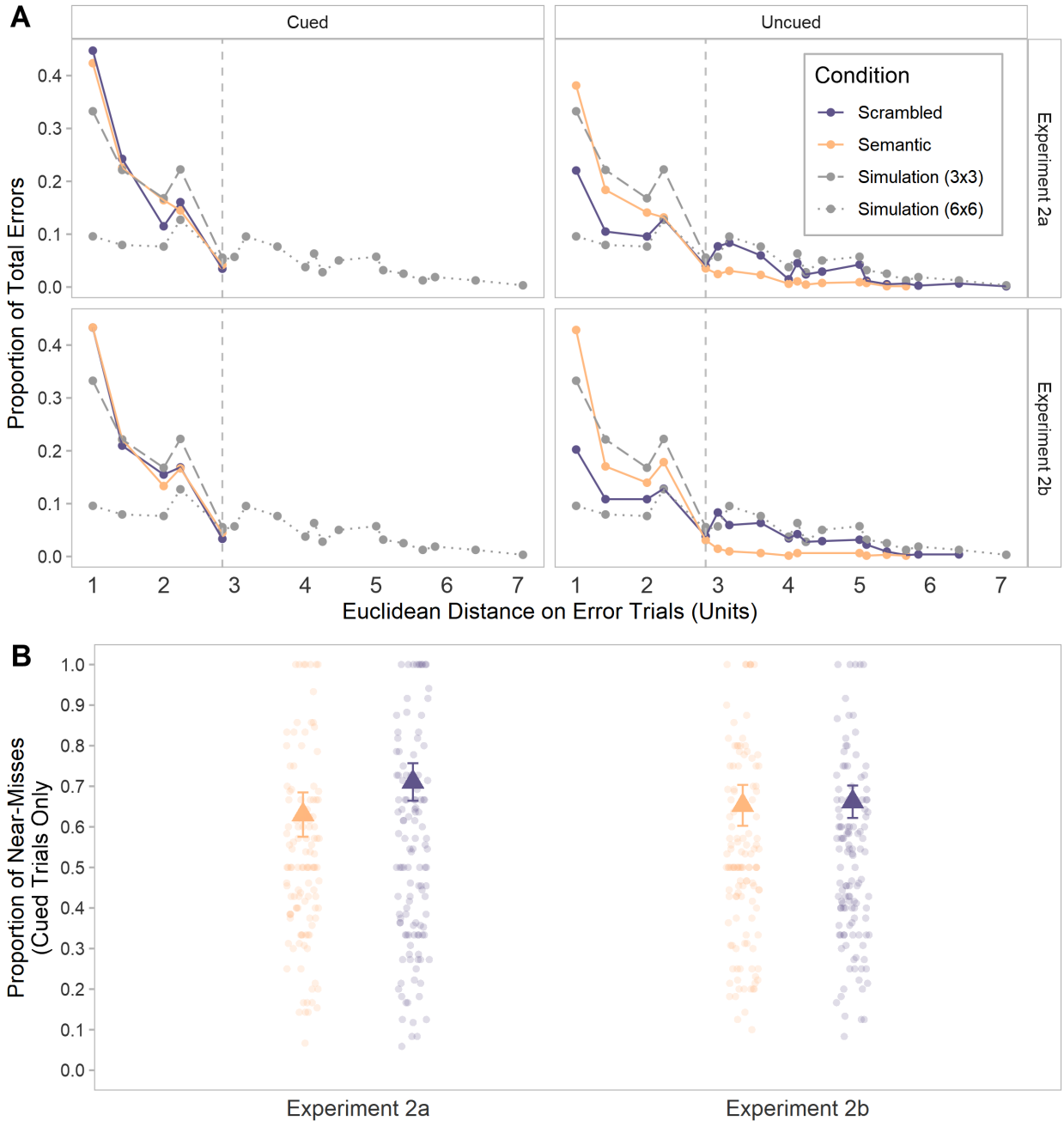


Figure 7. (A) Distribution of error distances in the cued and uncued trials across semantic and scrambled partitioning for Experiments 2a and 2b. Data points in black reflect simulated results of random guessing with 10,000 replications. Simulation refers to: simulating random selection within a quadrant (3x3 squares); random selection within the whole grid (6x6 squares). Dotted vertical lines denote the maximum distance for choice distances within a 3x3 quadrant. (B) Proportion of near-misses made across semantic and scrambled conditions for cued trials only in Experiments 2a and 2b. Circles in the background represent each participant's average performance per condition.

