# Another Brick in the Wall? A Null Effect of Boundaries on Spatial Memory Judgments in a Novel, Highly Immersive, First-Person Object-Placement Task

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**Abstract**

Spatial memory is evolutionarily important for many animals. Boundaries can systematically distort spatial memory in line with hierarchical models, while other evidence supports more metric path-integration theories. To test these competing theories, we developed a novel, highly immersive Object Placement Task (OPT) in virtual reality to examine the effect of boundaries on human spatial memory. Our task decomposes spatial memory into 3 components: 1) object-placement errors, 2) distance judgments, and 3) angular judgments (i.e., our single task provides multidimensional information about spatial memory). Thirty participants used the OPT to recall object positions in environments with or without a central boundary. Bayesian analyses showed that distance influenced memory performance, but boundary presence had no significant effect (Bayes factors favored the null models). These findings suggest a set of conditions in which boundaries may not impact memory. We discuss potential modulators of boundary effects and present our open-source task for future research.

**Keywords:** Spatial cognition; Memory; Virtual Reality (VR); Environmental boundaries; Path integration

## Introduction

Spatial navigation and episodic memory are essential to daily life. Thus, studying the accuracy and the underlying representation of spatial and episodic memory is of keen interest. Recent theories argue that boundaries fundamentally influence memory (e.g., Brunec et al., 2018; Radvansky, 2012; Zacks et al., 2007; Zacks & Swallow, 2007). Importantly, these theories find support from the study of spatial memory (e.g., Cohen et al., 1978; Kosslyn et al., 1974; McNamara, 1986; Newcombe & Liben, 1982), episodic memory (e.g., event boundaries; Horner et al., 2016; Sargent et al., 2019; Zacks & Swallow, 2007), and the discovery that regions of core spatial and episodic memory networks are preferentially activated and involved in the representation of boundaries (e.g., the hippocampus; Baldassano et al., 2017; Ben-Yakov & Henson, 2018; Reagh et al., 2020; Zacks et al., 2006; for review see: Brunec et al., 2018). Therefore, studying boundaries in immersive, lifelike contexts can thus reveal how broadly these theories apply.

Previous research has indicated that boundaries can negatively impact the accuracy of spatial memory judgments. For example, participants often overestimate distances across a boundary (e.g., Cohen et al., 1978; Kosslyn et al., 1974; McNamara, 1986; Newcombe & Liben, 1982). Likewise, previous research has used recall data to show that locations that are clustered in memory tend to exhibit systematically shorter distance judgments than locations in different clusters, even when overall physical distance is controlled, thus suggesting that the mental compartmentalization of environments exerts a fundamental influence on spatial memory judgments (e.g., Hirtle & Jonides, 1985; McNamara et al., 1989). Moreover, angular estimates of directions tend to be better within "rooms" or "neighborhoods" than between rooms or neighborhoods (i.e., across boundaries; e.g., Han & Becker, 2014; McNamara, 1986). Altogether, these findings have led to a theory of hierarchical spatial representations, which suggest that boundaries cause spatial memory to be distorted in systematic ways (e.g., Hirtle & Jonides, 1985; McNamara, 1986, 1991; Stevens & Coupe, 1978). These findings also generalize to episodic memory (Horner et al., 2016; Radvansky, 2012; Zacks et al., 2007), suggesting that boundary-related distortions may be a general memory phenomenon.

Our main goal was to create a novel, highly immersive and first-person (i.e., embodied) spatial memory test that would allow us to better understand spatial memory. We aimed to replace less embodied test methods (e.g., numeric estimates for distance, which may be biased, coarser, subjectively discretized, or less natural) and angular memory (e.g., more abstract tasks, such as the Judgment of Relative Directions [JRD] task) with more immersive tasks. Our object placement task (OPT) allowed us to simultaneously measure 1) object-placement errors (a composite measure of spatial accuracy), 2) distance judgments, and 3) angular judgments for spatial environments—all within a single, naturalistic interaction.

