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The Effect of Experience-Based Prototypes on Spatial Memory

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The Effect of Experience-Based Prototypes on Spatial Memory

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Abstract

The Category Adjustment (CA) model of spatial memory (Huttenlocher, Hedges, & Duncan, 1991) explains how bias towards the centers of spatial categories occurs when recalling locations for target objects. According to the model, this error is the product of Bayesian combination between the rapidly-deteriorating metric information of an object and its longer-lasting categorical information, a process which reduces error variance over time. This adjustment is robust, but previous testing has mainly relied upon remembering simple targets (e.g., dots) in geometric figures. Few studies have addressed whether objects' real-world expectations are incorporated into this paradigm and, if so, how this information is used. In the present study, participants from a major public university completed a dot-localization task in an ecologically-valid "table" setting. Targets were pictures of everyday objects one might expect in one of two spatial regions: in the center of a table and towards the edge of a table (e.g., a candle or a cup, respectively). I expected participants' responses would rely on and bias towards long-term prototypes as opposed to the default. On average, responses biased away from the center, with Central objects exhibiting greater magnitudes of bias. A significant portion of responses were replaced on or beyond the default prototype, suggesting participants used their imagined positions as landmarks. Differences between groups suggest possible ways in which long-term prototypes are used. The data will help us understand the contribution of experience-based, long-term prototypical locations for real-world objects in the combinatory processes of spatial memory.

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Introduction

Accurately remembering the locations of objects is essential for behaviors ranging from finding food to remembering where you left your car keys. Huttenlocher, Hedges, and Duncan's (1991) Category Adjustment model proposes that people represent object locations at two levels of detail: metric (the object's exact location in space) and categorical information (the general space in which the object was seen). Huttenlocher et al. proposed that a Bayesian combination of these sources is responsible for bias towards an angular prototype located at the 45° lines (a geometric prototype) and a radial prototype located at approximately two-thirds the distance from the center of the space to its circumference. According to Huttenlocher et al. (1991), using these prototypes maximizes overall accuracy and minimizes variance over time. The estimates follow Bayesian principles, and the relative weights of these sources of information vary depending on the degree of metric uncertainty of each representation.

This model is quite influential, but the majority of its empirical data derives from spatial memory tasks for targets with little to no semantic information (e.g. with dots-in-circles instead of real-world objects). Studies like those by Sampaio and Cardwell (2012) and Friedman, Montello, and Burte (2012) demonstrated exceptions when using targets with semantic information within larger geographic spaces, including fountains within a university plaza or when using cities within a state, respectively. This is important because as people interact with the world, they form expectations about the locations of real-world objects based on the object's surrounding environment (Brewer & Treyens, 1981; Hollingworth, 2005; Palmer, 1975) and the object's function within that space (Castelhano & Witherspoon, 2016). As a result, people develop prototypical locations for objects based on their experience (e.g., that candles go in the center of a table as opposed to the edge). These experience-based associations ought to establish a spatial prototype that would inform a small range of locations with high reliability.

My goal is to understand what contributions this long-term spatial prototype information makes towards improving the accuracy and reliability of memory in complex real-world spaces, beginning with understanding how it is integrated alongside the geometric prototypes in the dot-in-circle task. I hypothesize that individuals will implement experience-based prototypical locations when estimating the locations of targets representing real-world objects from memory, either relying upon them exclusively or using them in conjunction with geometric prototypes. Improving our understanding of the relationship between objects and their probabilistic placements in the environment will improve our ability to reliably and confidently predict and measure our memory in more applicable settings.

The Category Adjustment Model

Huttenlocher et al.'s (1991) Category Adjustment model provides an explanation for a prevalent bias in spatial memory. The model accounts for the bias by proposing that estimates are biased due to a combination of short-term, rapidly-deteriorating metric information and longer-term, spatial-categorical information. The model is based on Bayesian principles, where sources of information are weighed against one another concerning their reliability and their utility. Sources of information unsuitable for determining where an object was are overshadowed by sources that are more suitable, which are more heavily weighted. The final product is considered the most optimal synthesis of available information. Target locations shown within a circular space exhibit bias towards the center of the quadrant in which the target had appeared (the *prototypical point)* upon recall, implying that people divide the space into four quadrants and encode the target as belonging to that region. This limits long-term variability by utilizing the averaged position of the distribution available in the category (Huttenlocher, Hedges, & Duncan, 1991; Huttenlocher, Hedges, & Vevea, 2000).

A key premise of this model is that information about the spatial category, called the *prior*, is stronger during recall than the metric information of objects within its bounds. Individuals are thought to segment circular spaces into equal quadrants, creating spatial categories that aid in location estimation (the priors). A distribution of possible locations is taken into account with the averaged response lying on the 45° angular value and towards a two-thirds radial value between the center and the edges of the quadrant (the *default geometric prototype*; Huttenlocher, Hedges, & Vevea, 2000). As targets are unlikely to be found on the outlying edges of the quadrant, responses adjust towards the center to maintain reliability over time. This leads to a systematic bias. These default geometric categories have been described as “immutable” when remembering an object’s location in the circular space (Huttenlocher et al., 2004) as well as within simple shapes including triangles, ellipses, and pentagons (Wedell, Fitting, & Allen, 2007). Default prototypes are used even when stimuli presentation imply an alternative categorization scheme—such as one bounded at the diagonals (Huttenlocher, Hedges, Corrigan, & Crawford, 2004)—or when explicit alternative categories were presented during retrieval (Sampaio & Wang, 2010).

Huttenlocher et al. view these prototypical values as Bayesian priors, the pre-existing statistical likelihood of a target’s location before other evidence is considered. For example, if asked the question “Is it raining in Seattle?”, pre-existing knowledge regarding the temperature, climate, and meteorological history of the Pacific Northwest would be incorporated into your answer before being shown a weather report for that day. Similarly, during category adjustment, the prior knowledge of the geometric prototype is weighed against the remaining exact metric information (typically called a “metric trace”). Metric information and the geometric prototype are then combined to reach a compromise between the two sources.

One criticism of using Bayes' definition for priors in the standard dot-in-circle task is that the priors are unlike those used in other domains. Targets in this literature typically lack semantic information or identifying details. As a result, adjustments are made towards a geometric prototype, located at a category's center, as it provides the most reliable resource for estimation. However, these geometric prototypes are not "true" prior probabilities as they do not stem from experience beyond the testing environment.

This may not be the case with real-world objects: computational models like the Differential-Weighting Model (Eckstein, Drescher, & Shimozaki, 2006) and studies like that conducted by Hemmer and Steyvers (2009) demonstrate that we utilize pre-existing expectations about a target, including location, to help clarify an otherwise "noisy" metric trace. For instance, Eckstein and colleagues (2006) found that when people searched for a target "chimney" in a scene containing a house, the target was found faster and more accurately when it was in its expected position. When the target was not present, people still utilized the expected location as a resource and paid attention to where such an object should go. In this case, even before the presentation of a space, a target's identity provides information regarding an expected prototypical value. Using this information during recall would be an example of using a "true" prior.