Quadrant-Level Memory

Quadrant Accuracy. Since participants could only select locations within the correct quadrant on cued trials, we examined quadrant accuracy for the uncued trials only. Quadrant accuracy was higher in the semantically partitioned condition compared to scrambled, Exp 2a: $b = 1.09$, 95% CI [0.96, 2.74], $z = 16.45$, $p < .001$; Exp 2b: $b = 2.03$, 95% CI [1.56, 2.50], $z = 8.46$, $p < .001$. There was no significant main effect of log-search time when it was included in the model as a covariate, and the patterns reported above were unaffected.

Quadrant Accuracy for incorrect trials only. Within the uncued trials, we also examined quadrant accuracy for the incorrect trials only. Again, quadrant accuracy was higher in the semantically partitioned condition, Exp 2a: $b = 1.19$, 95% CI [1.04, 1.34], $z = 15.65$, $p < .001$; Exp 2b: $b = 2.07$, 95% CI [1.63, 2.52], $z = 9.15$, $p < .001$. There was no significant main effect of log-search time when it was included in the model as a covariate, and the patterns reported above were unaffected. Figure 4C shows the effect of semantic partitioning on quadrant accuracy for uncued and incorrect trials.

Discussion

The results of Experiments 2a and 2b replicated those in Experiments 1a and 1b: when individuals were presented with uncued trials, they demonstrated greater location memory accuracy in the semantically partitioned condition compared to in the scrambled condition. However, on cued trials when individuals were given a cue indicating the correct partition (quadrant), this semantically partitioned advantage was eliminated or greatly reduced. This pattern of results was confirmed in a series of combined analyses across both experiments. While semantic partitioning was associated with reduced search time in the search task, controlling for search time did not impact any of the recall task results. Altogether, these results strongly suggest that the memorial benefit of semantic partitioning (in a spatial environment composed of multiple partitions that each contain items from a single category) is largely driven by increased partition-level accuracy.

We did not find evidence for the hypothesis that within-partition location memory precision would be lower in the semantically partitioned condition (vs. scrambled). On trials where the correct partition was cued, there was no benefit or cost of semantic partitioning on location accuracy or Euclidean distance. A series of combined analyses across both experiments confirmed the significant interaction and revealed a robust semantic advantage on uncued trials, but no significant semantic advantage on cued trials. To quantify the evidence for the latter result, the obtained Bayes factors were suggestive of moderate evidence for a null effect of condition on the trials where the correct partition was cued. We also examined the distribution of participants' choice distances (Euclidean distance between target location and chosen location) on cued trials (see Figure 6). When we compared the rate of "near-misses" in the semantically partitioned versus scrambled displays (cf. Solman & Kingstone, 2017a), there was little evidence

for reduced memory precision in the semantically partitioned condition. While there was a lower proportion of near-misses (i.e., a higher proportion of misses were far-misses) in the semantically partitioned compared to scrambled condition in Experiment 2a, this difference was not found in Experiment 2b. A combined analyses across both experiments also yielded a non-significant result, which is consistent with the true result being a null rather than a cost or a benefit.

General Discussion

We set out to address three questions with respect to the impact of semantic partitioning (where the partitions serve to group together in space objects from a single category) on performance in a location memory task: (1) whether semantic partitioning benefits overall location memory performance over and above visual partitions; (2) whether semantic partitioning benefits partition-level memory performance, that is, in choosing the correct partitioned space; and (3) whether semantic partitioning benefits (or harms) location memory performance for the items within a categorically defined partition. We address each question below in turn.