The key manipulation in our experiment was the presence or absence of a boundary during the learning phase. In half of the trials, the environment featured a central wall with a door (see Figure 1). We tested whether spatial memory aligns with hierarchical models (which predict systematic distortions due to boundaries, including increased errors, overestimated distances, and greater angular errors) or metric representations (e.g., path integration models), which might suggest boundaries have minimal influence. By addressing the influence of boundaries on spatial memory within an immersive VR paradigm, our study offered an opportunity to bridge theoretical insights with practical applications, providing a novel methodological contribution to the study of human navigation and memory.

## Methods

### Study Design

We preregistered our study on OSF (https://osf.io/u58ng). For consistency with our preregistration, we reproduced our wording from our preregistration in the Methods here as well as some parts of our Introduction. We employed a within-



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subjects design. Participants completed a fully immersive memory task using a virtual reality (VR) headset. The primary manipulated variable was the presence of a central dividing wall with a door in the experimental boundary (Figure 1). Participants completed object-location memory task trials, alternating between boundary and no-boundary conditions, with randomized spatial layouts.

## Participants

We recruited 35 (20 female, 13 male, and 1 non-binary) aged 18 to 24 (M = 20.34, SD = 1.33) through word of mouth, school-sponsored advertisements, and the SONA participant recruitment pool. Participants either received monetary compensation ($10 per hour) or course research participation credit. Participants who did not complete all 50 trials of the task or did not have a significant Spearman rank correlation between response distance and ground-truth distances were excluded (i.e., to only include participants that could perform our task significantly better than chance), resulting in a final sample of 30 participants (our preregistered target). All procedures were approved by the IRB at Colby College.

## Apparatus

The task was conducted using an Oculus/Meta Quest 2 VR headset. We developed our environment in Unity/C# (v2019.4.13f1, Unity Technologies) using a modified version of the Landmarks package (Starrett et al., 2021) with our custom (OPT) task (code available via GitHub in the pto_sinan_djh branch: https://github.com/huffman-spatial-cognition-lab/Landmarks/tree/pto_sinan_djh). Participants interacted with the environment by walking and using a hand controller to place objects in remembered locations using raycast functionality (Figure 1 and 2).

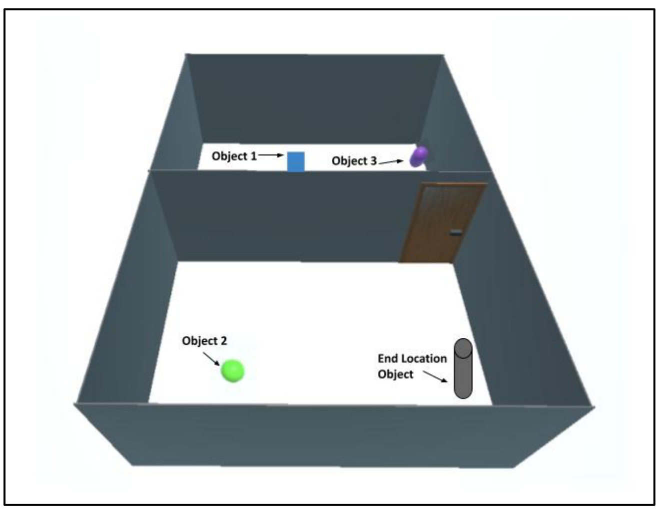


Figure 1: A view of the environment on a "boundary" trial. On "no-boundary" trials, the outer walls would be the same but the central wall and door would be removed. Participants navigated by walking while wearing an Oculus/Meta Quest 2 head-mounted display. Note that participants could only see one object at a time.