Knowledge about a target's expected location varies depending on the degree of familiarity one has with the target object. Therefore, we could classify it as an *experience-based prototype*. I expect that familiar items in a common setting (e.g., a dining-room table with lamps, cups, vases, etc.) have these specific priors in memory that serve to inform an object's probable location. For this experiment, a "table" setting will be used, with target objects being ones typically found upon that table. This tends to be a space which undergoes segmentation between a *central* space and a *distal* space, wherein certain objects are typical of one region and not the other (e.g. you wouldn't typically find a candle on the edge of a table but would expect it to be in the middle of the table). If people use these prototypes to help inform memory, this might provide an additional resource that is compared against geometric-categorical information during Bayesian combination.

Friedman, Montello, and Burte's (2012) study underscores the complex relationship between these sources of information. They tested students from an Albertan and a Californian university regarding the locations of real-world cities within their respective regions. When given only the names of cities within an identified space (*names-only*) and asked to click where they thought that city belonged, responses erred towards the center of the region. However, when presented with the true location (*dots-only)* and with both the true location and the name of the city (*dots-and-names)*, responses moved away from the central prototype to a small but significant degree.

They note that their findings "represent the first time that estimates from perception alone (i.e., dots-only) have exhibited this behavior" (pg. 1350). The anomalous results of their dot-and-name condition are also curious; had geometric (i.e. default) and long-term information been combined in a Bayesian fashion, a bias towards a midpoint between the two sources would be expected. To explain their findings, they proposed that personal experience and knowledge regarding the target cities (e.g., climate, geography, and proximity to neighboring cities) could help in the creation and use of regions in the space associated with the target city. These regions could be very specific, personalized regions instead of Cartesian quadrants, and could provide additional resources alongside geometric information. Additionally, the relative difficulty of their task could factor into prototype use: cities-in-regions present a greater challenge than dots-in-circles, and alternative information could be used to help refine responses. Finally, citing work by Uttal, Friedman, Hand, and Warren (2010), they propose that other contextual information and a long history of personal experience could play a role in how people create and use prototypes within specific contexts.

I will focus on how this information may be used in accordance with Huttenlocher et al.'s original framework: as one contributing source to be weighed against default geometric prototypes to help inform memory. To account for the above concerns, the present study will adapt Huttenlocher et al.'s (1991) paradigm using a simple, familiar setting with representations of everyday objects. A circular testing space will be used, with targets being pictures of familiar objects.

Experience-Based Prototypes

In a separate literature, there is a wealth of knowledge regarding how people create and maintain categories for objects in the real world. The way in which these experience-based categories are used may also apply to spatial prototypes in Huttenlocher et al.'s dot-in-circle paradigm.

Hollingworth (2005) conducted an object-replacement task using pictures of everyday objects and familiar spaces (e.g., replacing a barbell in a gym setting). His goal was to ascertain the impact that scene context had on memory and how a target's identity could guide accurate replacement. Three conditions were identified: one where a target object was present in the scene (*target present preview)*, one where the target was absent (*target absent preview*), and one where no scene or target were presented (*no preview*). Participants saw a picture of a detailed virtual environment with a target object (present or absent, depending on condition). Those in the *no preview* condition did not see such an environment. After a delay, participants were shown the identity of the target. Participants clicked on the position where they had either seen the object (*target-present*) or where such a target would be in the scene (*target-absent/no preview* conditions). Participants with no knowledge of the target object were only slightly less accurate than those who had seen both the location and identity of the target. His results indicate that experience-based information could be used both in the absence of clear physical boundaries and in complex environments, even when no physical prior distributions were enforced by the researchers.

Other real-world tasks like Brewer and Treyens' (1981) famous study have shown experience in real-world environments plays a role in how people remember or expect an object's position in space. In their case, participants' schemas for what belonged in a "graduate student" office aided in their ability to remember objects typical of that environment but hindered their ability to remember atypical objects like a skull, picnic basket, or bottle of wine. Participants were even found to remember the presence of objects which were not there, including textbooks. These long-term prototypes for what objects belonged in the space and their expected locations are a good example of employing priors from long-term memory to aid in estimation.

Typical dot-in-circle tasks use enclosed geometric shapes devoid of detail, color, or identifying characteristics, wherein geometric regions are implemented to organize the space into disparate quadrants (Crawford & Jones, 2007); the priors are located at the center of the quadrant. This does not necessarily mean those prior distributions are inherent in the space. The default prototypical value of the quadrant used is not pre-existent, but instead a malleable value which can be altered depending on the information presented (in this case, where the geometric boundaries are imposed; Huttenlocher et al., 2004). Sampaio and Wang (2010) and Crawford and

Jones (2011) provide examples using dot-in-circle tasks with colored shapes as targets as opposed to black dots. Their aims were to better understand how the presentation of alternative classification schemas (color, shape, membership, etc.) impacted the types of information utilized when making estimates from memory. Objects were presented for a brief period in a circular space, then removed from view. Participants then clicked or moved objects to the location where they had been seen. Non-default prototype use (towards prototypes at 45°, 135°, 225°, and 315°) was found when there was a clear associative relationship between the objects shown and the quadrants available to participants, both when the boundaries were explicitly marked (Sampaio & Wang, 2010) and when they had to be inferred through exposure (when multiple objects were to be remembered simultaneously; Crawford & Jones, 2007, 2011). In short, when reliable alternative categorization schemes are made available, they may be used in lieu of default prototypes under proper conditions.

Castelhano and Witherspoon (2016) found similar trends using visual-searching tasks. Ambiguous, 3D objects were shown in a realistic household scene. Objects were either presented in a neutral form (having no identity or function) or imbued with an identity conducive to its placement in the scene (e.g., a "soap-dispensing" object placed beside a sink in a kitchen). They found that participants found objects faster and more accurately when target objects were imbued with a purpose congruent with their position in the scene and when they were located in that position in space. Object identity was a determining factor in where an object belonged in a space, with objects being located faster when they were located in the ideal position for objects of that group. This view is dependent on both an understanding of the context of the scene (e.g., that tables are where vases are typically placed) and the object being remembered (e.g., that a target object is classified as a vase) (Hollingworth, 2005; Palmer, 1975).

As people interact with the world, they develop expectations for where objects should go in a scene (Brewer & Treyens, 1981; Carlson-Radvansky, Covey, & Lattanzi, 1999; Hirtle & Mascolo, 1986; Hollingworth, 2005). Objects whose use is congruent with their placement in the scene are more easily found and remembered (Castelhano & Witherspoon, 2016; Eckstein, Drescher, & Shimozaki, 2006; Oliva & Torralba, 2007; Palmer, 1975), especially when people are exceedingly familiar with those objects in that environment (Brockmole, Hambrick, Windisch, & Henderson, 2008). I expect that, as people consistently encounter objects in specific locations in real-world spaces, information denoting not only what an object is, but *where it should be*, is encoded. People may create prototypical locations for an object based on the degree of typicality for that object in that position.

For example, if one always sees a vase in the center of the table, they should be more likely to replace that vase in the center of future tables than on the edges of those tables. In this instance, the typicality of having the vase in the center of the table would be relatively high. A distal placement for the vase would be highly atypical, as vases are not typically found on the edges of a table. This changes for an object like a glass of wine, which would typically be placed within reach (i.e., towards the edge of the table) and not in the center of the table. This interaction would depend not only on a target's identity and utility in the surrounding space, but successful experience one has with that object in that specific place. Without these, no valid long-term priors would be available for later use.