Overall Location Memory and Partition-Level Memory

In all experiments, we found that semantic partitioning significantly improved overall location memory performance over a purely visually partitioned display (where each partition contained a scrambled assortment of objects from multiple categories). This was true when measured in terms of both increased memory accuracy as well as shorter distances from the target location. Furthermore, the semantically partitioned display was associated with improved partition memory accuracy (i.e., the ability to choose within the correct partition, even on trials where the exact location chosen was incorrect). Within this multiple-partition context, the

observed improvement in location memory accuracy for semantic partitioning over pure visual partitioning was chiefly driven by an increase in the ability to identify the correct partition, rather than an increased ability to identify the locations of individual items. If semantic partitioning improved memory precision for a given item—that is, an increase in one's ability to discriminate between different items' locations—over and above presenting individuals with scrambled visual partitions, then we would have expected that presenting individuals with a cue to the correct partition would still yield higher location memory accuracy in the semantically partitioned condition. However, when the benefit to partition memory accuracy was accounted for by cueing participants to the correct partition at test in Experiments 2a and 2b, the advantage of semantic partitioning was significantly reduced, with moderate evidence for a null effect on these trials. These results held even after controlling for presentation order effects (see Supplemental Material). Since the cueing manipulation occurred at test, it would appear to preclude an alternative explanation of enhanced encoding of individual items. Instead, our results strongly suggest that much of the benefit associated with semantic partitioning came from the ability to encode and/or retrieve the category-partition association in that display.

One way that category-partition cueing could benefit object location memory accuracy in this manner is via constraining memory search during retrieval (Kimball et al., 2007; Raaijmakers & Shiffrin, 1981). When participants are asked to recall the location corresponding to a given object, knowledge of the correct partition associated with that object's category allows the restriction of memory search for the correct location representation to a given subset of candidates, thereby increasing the likelihood of retrieval. Another way that category-partition cueing can benefit object location memory performance is by simply increasing the probability of making a correct guess (in our experiments, 1/9 vs. 1/36). This is also consistent with the idea

that the semantically partitioned display allowed for a more "restricted" search space and hence more accurate guessing rate. These and other possibilities are unlikely to be mutually exclusive. Nevertheless, any hypothesized mechanisms for the benefit of semantic partitioning must contend with the effect occurring almost exclusively at the partition-level, as we have demonstrated here.

Within-Partition Location Memory

In the Introduction, we considered research suggesting that semantic partitioning might impair location memory performance by increasing interference (and decreasing distinctiveness) between item representations within a partition, as those items would all share common semantic features (Saint-Aubin et al., 2005). We observed limited support for this idea. A combined analysis across Experiments 2a and 2b revealed that while the semantic benefit was indeed eliminated on trials where the correct partition was cued, it did not become a cost. Similarly, in Experiment 2a, when examining trials where the correct partition was cued, we found a decrease in the proportion of near-misses (vs. far-misses) for the semantically partitioned compared to the scrambled condition, suggesting a decrease in memory accuracy (i.e., errors made tended to be further from the target); however, this result was not significant in Experiment 2b, nor in the combined analysis. In sum, while we found evidence that was consistent with semantic partitioning having no benefit to location memory within a partition, there was no strong evidence for a cost. The lack of relatedness cost within-partition is consistent with previous research showing a null effect of semantic relatedness on memory for serial order (e.g., Neale & Tehan, 2007; Neath et al., 2022; Saint-Aubin & Poirier, 1999). We note that a limitation of the current work was that the displays contained discrete locations and not continuous ones, which limited the range of Euclidean distances in the analysis. Future investigations can opt for an

unstructured display that allows for finer investigation of any potential differences in within-partition accuracy.

Visual Partitioning vs. Semantic Partitioning

While previous research has suggested that memory for location/distance is biased by perceptually and semantically delineated categories in a similar manner (Huttenlocher et al., 1991), our results suggest that they might have potentially different effects on location accuracy. That is, when adding visual partition lines to a display, Solman and Kingstone (2017a) found that this increased location memory accuracy, which they hypothesized to be a result of the additional reference points to define the search and retrieval space. However, we found here that semantic partitioning (on top of visual partitioning) did not appear to improve performance with respect to the specific item locations; instead, the benefit associated with semantic partitioning was entirely attributable to an increase in individuals' partition-level memory. An important caveat here is that our semantic partitioning manipulation was in addition to pure visual partitioning; we did not compare visual partitioning to a condition where semantic partitioning existed *without* visual partition lines. Nevertheless, our results do suggest that semantic partitioning had a distinct benefit to location memory that was separate from the effect of visual partitioning found by Solman and Kingstone (2017a). More research is needed to disentangle the effects of semantic and visual partitioning as well as the possible interplay between the two.