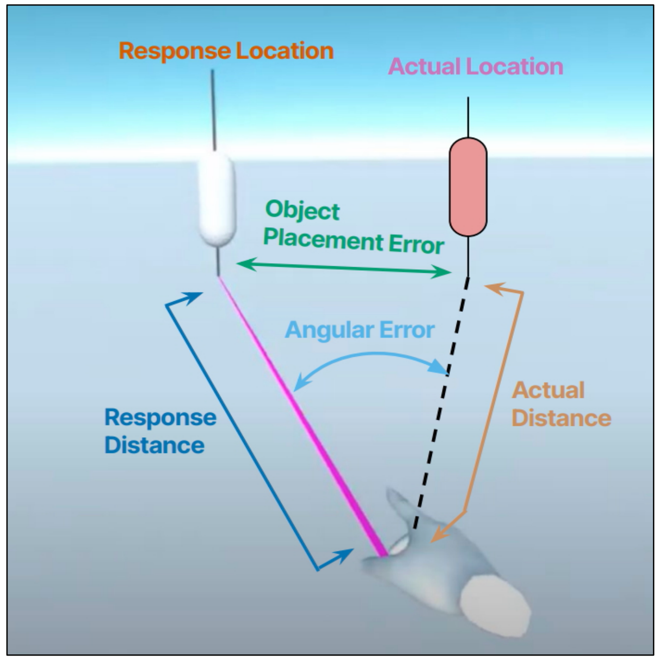


Figure 2: The immersive, first-person object-placement task (OPT). Participants used the Oculus/Meta Quest controller to point to their remembered location of each object of a given layout. Each trial consisted of being asked to remember 3 object-location associations (Figure 1). The participants moved the object via the raycast and the object was positioned at the location at which the raycast hits the ground.

## Procedure

The study began with a practice phase, where participants completed two single object trials to familiarize themselves with VR navigation, interaction with the central door, and OPT mechanics. Afterward, participants could ask questions before proceeding the main task.

In the main task, participants located three objects (3 shapes: capsule, cube, sphere; with 8 possible colorblind friendly colors; for a total of 24 unique combinations) within a 10 x 7.5 m 4-wall boundary. Objects appeared one at a time, requiring participants to physically walk to each object and use the right-hand controller to swipe through it, causing it to disappear and triggering the next object's appearance. Once participants located all three objects, they navigated to an "end location" object (black cylinder) to complete the trial. Following the navigation phase, participants performed the object-placement task (OPT) by placing the three objects in their remembered locations using the controller and raycast functionality (Figure 2). The OPT trials followed the same order as the original learning phase.

Half of the trials feature a central dividing wall with a door, segmenting the space, while the other half occurred without the wall. Trials alternated between these conditions, and each spatial layout was presented twice, once per condition. Spatial layouts were randomized, with a minimum lag of five trials between repetitions, and some layouts were mirrored to prevent learning effects. We instructed participants to focus only on the object-location associations for that specific trial.

## Measures

**Object Placement Errors** For each trial, we determined the object placement errors by calculating Euclidean distance between the participant's placement of an object and the object's true location, thus providing a composite measure of participants' accuracy in placing objects in their remembered locations (Figure 2). We used the x and z axes in Unity were used to capture the horizontal coordinates of the objects, while the y-axis (height) was fixed to the level at which the objects were originally presented.

**Distance Measures** For each trial, we calculated the response distances using the Euclidean distance between the participant's standing location and the coordinates at which they placed each object (Figure 2), thus providing a measure of the participants' subjective estimates of spatial distances. Thus, the distance estimates here provide a highly immersive, first-person measure of the participants subjective distance of target objects (i.e., as compared to the numeric estimates in previous tasks). Additionally, we calculated the actual Euclidean distance between the participant's standing location and the true coordinates of the object during the learning phase (Figure 2). We used both subjective response distances and actual distances in our regression analyses to evaluate participants' performance on the task.