The following experiment explored whether this kind of association is used. A common table setting was used, with targets being everyday objects one would typically find on that table. In this particular environment, there tends to be clear delineation between objects you would commonly find in the center and towards the edge of the table. Because of this, I focused on radial bias between these two prototypes, or the degree of error along the continuum between the center and the circumference of the space. Adjustment towards alternative categories (to the center or the edge of the space) would denote the use of long-term experience-based prior use as opposed to the default geometric prototype (towards the two-thirds radial position).

Present Study and Predictions

The inclusion of a second categorical influence in this Bayesian process means the combinatory mechanism behind this bias might differ from past experiments using the dot-in-circle task. As categorical influences become more discrepant, one source is typically selected over the other to use during combination. In contrast, sources similar in reliability and utility can be combined into a single estimate (Cheng, Shettleworth, Huttenlocher, & Rieser, 2007). If the experience-based and default geometric prototypes are being combined, we might expect a response to err towards a point between the geometric and experience-based prototypes. In contrast, if experience-based information is lacking or is not being used, its Bayesian weight would be relatively low leading to a default adjustment.

Participants were shown real-world photographs of household objects in a blank circular space. Each object was a member of a pair and possessed one of two identities: one where the expected location for that object is the middle of the table (e.g., *cake*, *basket,* or *vase*), or one where the expected location is toward the outside edge of the table (e.g., *cup*, *napkin*, or *plate*). Both objects in each pair were shown in the same location. A photograph of the object was displayed briefly on the computer screen, then removed from view. Participants clicked on the location where the object was seen. Comparing differences in replacement between shapes (distal vs. central) on the table will allow us to understand whether and how experience-based prototypes are used in estimating locations.

I predicted that if experience-based spatial prototypes are exclusively used in estimates, then placements from memory would be biased towards the middle (for Central objects) or towards the edges of the space (for Distal objects). If this information was combined with default geometric prototypes—robust in dot-in-circle tasks—then estimates would be biased between the two prototypes (with the specific location reflecting the weight of each prototype). If experience-based prototypes were not used, then estimates would be biased towards the default geometric prototype regardless of shape's identity.

Method

Participants

35 undergraduate participants (60% Female) were recruited on a voluntary basis from the Western Washington University student population to participate in a 30-minute experiment. Participants received course credit for their participation.

Materials

The *E-Prime* experimental suite was used to create a dot-localization task in a blank, two-dimensional space. 40 pairs of objects were established by the experimenter, with each pair containing one Distal object and one Central object for a total of 80 objects. Images were selected from the Bank of Standardized Stimuli (Brodeur, Dionne-Dostie, Montreuil, & Lepage, 2010), the Amsterdam Library of Object Images (Geusebroek, Burghouts, & Smeulders, 2005), and from the Massive Memory database (Brady, Konkle, Alvarez, & Oliva, 2008). Selected objects were those one would typically find in a household "table" setting and were accompanied by a real-world picture of the object.

The intention was to have each target position determined based on a norming study. In the norming study, a separate group of participants were shown pictures of everyday objects and asked where they believed the objects should be placed within the table. The range for target placement in the experiment was intended to be determined by the upper (Central) and lower (Distal) *prototypical* responses provided by these participants (i.e., the highest and lowest positions where they thought objects *should* go). These values were averaged to create initial target locations for a pilot study. A random-number generation equation was intended to be used to then select initial Y-values for each pair of objects within this range. However, the researcher used the averaged recalled midpoint positions from the pilot study instead of the original norming study bounds. The error resulted in a lower and more restrictive range of possible locations. This means that the target positions were lower than intended and did not encompass all radial positions in the bottom hemisphere of the space.

The environment was presented on 22” Dell UltraSharp 2208WFP monitors seated approximately 18 inches from the participants. Screens were cleaned regularly to ensure dust, debris, and other residue did not influence responses. See Figure 1 for an example of the testing environment presented to participants.

To prevent objects in the same pair from being presented sequentially, two lists containing 40 targets each were used. List A contained one type of object from each pair (e.g., the Distal object from Pair 1, the Central object from Pair 2, etc.) and was presented randomly without replacement. List B contained the other object of the pair (e.g., the Central object from Pair 1, the Distal object from Pair 2, etc.). List A was presented first, with objects presented in a random order for each participant. List B was then presented, again with objects randomly presented.

Procedure

Pilot. A pilot was conducted beforehand to establish experience-based prototypes as a reference for the experiment. 34 participants were given a written briefing followed by a written and verbal instructional period. Additional instructions were presented in the *E-Prime* program. Participants were presented with a circular space labeled as a “table”. The interior of this space was white and its boundaries were black. Participants were randomly presented with an object belonging to one set of objects. For example, they were told what the shape represents (e.g., “This object is a cup”), followed by instructions to “click on the location where the cup belongs on the table”. Once the object had been placed, the screen went blank and another object was presented at random. Each object was presented once before being removed from the pool (20 trials per individual). Once all objects had been presented, participants were debriefed and the session concluded.

Experiment. The experiment followed a dot-localization procedure similar to ones used in the Category Adjustment literature. Prior to testing, participants submitted written consent. Participants were given verbal instructions regarding their task. These instructions were repeated upon beginning the program. Participants were given as much time as needed to become familiar with the instructions before beginning. Real-world pictures of the target were displayed for a period of 4000 ms below a prompt naming the object. This prompt and the object were then removed from view. The blank circular space appeared for a period of 1000 ms. Targets were presented briefly on the bottom half of the space for a period of 500 ms. The space was masked with an image of visual noise (TV static) for 2500 ms. Participants were then shown the blank circular space. Participants clicked on the location where they saw the center of the object. Once participants made their response, the target and the space disappeared. A black screen was displayed for a period of 2500 ms, after which the process repeated until all objects had been displayed. A brief resting period was granted between the two blocks of objects (after 40 trials) to prevent fatigue.

Once completed with the experiment, participants completed a short survey with questions regarding their experiences with the objects presented. The images of the real-world objects used in the study were displayed. Participants were asked whether they believed the objects they had seen had a prototypical location on the table (*Yes, towards the edges; Yes, towards the center;* or *No*). Two 5-point Likert scales followed. The first asked participants "How familiar are you with this object?" with possible responses ranging from 1 (*Not at all Familiar)* to 5 (*Extremely Familiar*). The second asked "During the average week, how often do you interact with this object?” with possible responses ranging from 1 (*Never*) to 5 (*Every day*). These questions were repeated for each type of object presented. Upon completion, participants received a written debriefing and were thanked for their participation.

Data Analysis

Targets were displayed directly on the North-South axis. A target’s position in the scene was calculated by measuring the Euclidean distance between the target and the center of the space. Bias was calculated by subtracting each target’s initial Euclidean distance from its corresponding response distance. Negative values correspond to adjustment towards the center. Positive difference values would indicate an adjustment towards the edges of the space (towards the distal prototype), but not necessarily towards the bottom of the screen. These distances reflect movement along the dimension ranging from the center to the outside edges of the space. Replacements made on either side of the midline may still be categorized as “further” or “closer” from the center as long as the distance between the estimate and the center is greater than or less than it was during initial presentation, respectively. Responses beyond 2 SD from the mean bias were excluded from analysis to help eliminate the possible effects of outliers.