Semantic Partitioning and Search Time

An unintended effect of semantic partitioning was on search times in the encoding task. In three of the four experiments, the semantically partitioned condition was associated with shorter search times compared to the scrambled condition. This finding makes intuitive sense as

semantic partitions have the effect of grouping same-category items together, thereby reducing the search space and increasing search efficiency compared to in the scrambled condition. Importantly however, controlling for search time did not impact any of our recall task results, and the main effect of search time tended not to be significant across analyses. On the rare occurrence that the main effect of search time was found to be significant, it was in the opposite direction from what one might expect. That is, rather than longer study times being associated with greater memory performance, the opposite was found—longer study times were sometimes associated with poorer memory performance. While this finding could certainly be spurious, one possibility is that search time is an indication of difficulty. For instance, it could be that some items with longer search times are more difficult for individuals to discriminate within the set that they were presented with. Future research may opt to strictly control encoding times (albeit possibly at the expense of participant engagement and ecological validity).

Location Memory in Real-Life Spaces

Finally, what implications might the current results have for our use of real-life spaces? The scenarios presented here, with items arranged neatly blocked into quadrants, are obviously contrived; nevertheless, they can be considered analogous to a real, compartmentalized space. For example, a house has different types of rooms (kitchen, bedroom, bathroom, garage), and these rooms can each be expected to contain different types of objects. Here we have demonstrated that these semantic/category-based partitions can aid us remembering where objects are located. This benefit arises because semantic/category labels serve as powerful cues for a given partition (e.g., tools—garage). However, this type of partitioning does not increase location memory precision for items within the partition (e.g., recalling that tools are kept in the

garage is unlikely to assist us in pinpointing where a specific tool might be located within that room).

Of course, real-life spaces tend to be much more varied and richly structured than the artificial ones we have presented here. For example, the correspondences between real semantic categories and spatial environments are rarely as clear-cut as they have been presented here. Furthermore, some objects might be considered members of more than one category (e.g., you might find sponges in both the bathroom and the kitchen). Future research could explore whether the category-partition cueing benefit extends to these different kinds of spatial configurations, potentially in more ecologically valid settings. Further, in real-life spaces, we often create further partitions within partitions (e.g., a fridge or a drawer within a kitchen, or a closet and a dresser in a bedroom). Investigating how such higher-ordering partitioning might influence memory for locations would be illuminating beyond the first-order partitioning here.

Conclusion

In our lived environments, we often organize objects in our spaces in systematic ways, such as placing cookware and cutlery in the kitchen, and clothing items in bedroom closets. Here, we have shown that such semantic partitioning of objects in space can indeed benefit location memory performance in addition to any effects of visual partitioning. This benefit appeared to be largely attributable to category-partition cueing, allowing the functional search space at retrieval to be reduced to the items in a given partition. However, this type of semantic partitioning did not improve location memory performance with respect to the items within a partition. Future investigations can consider how different visual- and semantic- based spatial organization schemes might influence memory for location.

Acknowledgements

We would like to acknowledge and thank Ang Gai, Batul Karimjee, and Brinda Patel for their assistance in stimuli preparation, and Hao Zhang for his assistance with the distributions of random guesses.

Funding

This work was supported by a Discovery Grant (#04091) from the Natural Sciences and Engineering Research Council of Canada (NSERC), an Early Researcher Award from the Province of Ontario (#ER14-10-258), funding from the Canada Foundation for Innovation and Ontario Research Fund (#37872) and from the Canada Research Chairs (#950-232147) program to E.F.R, and Alexander Graham Bell Canada Graduate Scholarships from the NSERC to X.L. and M.J.H.Z.

Declarations of interest: None.

Open practices statement: The data and R scripts for these experiments have been made available on a third-party archive (https://osf.io/68d2g/).

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