**Angular Measures** We calculated the response angle between the participant's standing location and the coordinates where they placed each object, using the arctan2 function in Python via numpy. Similarly, we calculated the actual angle between the participant's standing location and the true object coordinates from the learning phase. We calculated the absolute angular error by comparing the response angle to the actual angle (Figure 2), providing a measure of directional accuracy.

**Statistical Models** As we stated in our preregistration (see link above), we employed a fully Bayesian analysis of our data. Importantly, Bayesian analyses are able to provide evidence in support of competing predictions (e.g., the predictions of hierarchical vs. path-integration models). Here, we specifically employed mixed-effects regression models to account for variability both within and between participants (i.e., because we employed a fully within-subjects design). Based on previous findings with distance-estimation data, we used linear regression models to analyze the distance data (e.g., Hirtle & Jonides, 1985). Specifically, given that linear models exist within both the lme4 and BayesFactor packages, we employed both the BIC approximation and the BayesFactor methods to calculate Bayes factors. In contrast, given that the data from the object-placement task and angular errors would likely be nonlinear, we used generalized linear models with a gamma family distribution for these analyses. These models allowed for a comprehensive evaluation of how participants' spatial memory performance differed across conditions, specifically in the presence versus absence of the central boundary wall.

Table 1: Bayes Factor Results for Spatial Memory Analysis

| Model Comparison | Bayes Factor Package (BFP) | BIC Approx. | brms |
|---|---|---|---|
| Model 2 vs. Model 1 | N/A | 11.41 | 982.39 |
| Model 2 vs. Model 3 | N/A | 5.10 | 2.29 |
| Model 5 vs. Model 4 | 1.92e+13 ± 2.13% | 1.76e+12 | 2.79e+77 |
| Model 5 vs. Model 6 | 10.44 ± 2.5% | 40.82 | 10.74 |
| Model 6 vs. Model 7 | 2.24 ± 2.84% | 16.98 | 18.50 |
| Model 5 vs. Model 7 | 23.34 ± 3.31% | 694 | 467.29 |
| Model 8 vs. Model 9 | N/A | 26.3 | 5.13 |

Our approach provided robust insights into the relationship between participants' spatial navigation behavior and their accuracy in recalling object locations. We pre-registered our study stating that we would analyze the data as we have stated thus far, but also stated that we planned to assess alternative models for the non-linear analyses. Thus, to ensure the robustness of our results across a variety of Bayesian frameworks, we conducted analyses using the brms package. All three approaches supported the same conclusions, reinforcing the reliability of our findings and ruling out the possibility that our results were driven by a specific assumption of one of the Bayesian approaches.

# Results

## Object Placement Errors are Influenced by Distance but not the Boundary

First, we analyzed the object placement errors (Figure 2). We found that the models were in favor of the distance-only model (2) over the null model (1) (see Table 1, row 1), thus suggesting that the magnitude of participants' object-placement errors varied as a function of the distance of the object's correct location relative to the navigator.

distance_error ~ 1 + (random_effects) (1)
distance_error ~ actual_distance + (random_effects) (2)
distance_error ~ boundary_condition + actual_distance + (random_effects) (3)

We next tested whether the boundary condition (i.e., wall vs. no wall) influenced the object-placement errors, which would be consistent with the hypothesis that boundaries exhibit a fundamental influence on human spatial memory judgments. We found that the models were in favor of the distance-only model (2) over the distance and boundary-condition model (3), thus providing evidence in favor of a null effect of the boundary condition (see Table 1, row 2 and Figure 3, i.e., the object-placement errors were similar on the boundary vs. the no-boundary trials).

Altogether, the most parsimonious model for the object-placement errors was the distance-only model (2), thus suggesting that object placement errors are influenced by the distance between the navigator and the to-be-remembered object's location but not the presence-vs.-absence of a boundary (i.e., at odds with our predictions from non-Euclidean theories like the hierarchical memory model).