Differences between Distal and Central responses would indicate that participants are using different prototypes depending on the identity of the object. If alternative prototypes are used exclusively, there should be a larger degree of bias towards experience-based prototypes. This would be indicated by large negative difference values for Central objects and large positive difference values for Distal objects. If alternative prototypes are being combined with the geometric prototype, then we might expect this combination to result in bias towards a point between each object’s corresponding alternative prototype and the default radial value. If alternative prototypes are not being used, then targets should be replaced towards the two-thirds default radial value regardless of identity.

Results and Discussion

It should be reiterated that the targets only appeared within a limited range at the bottom of the circle. The range used in this study was between Y=756 to Y=836 rather than Y=665 to Y=836. As a result, target placement for the experiment was much more restricted and lower than intended.

Participants' responses take the form of a Cartesian coordinate, with the origin (at 840,525) located in the exact middle of the circle. Positive degrees of bias indicate adjustment towards the edges of the space, while negative bias indicates adjustment towards the center. All participants followed instructions, resulting in zero omitted participants. Because all objects were presented in the bottom-hemisphere of the space, responses made above the X-axis were determined to be the result of guessing. These responses were eliminated from the study (.001% of data). Additionally, responses beyond 2 SD from the mean response bias were omitted (4.4% of remaining data). Responses were then aggregated into two mean scores for each participant, one for each object type. Reported numbers are rounded to two significant figures. A full graph showing participants' responses is presented in Figure 2. On average, responses were made within 23.75 pixels of their initial position (SD = 15.40), equivalent to 6.28 mm.

A paired-samples t-test looked at whether there was a significant difference in directionality between Central and Distal objects for each subject, which would indicate possible use of long-term alternative prototypes. This t-test showed that there was significant positive bias for both Central (M =18.77, SD= 12.30) and Distal objects (M= 14.43, SD= 11.44), $t(34) = 6.10$, $p < .001$. Overall bias was significantly different from zero, $t(34) = 8.41$, $p < .001$. Splitting by object type, bias was significantly different from zero for Central objects, $t(34) = 9.03$, $p < .001$; and Distal objects, $t(34) = 7.46$, $p < .001$. The large positive difference values for Central objects indicate that prototypes were not combined during estimation, as combination would predict adjustment between the proposed alternative and default radial values, resulting in patterns of slightly negative bias.

Comparing the trends between the pilot and this experiment affords the opportunity to better understand the impact geometry has on incorporating long-term expectations into this paradigm. Therefore, the aforementioned analyses were replicated using the pilot data with responses collected from 34 undergraduate students (23 Female). Results beyond 2 SD mean response bias were excluded (5.88% of data). Participants' responses were then aggregated to acquire a mean value for Central and Distal objects. Values have been rounded to 2 significant figures.

A paired-samples t-test was used to determine whether there were significant differences in direction between Central and Distal objects for participants in the Pilot study. The test was one-tailed, as we expected different degrees of bias depending on the objects' type. Differences in direction would indicate that participants were using long-term alternative prototypes instead of the default prototype, which would predict uniform positive biases for all objects. Significant differences existed between bias for Central (M = 9.32, SD = 17.90) and Distal (M = 11.64, SD = 16.44) objects, $t(33) = 1.77$, $p < .05$. Splitting by object type, one-sample t-tests showed that Central objects, $t(33) = 3.04$, $p = .005$; and Distal objects, $t(33) = 4.13$, $p < .001$, were both significantly different from zero. These results indicate that alternative long-term prototypes were not relied upon during replacement, as there was no significant difference in direction between object types.

These results indicate that pre-existing expectations regarding object position are not influencing bias in the same manner as the geometric influences detailed by Huttenlocher et al. The geometry of the space still heavily influences accuracy despite pre-existing expectations; responses were still biased away from the center regardless of object type, contrary to my predictions. Future studies should manipulate individual aspects of the current design to better understand the individual impact of specific variables, such as relative object size, shape, and the availability of affordances present when working with real-world objects.

My primary hypothesis that objects would err in the direction of their experience-based prototypes was not supported. Instead, results are similar to those found by past category adjustment literature, with objects erring in the direction of default geometric prototypes. Comparing the pilot data to the data gathered for the experiment proper, we see a similar trend: participants erred towards the outside edges of the space regardless of object type. However, we see two different patterns stemming primarily from the differences between initial target range. Bias for Distal objects was significantly greater in the pilot, but bias for Central objects was significantly greater in the current experiment. I strongly suspect the lower initial target placement as the factor responsible for this difference. However, another explanation for this trend could be that long-term information is not implemented in the form of a fixed, global location as predicted. Instead, it could play a role in how people attend to objects incongruous with their position in the scene.

Studies exploring *frame theory* (Minsky, 1975) have shown that we make sense of our environment by understanding how specific objects fit within surrounding spaces. This processing is relatively automatic, with familiar objects being recognized faster than novel ones (Friedman, 1979). Explorations into the idea of *novel pop-out*, or NPO (Johnston, Hawley, &

Farnham, 1993; Johnston, Hawley, Plewe, Elliott, & DeWitt, 1990), have shown people pay more attention to objects or occurrences which "stand out" in their surrounding environment (e.g. a vacuum cleaner atop a coffee table as opposed to on the floor beside it). This idea was tested in recent Category Adjustment literature in the field of facial recognition, which found attenuated (albeit insignificant) bias for eyes viewed as extreme distances from the prototypical "eye" location (Adams, 2013).

A similar trend could explain the present results and provide an explanation as to why two different patterns of bias were found. For example, a Distal object (bowl of cereal) could be considered more appropriate when seen towards the edges than its Central counterpart (a candle), which would be found in the center. If the expected position of the object and its initial position are consistent, the initial reliability of the placement could be considered greater, leading to less reliance on the default; if the object is generally where it should be, then the need to rely on default information would be lower as it is within its expected range. If that object is out-of-place upon initial presentation, any pre-existing expectations could be rendered unreliable, thereby increasing reliance on the metric position. However, as metric information decays almost immediately after presentation, responses would err towards a default for lack of reliable alternatives. This may explain why schema-inconsistent objects erred more than schema-consistent objects.

Ultimately, I believe that the trends in our data can be explained as a combination of two factors: long-term information being applied to determine the validity of a target's initial placement, and the Bayesian combination between long-term and default information. Bias in the direction of the default radial category was found across objects and between the pilot and the experiment. However, it seems the degree of bias was mediated by whether or not the object displayed was presented in a space consistent with the object's identity. I expect that people are applying their knowledge of where the object should go during initial presentation to support the validity of the metric information they have for where an object was, thereby informing them as to an expected long-term prototype alongside the default information already inherent in the space.

When objects break this assumption by being seen in a schema-inconsistent region upon initial presentation (e.g. the lower Central objects in the experiment and the higher Distal objects in the pilot), the long-term prototypical information is weakened. This, combined with the deteriorating metric accuracy, leads to the use of the default. When the expectation is upheld, the long-term information maintains its validity, informing participants that the initial location is indeed reliable as it conforms to long-term expectations. This leads to smaller combination between the two prototypes and an overall reduction in bias. Whether or not the metric information of schema-consistent objects is maintained better than schema-inconsistent information cannot be ascertained with the present data. I would expect, however, that deterioration of this information is attenuated when the surrounding range of long-term values is congruent with the object's identity.