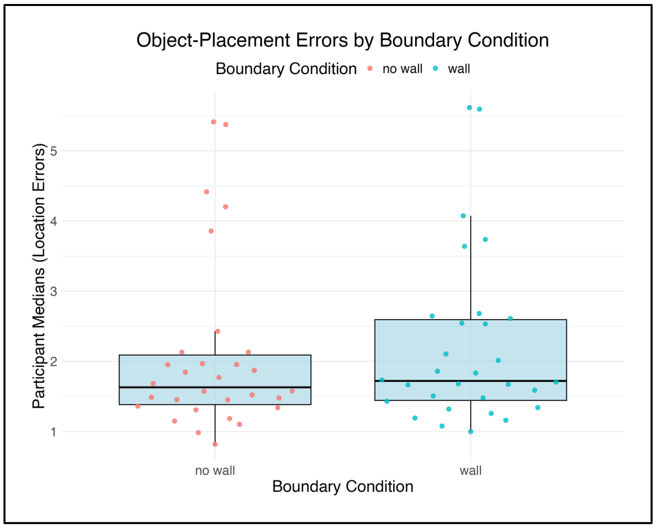


Figure 3: For the object-placement errors, Bayes models revealed evidence in favor of a distance effect (i.e., errors were modulated by the distance between the navigator and the to-be-remembered object's location) but a null effect of boundary condition (note the largely overlapping distributions between the "wall" and "no wall" conditions). For visualization purposes, each data point depicts the median object-placement error for each participant and the box-and-whisker plots indicate the median and 25-75% interquartile range.

### Distance Placements were Strongly Influenced by Actual Distances but not the Boundary

Second, we analyzed the relationship between the actual distance between the navigator and the correct object location (i.e., the "correct answer" of the distance) and the distance at which the navigators placed the object relative to themselves (for visual depiction of these measures see Figure 2). If participants performed better than chance, then we would expect to see that a distance-only model (5) would provide a better fit of the data than a null model (4). Consistent with this prediction, we found a strong preference for the distance model (5) over the null model (4) (see Table 1, row 3).

We next tested whether the boundary condition (i.e., boundary vs. no boundary) influenced the distance at which the navigators placed the objects relative to themselves, which we predicted would be the case based on previous results and our results with the SR model (i.e., we predicted a boundary expansion effect). We compared both a main effects model (i.e., assuming that the boundary condition may increase the distance of the placements across the boundary but not change the slope) and an interaction model (i.e., predicting that there could be a change in the slope; e.g., objects near the wall might exhibit a relatively larger boundary-expansion effect).

In contrast to our predicted results, we found that the models were in favor of the distance-only model (5) vs. the distance and boundary-condition model (6) (the main effects of boundary-condition model; see Table 1, row 4), thus providing evidence in favor of a null main effect of boundary condition (i.e., the distances at which the navigators placed the objects were similar on the wall vs. the no-wall trials).

distance_response ~ 1 + (random_effects) (4)
distance_response ~ actual_distance + (random_effects) (5)
distance_response ~ boundary_condition + actual_distance + (random_effects) (6)
distance_response ~ boundary_condition * actual_distance + (random_effects) (7)

Similarly, the models favored the main effects model (6) (the distance and boundary-condition model) vs. the interaction model (7) (see Table 1, row 5), thus providing evidence in favor of a null distance x boundary-condition interaction (i.e., the slopes of distance-placements were similar on the wall vs. the no-wall trials). Finally, we found that the models were in favor of the distance-only model (5) vs. the distance x boundary-condition interaction model (7) (see Table 1, row 6 and Figure 4), thus providing further evidence in favor of a null interaction and null main effect of the boundary.

Altogether, similar to the results above, we found that the most parsimonious model was the distance-only model (5), suggesting that the boundary-condition did not exert a strong influence on object placement distances (see Figure 4; i.e., inconsistent with the prediction of a boundary-expansion effect that was observed in other papers).

### Angular Errors weren't Influenced by the Boundary

Third, we analyzed the angular errors, testing whether the boundary-condition modulated the angular errors of the object placements. Contrary to predictions that boundaries disrupt spatial memory, model comparisons favored null model (8) vs. the boundary-condition model (9) (see Table 1, row 7). Thus, providing evidence in favor of a null boundary-

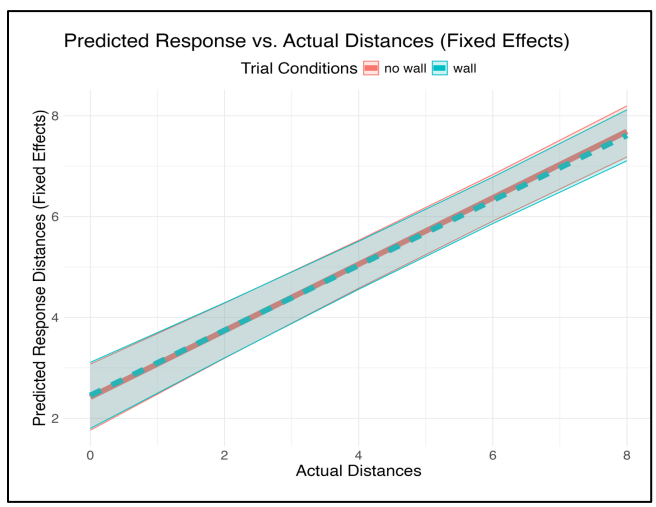


Figure 4: Bayes factor analysis revealed that there was a strong relationship between the actual distances and the participants' predicted distances (note the strong positive linear relationship), but there was a null effect of the boundary condition (note the overlapping error bars).

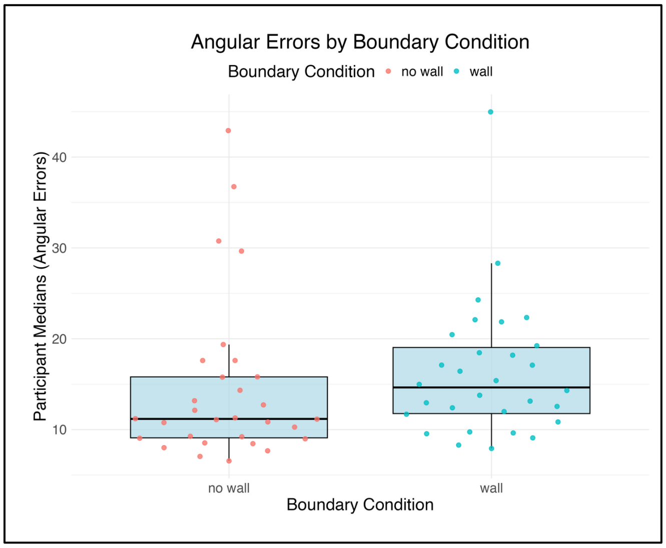


Figure 5: Bayes models revealed evidence in favor of a null effect of the boundary condition on angular errors (note the overlapping distributions between the "wall" and "no wall" conditions). For visualization, each point depicts the median angular error for each participant and the box-and-whisker plots indicate the median and 25-75% interquartile range.

condition effect (see Figure 5; i.e., the angular errors were similar on the wall vs. no-wall trials).

absolute_angular_error ~ 1 + (boundary_condition | participant_ID) (8)
absolute_angular_error ~ boundary_condition + (boundary_condition | participant_ID) (9)

## Discussion

We aimed to develop a framework for testing the influence of boundaries on human spatial memory. We argue that there are four major strengths to our approach here:

First, we developed a novel and highly immersive behavioral task, the OPT, for studying the resolution of human spatial memory. Importantly, our task combines features that are common across many spatial memory tasks: i.e., distance estimation and angular estimation.