Evidence from the survey data lends some credit to the idea that pre-existing expectations, familiarity, and increased interaction play a role in bias. Differences in bias between the levels of each variable was explored with a one-way ANOVA and a Tukey's post-hoc follow-up test. When asked about their expectations for where targets should go within the experimental space, participants' results indicate that objects which were expected to be "towards the edges' (M = 14.58, SD = 19.34) erred significantly less than objects expected "towards the center" (M = 17.55, SD = 21.13), $F(2, 78) = 6.06$, $p = .002$. When reporting their history of Interaction with the targets, participants who “never” (M = 17.17, SD = 21.12) or “almost never” (M = 17.80, SD = 20.88) used a target during an average week exhibited significantly more bias on average than those who used a target “every day” (M = 13.35, SD = 19.41), $F(4,78) = 3.25$, $p = .011$. See Figure 3 for more details. Similarly, bias was significantly greater for “not at all familiar” objects (M = 21.32, SD = 22.10) compared to “extremely familiar” objects (M = 15.02, SD = 19.58), $F(4,78) = 3.76$, $p = .005$. Although we still see error away from the center for all objects, participants’ responses became less varied as Familiarity increased (See Figure 4).

It could be that people relied upon their imagined positions as a landmark in the experiment, and that bias is reflective of people’s adjustments towards themselves instead of the default. The data indicate that when objects were presented at a lower position on the screen during the experiment, the degree of error was higher than when presented during the pilot. The two-thirds radial prototype was at Y=837, which is 312 pixels away from the center of the space. In the experiment, approximately 26% of participants’ responses were at or beyond this value, meaning they replaced the object beyond the default prototype. This is contrary to previous findings which shows bias approaching, but not exceeding, this value. Previous work has demonstrated the impact of local and distal landmarks on memory for location (Li & Gleitman, 2002; Wang & Spelke, 2000) as well as the influence of initial learning angles and frames of reference (Rump & McNamara, 2013; Jiang & Swallow, 2013; Sargent, Dopkins, & Philbeck, 2011). Experimentally manipulating learned and imagined reference angles within this paradigm could explore if people are using landmarks outside the space to help understand distance. We could find that when people are asked to recall the position of a presented object after the environment has been rotated, their responses show bias towards themselves as opposed to the intrinsic quadrants of the space.

Relative object size may also influence how people report where objects were in a space, with variability in response accuracy increasing as objects become larger. For instance, a roast turkey dinner necessitates a larger relative size compared to a dinner plate, as the former is intended for multiple people while the latter is for the individual. A larger size could lead to increased metric uncertainty regarding the centers of objects, thereby increasing bias in memory. To address whether this had an impact, I performed a linear regression looking at the impact of objects' dimensions (Height, Width, and Total Area) on mean bias for each object. I expected that as an object increased in size along the Height and Total Area dimensions, we could expect greater degrees of radial bias, whereas Width would not predict radial bias. The adjusted R^2 value for the three dimensions showed that those dimensions predicted 54.5% of the variance. Closer examination at the individual coefficients highlighted that only object height was significantly different from zero, $t(76) = 4.98$, $p < .001$, and that it predicted a .164 pixel increase in radial bias for every pixel an object increases in height. We cannot determine whether this difference is due to the memory itself becoming distorted or merely a by-product of the test itself, although I highly suspect the latter. Further exploration is necessary and encouraged.

As a goal of this study is to better understand environmental influences on spatial memory and replicate real-world human behavior, expansion into virtual reality or with actual objects is encouraged. Objects' affordances (e.g. if they can be grasped, clasped, eaten, etc.) could play a role in how people remember their positions. It may be that objects which undergo or have undergone more physical manipulation in the past are remembered more accurately in memory. Work surrounding the *two-stream hypothesis* has shown that humans are especially attuned to changes in object orientation and identity (Goodale & Milner, 1992; Valyear, Culham, Sharif, Westwood, & Goodale, 2006), factors which are typically not-present using dots-in-circles. Additional work has even shown that rapid-reaching tasks can employ probabilistic interpretations of space to maximize accuracy when predicting the location an object found in that space (Chapman, et al., 2010). In future work, studies should focus on understanding this relationship: To what extent does physical manipulation and action influence memory? Would the long-term "true" priors suggested in this paper come to light when interacting with actual objects?

This study cannot definitively state that long-term, global prototypes are applied in the dot-in-circle paradigm. The expected patterns of bias which would corroborate this were not observed. Although the differences in bias between object types within and between the pilot and the experiment could suggest that long-term information is being applied to determine the schema-consistency of objects and their subsequent initial validity, the unintended lower positioning of the objects prevents us from disentangling explanatory factors and stating definitively that this is the case. Future replications should emphasize encompassing a greater range of radial and angular space and establishing pair-specific prototypes, as well as placing greater attention on using physical objects as opposed to two-dimensional targets to help remove potential barriers to our understanding of how long-term prototypical information is used in the real-world. As it stands, further research will be required to understand whether this information is being used in the Category Adjustment model.

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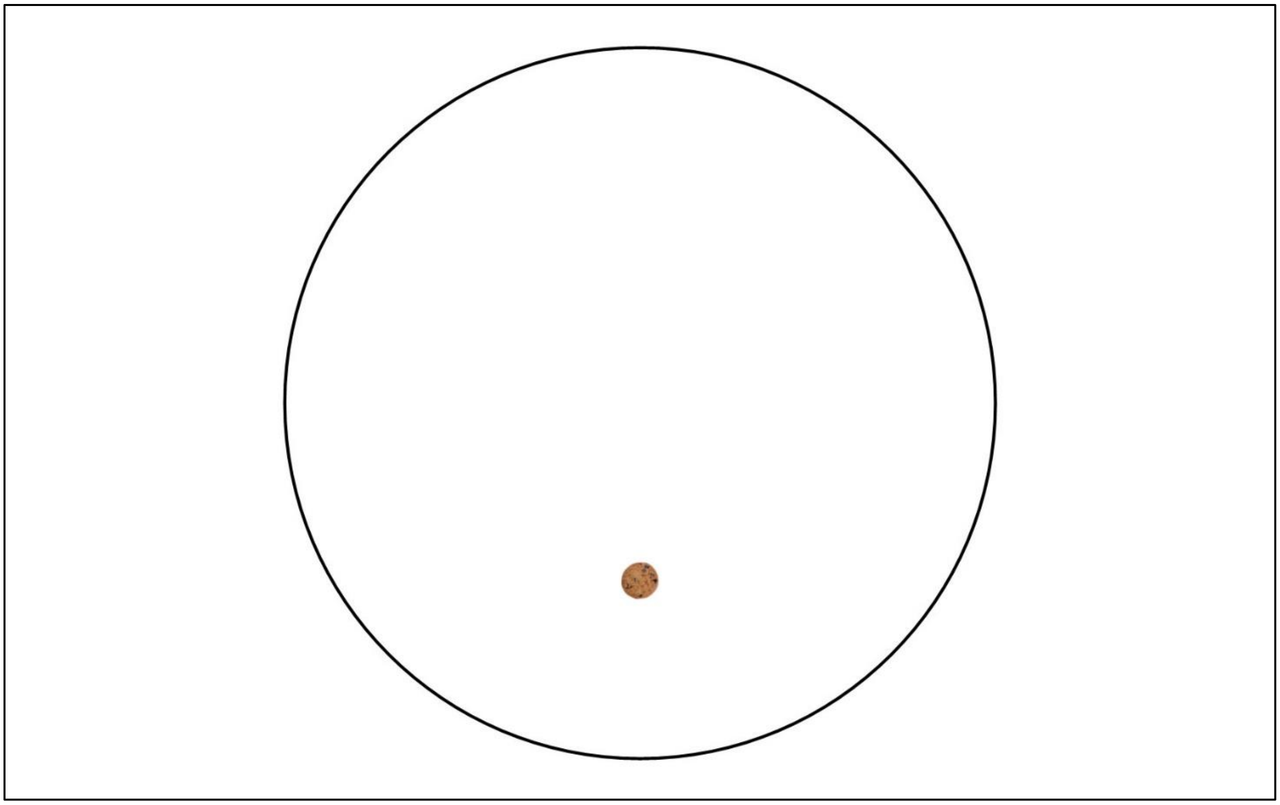