Second, we followed open science practices: we preregistered our procedures. Moreover, upon publication (i.e., post-peer review) we will make our code for our OPT task fully open source, allowing researchers to easily implement it in their own experiments (see below for specific examples). Moreover, our code base works "out of the box" on the Meta Quest 2, which is an affordable all-in-one head-mounted display (HMD), enabling broader research access, even in lower-resource labs.

Third, we tested competing models: those proposing boundaries fundamentally influence spatial memory (e.g., hierarchical models) vs. those that do not (e.g., path integration models; see below). We argue that results that are in support of either theory would be important. Using a fully Bayesian analysis pipeline, we found that distance modulated the object-placement errors and distance placements. However, the models consistently favored a null effect of the boundary condition, suggesting no significant differences in errors or placements in trials with and without walls. While this contradicts hierarchical models, factors like memory demands, task design, and encoding strategies may have influenced results, warranting further study (see below).

Fourth, we outline a comprehensive framework for future research that can further explore conditions under which boundaries might influence spatial memory.

## Evidence for One End of a Continuum in which Boundaries do not Impair Memory

We argue that our results provide evidence for one end of a continuum in which boundaries do not appear to impair the resolution of spatial memory. We note that while our task was highly immersive and ecologically valid, we necessarily and intentionally made specific design choices about 1) task demands (e.g., more egocentric vs. allocentric), 2) the duration of memory retention (e.g., possible differences between working memory and longer-term memory), 3) the environmental complexity, 4) repeated exposure to the same environment with vs. without the boundary (i.e., the within-subject design), 5) the sequential nature of the learning task, and 6) we note the possibility that participants might automatically segment the environment even without the boundary. Thus, here we begin by briefly reviewing other theories that may account for our results and we provide ideas for future experiments to test each of these possible influences on the effect of boundaries.

If our data are not consistent with hierarchical models (see Introduction), then what theories can explain our results? Competing theories might suggest that boundaries would exhibit a more modest effect on spatial memory. For example, studies of the path integration system would imply that animals can integrate information about translation (e.g., walking) and direction changes (e.g., body rotations), perhaps allowing for relatively similar accuracy of spatial locations across boundaries (e.g., Etienne et al., 1998; Etienne & Jeffery, 2004; Mittelstaedt & Mittelstaedt, 1980; Mou & Wang, 2015; Wang & Spelke, 2002). Likewise, the neuroscientific discovery of the seemingly metric nature of place cells, grid-cells, and head-direction cells led to theories that such neural responses may provide an underlying Euclidean metric for the representation of space (e.g., Hafting et al., 2005; Moser & Moser, 2008; O'Keefe & Dostrovsky, 1971; O'Keefe & Nadel, 1978; Samsonovich & McNaughton, 1997). Thus, these theories might suggest that the influence of boundaries may depend on the nature of the memory task itself. For example, in a condition in which the navigator has access to body-based cues about translation and rotation, the effect of boundaries might be attenuated (cf. Mou & Wang, 2015). Thus, we think it will be interesting for future studies to further untangle the role that path integration plays in mitigating the boundary effect, as we detail below.

An important difference between the data that support hierarchical models vs. path-integration-based models of spatial memory exists: studies that supported the former typically consisted of participants making relatively disembodied spatial judgments (e.g., numeric estimates of distances) whereas the study of the path integration system is done as the navigators are physically situated within the environment (i.e., a more embodied approach). Thus, our results in favor of a null boundary effect raises the question: does the influence of boundaries on spatial memory depend on the nature of the memory task? Specifically, the fact that we used a more ecologically valid, embodied, first-person memory task may explain the mitigation of the nature of the influence of boundaries on the resolution of spatial memory.

Thus, the first factor that may moderate boundary effects is the nature of the task demands, specifically whether the task relies on embodied vs. disembodied judgments. Embodied tasks[1], such as our Object Placement Task, ask participants to recall locations as they are oriented within the environment (thus having access to the path integration system and other body-based cues). In contrast, disembodied tasks[2] place greater demands on participants to encode locations relative to a fixed external reference. It is possible that embodied tasks minimize the influence of boundaries, as participants rely more on path integration mechanisms rather than abstract representations. We can imagine several extensions of our OPT trials to further test the role of the path integration system (e.g., disorientation of the participants between the learning and testing phases, cf. Wang and Spelke, 2000; or asking participants to imagine they are standing at a certain position and orientation before the trials, akin to an immersive JRD task).

A second key factor that may have influenced our results is the duration of memory storage and retrieval. Our task primarily engaged working memory, as participants recalled object locations over a retention on the order of seconds. However, Waller and Hodgson (2006) suggest that boundaries may play a more substantial role in long-term spatial memory, where spatial representations are consolidated over extended periods. It is possible that boundary-related distortions accumulate over time, such that the effects become more apparent after longer delays. Future research should test the influence of delay by manipulating retention intervals—for example, testing participants immediately versus after a delay of minutes, hours, or days—to determine whether boundary effects emerge at different time points. Likewise, we can imagine that the number of to-be-remembered object locations (i.e., 3) might have placed stronger demands on working memory than long term memory; thus, future experiments could manipulate the number of objects and the amount of exposure to each layout to see if these change the effect of spatial boundaries.

A third key factor for boundary conditions could relate to the environmental complexity. We used a 7.5 x 10 m environment, and we note that it is possible that larger scales of space (e.g., hundreds of meters to kilometers in size) could exert larger influences of boundaries; for example, due to error accumulation in the path integration system. Moreover, our environment consisted of a rectangle, which could have made the environment easier to learn than more complex environments with complex boundaries and shapes (e.g., akin to exploring a dense forest).

A fourth key factor that may have mitigated the influence of the boundary effect was the participants' continual exploration of the environment throughout the task. Specifically, given the statistical power of a within-subjects design (e.g., minimizing the impact of between-subjects variance), we opted for a fully within-subjects design. However, this meant that each participant was seeing the same environment with and without the central boundary. Thus, participants may have integrated information about the environment across trials (e.g., via path integration). Future studies could implement procedures to inhibit learning of the same space with and without a boundary (e.g., between-subjects designs, disorientation between conditions).

A fifth key factor is the sequential nature of our learning task. Specifically, participants could only see (and thus encode) one object at a time. It is possible that under these conditions, participants placed greater emphasis on learning single locations rather than the overall conglomeration of locations between all objects (e.g., in a condition in which all objects are simultaneously visible; e.g., McNamara, 1986).

Finally, the sixth key factor for boundary conditions that we consider here is that participants might automatically segment or compartmentalize the environment, even without the presence of occluding boundaries (e.g., Huttenlocher et al., 2004; McNamara et al., 1989). Thus, future studies could test whether participants create subjective boundaries in the environment (e.g., possibly by using a recall paradigm).

Altogether, we found evidence of perhaps one end of a possible continuum of the influence in which the boundary did not exhibit a fundamental influence on human spatial memory. While our findings align more closely with path integration theories, the support here is indirect: we did not isolate or directly manipulate body-based cues. At the same time, the data did not refute hierarchical models entirely as boundary effects may emerge under different task conditions (examples above). Nonetheless, our null effect for boundary presence, combined with our high ecological validity, offers a valuable starting point for future research. We anticipate that our fully immersive, open-source task—designed for use on an affordable, standalone HMD (Meta Quest 2)—will enable future studies to further interrogate the influence of boundaries on spatial memory and we hope that such studies will make use of the core parameter spaces we discussed here.

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[1] We note that some researchers use the term "egocentric" to describe such tasks.

[2] Likewise, we note that some researchers use the term "allocentric" to refer to such tasks; however, we prefer to use the terms we use here since they carry less baggage and focus more on whether the participant is either oriented within the physical environment or not (i.e., closer to the experimental manipulation than making inferences about underlying representations).

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