Figure 1. Example of the Experimental Space as viewed by Participants. Targets were pictures of real-world objects (e.g., the round cookie in the bottom-half of the circular space) as viewed from a top-down perspective.

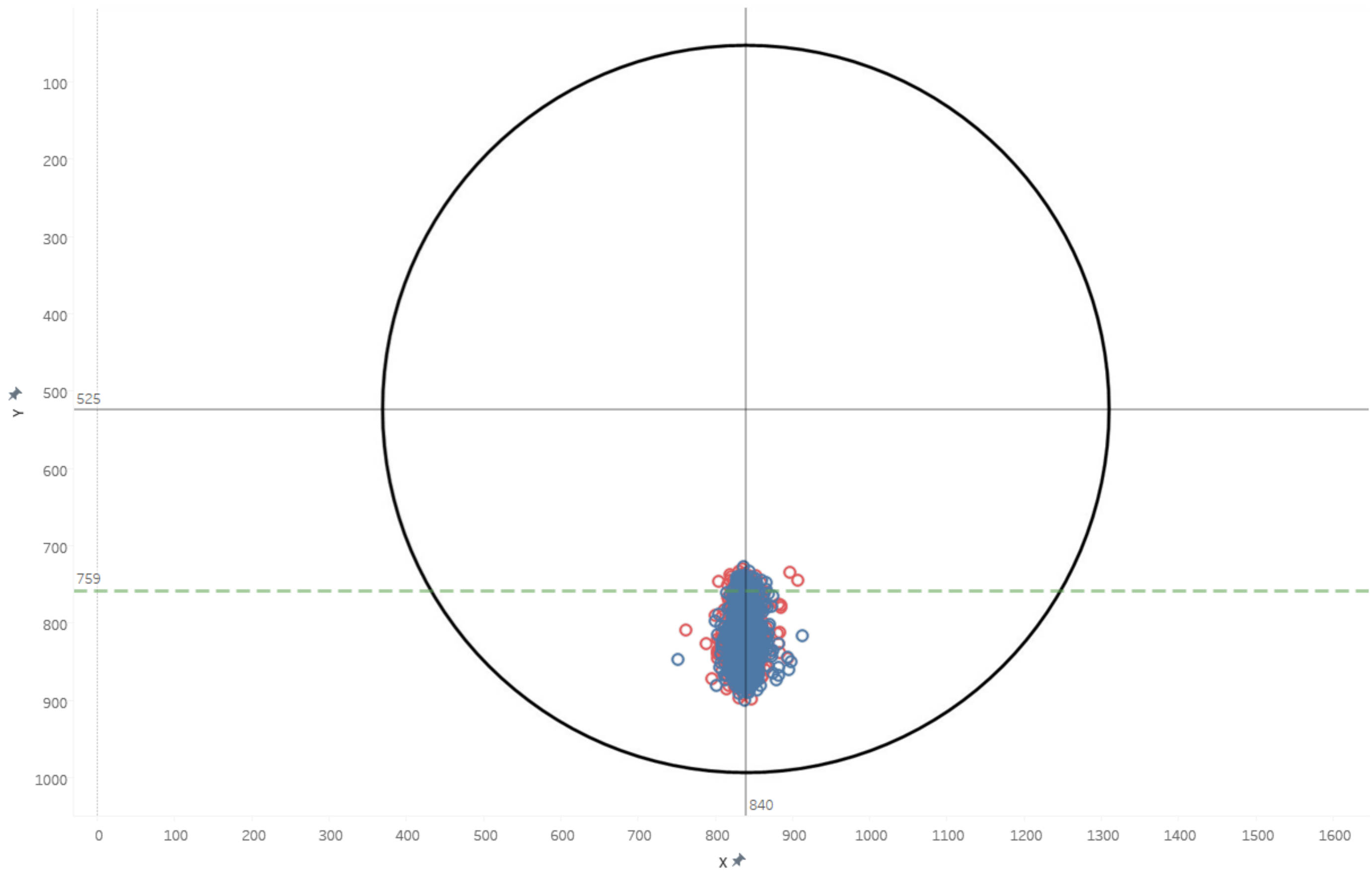

Figure 2: Responses sorted by Object Type. The solid vertical and horizontal lines indicate axes in the environment, with the vertical (at X = 840) indicating the midline upon which targets were displayed. The dotted line indicates the midpoint of the bottom half. Most objects were shown and replaced within this bottom-half as a result of error. Blue circles indicate Central objects, and red circles indicate Distal objects.

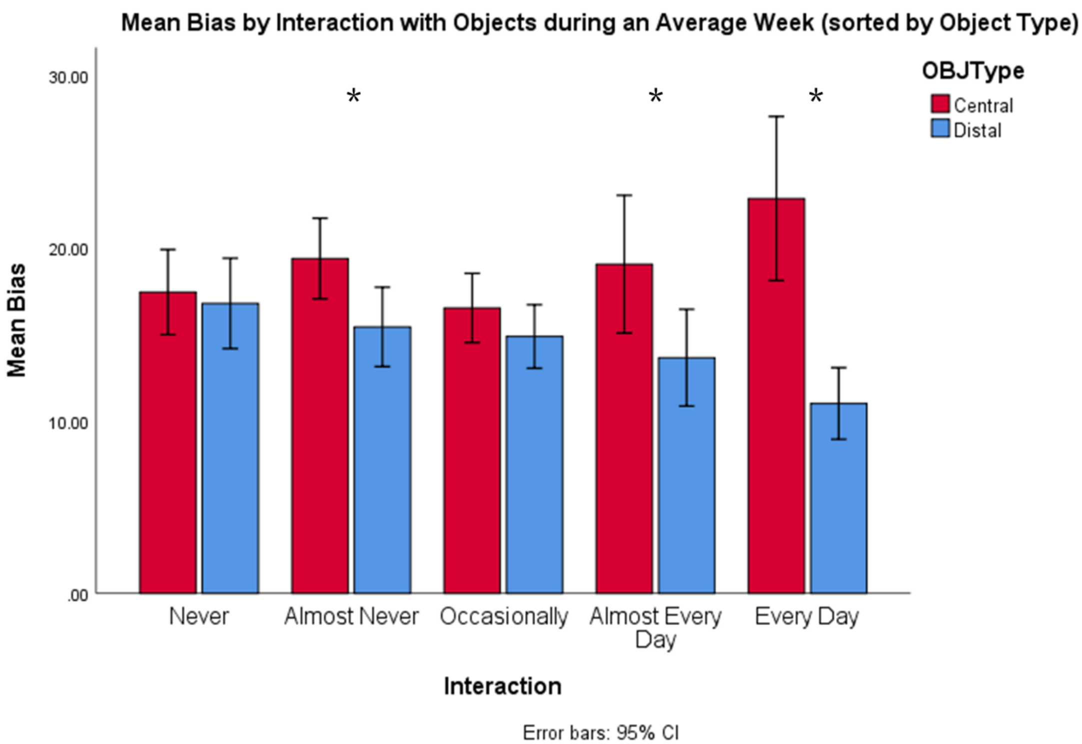

Figure 3: Bar Graph: Self-Reported Interaction scores against Bias. Red bars denote Central objects, and blue bars indicate Distal objects. Error bars denote 95% confidence intervals. Asterisks indicate significant differences between object types for each level. Here, we see bias decreasing with increased interaction for Distal objects, but not for Central objects. This could indicate that people are paying attention to where objects should go, and that error increases when that expectation was not upheld. Future exploration is necessary.

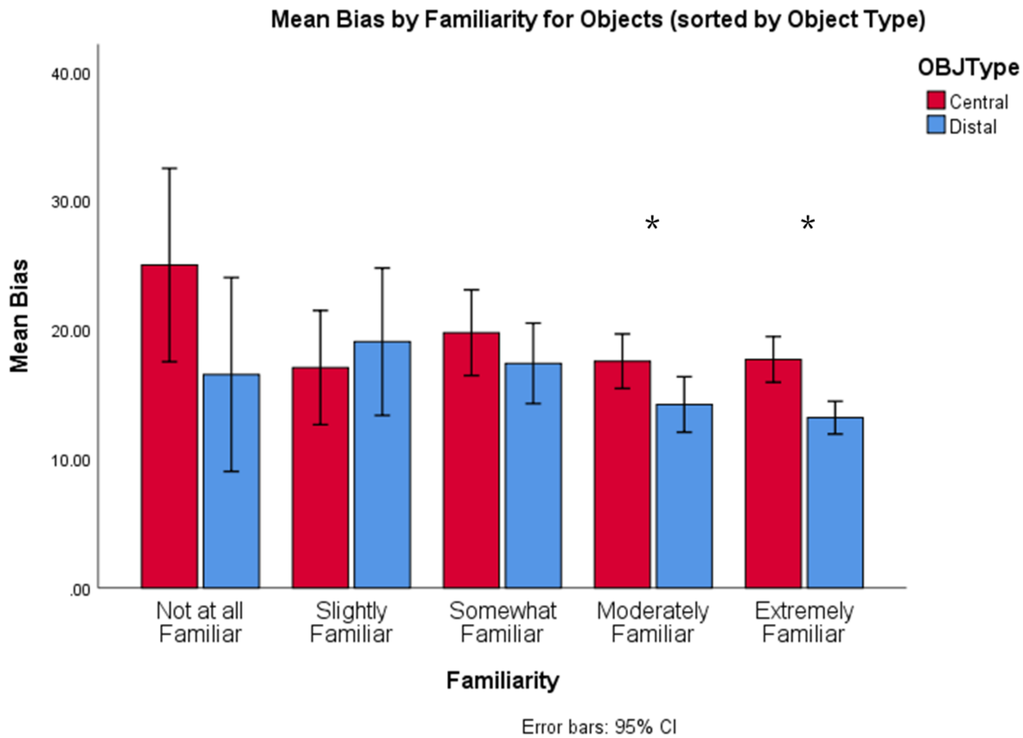

Figure 4: Bar Graph: Bias as Self-Reported Familiarity Increases. Asterisks indicate significant differences in bias between object types for each level. Here, we can see that the degree of variance in responses decreases steadily as Familiarity with the target increases. Though this did not change the magnitude of the bias, it does give some indication that Familiarity with the objects in the space gave reliability to the estimate and helped decrease error.

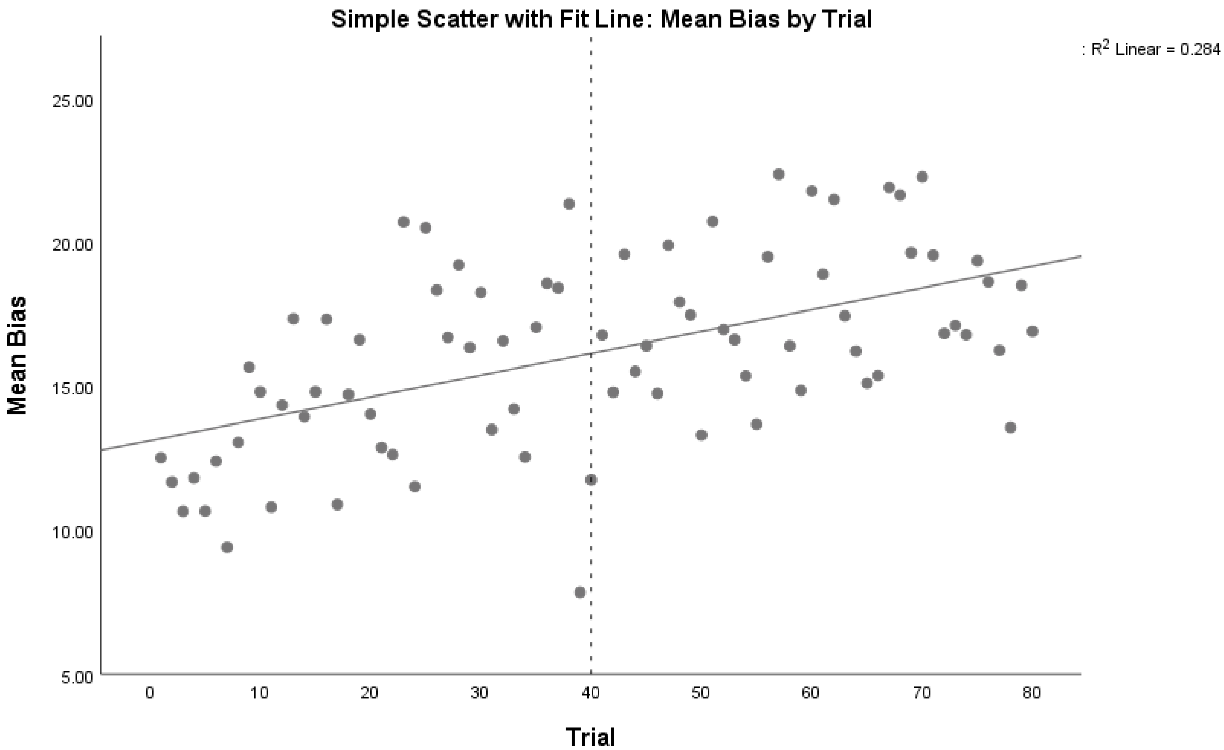

Figure 5:Scatterplot of Mean Bias by Trial. The dotted vertical line indicates the break between blocks of objects. The solid line indicates the linear-fit line. As participants completed successive trials, mean radial bias increased slightly. This could indicate the fatigue played a possible role in radial bias.

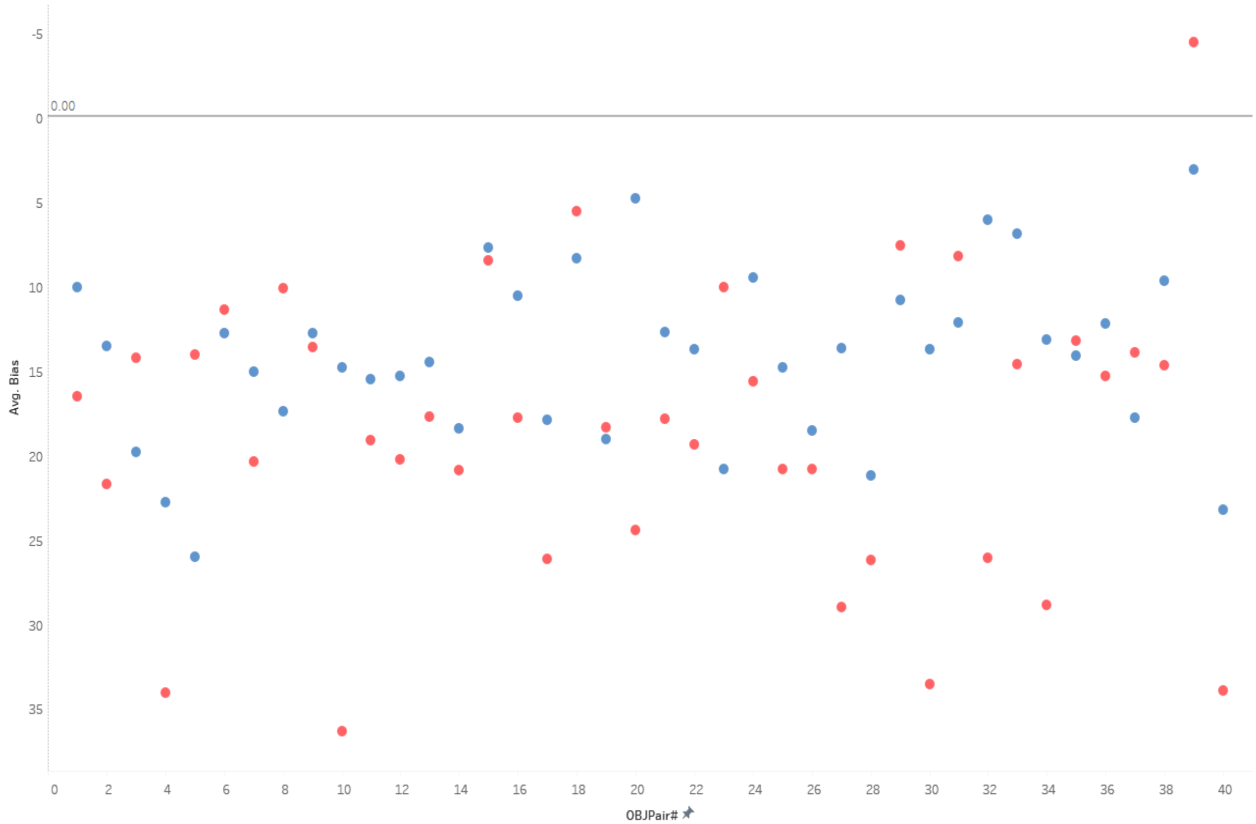

Figure 6: Scatterplot: Means for each object sorted by Object Type. The filled circles represent the average bias across participants for Distal and Central objects. Blue circles indicate the Distal object of the pair, while red circles indicate the Central object. Though each pair varied, the overall trend shows Central objects biasing to a greater magnitude than their Distal counterparts. Pair 39 shows the hypothesized pattern of bias, with the Distal object exhibiting positive bias and the Central object exhibiting negative bias.

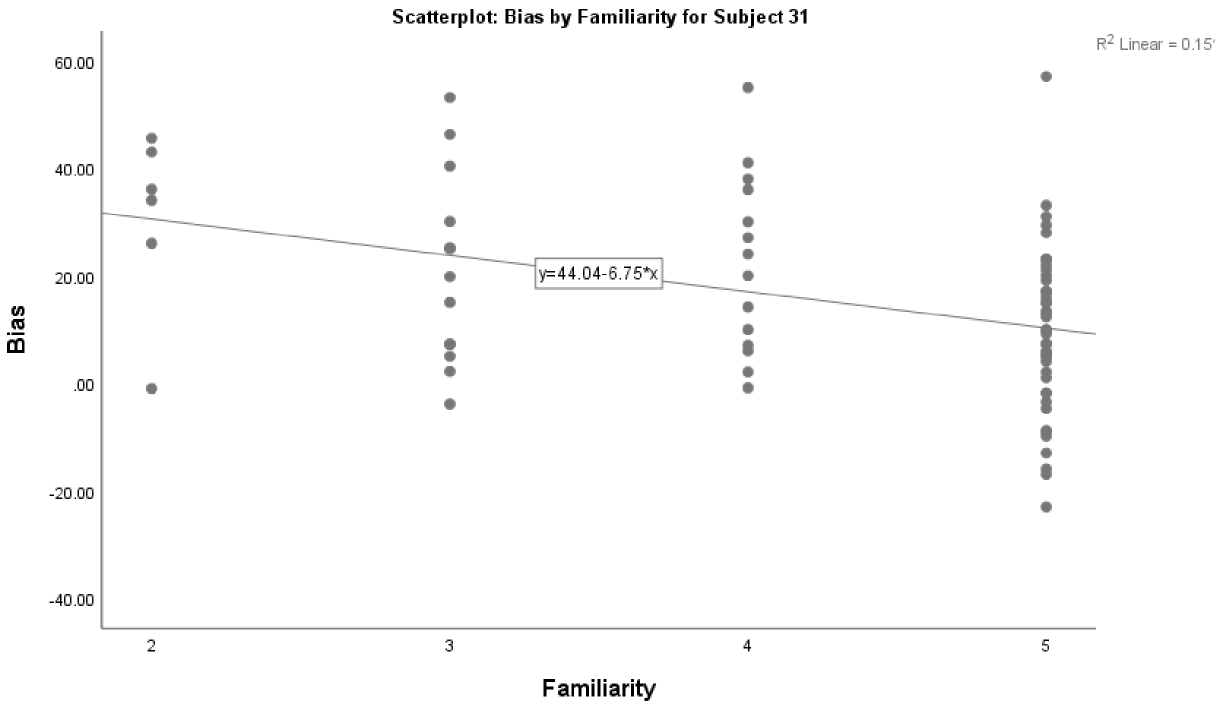

Figure 7: Scatterplot of Bias by Familiarity for Participant 31. Example of the expected trend between Object Familiarity and Bias. Dots indicate response bias for individual items. The fit line and the R^2 coefficient indicate that Familiarity impacted bias, with increasing familiarity predicting a lower degree of bias. However, this trend was not universal across participants. This could be explained by participants' subjective understanding of where certain objects should be.

Table 1

Regression Coefficients for Object Dimensions' Effect on Bias

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
	(Constant)	5.740	3.710		1.547	.126
	OBJWidth_mean	-.039	.027	-.337	-1.443	.153
	OBJHeight_mean	.164	.033	.954	4.980	.000
	OBJArea_mean	.000	.000	-.303	-.891	.376