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Graph properties drive navigational selection between equidistant routes

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ABSTRACT

Cognitive maps, traditionally considered metrically accurate mental representations of space, have been central to navigation research. However, recent studies suggest human navigation often deviates from the predictions of cognitive maps. Instead, *cognitive graphs* - spatial representations based on landmarks (nodes) connected by routes (edges) with relative distances, angles and limited metric information - may more accurately describe mental spatial representation. Unlike cognitive maps, cognitive graphs emphasize structural relationships over precise details. We designed a two-alternative forced-choice navigational task where participants explored and navigated virtual environments with three ways to a target: left, middle, and right. Critically, the left and right routes were always identical in length but varied in structural features like the number of turns, length of the first path of the route, or the size of unpaved areas. After exploring, the middle route was blocked and participants chose the left or right route to navigate to the target. Across two experiments, participants completed the task using an immersive walking virtual reality interface or a desktop computer to view top-down images. Participants in both experiments preferred routes with fewer turns and larger inner and outer areas despite being metrically identical, but showed no preference for routes with a shorter initial path. These findings suggest that participants did not rely on metrically precise cognitive maps when deciding which route to take to a navigational goal. We interpret this as evidence for the use of topological or labeled graph representations and discuss heuristics that are compatible with or may drive reliance on cognitive graphs over cognitive maps. These findings build on prior evidence for cognitive graphs in physically impossible environments (e.g., wormholes) by showing a bias in the absence of route length differences.

1. Introduction

Imagine you arrive in a small town and explore the area. Later, at your cabin, you are hungry and remember passing a restaurant. Multiple routes lead there, all exactly one mile long. Which do you choose? Will you select the most efficient route, or will your knowledge of the structural features of the routes, such as the number of turns, long straight sections, or unpaved areas shape how you mentally picture the environment, perceive routes, and make decisions when navigating? Although it may seem that humans would optimize route selection by choosing the shortest distance, participants rarely select the most optimal route (Lima et al., 2016). Here, we focus on the question of route choice and the impact of structural features on navigational decisions.

Previous work has found that there are substantial differences in the routes that participants take between locations. For example, Bailenson and colleagues (1998, 2000) showed that participants took different routes when going to and returning from a place, suggesting that human navigation is flexible and dependent on contextual factors. They found that participants prefer long, straight initial segments over initial segments that were curved or had more turns. Others have similarly found that the straightness of the initial path of a route is important, as are topological features (Brunyé et al., 2015; Christenfeld, 1995) In contrast, Hochmair and Karlsson (2005) found that participants generally preferred shorter initial segments when choosing between roads with equal lengths and similar angles of deviation from the target. Together, these studies suggest that participants use a number of heuristics when making navigational decisions that are not necessarily related to the metric distance that is traveled (Manley et al., 2015).

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However, these attempts to understand route choice and the heuristics involved have largely used overhead maps of the entire environment, rather than first-person learning. Here, we examined route choice heuristics in both a first-person and a top-down map display, allowing us to examine how these features affect choice differently in these modalities.

The type of spatial knowledge that participants use may play a role in route choice. The most basic form of spatial knowledge - route knowledge - involves recognizing landmarks and knowing the actions to take at specific points to navigate between them (Kim and Bock, 2021; Siegel and White, 1975). Route knowledge is computationally light and efficient and dependent on basic sequential association compared to a more advanced form - survey knowledge - which provides a global understanding of an environment and incorporates metric distances and directions between landmarks (Golledge, 1995). Survey knowledge, often referred to as a cognitive map, enables greater flexibility in navigation by allowing the use of novel shortcuts and detours, unlike route knowledge, which may not (Tolman, 1948). However, some researchers argue that cognitive maps imply an unrealistic amount of metric and distance accuracy requiring computationally intensive processing (Kuipers et al., 2003; Meilinger, 2008; Warren, 2019; Werner and Schmidt, 2000). Instead, they propose that cognitive graphs, which combine the sequential structure of route knowledge with approximate spatial information about direction and distance, more accurately describe human spatial representations. Thus cognitive graphs strike a balance between flexibility and efficient navigation, while still enabling the creation of shortcuts and adaptable paths (Chrastil and Warren, 2014).

In the cognitive graph model, landmarks can be conceived of as nodes connected by edges (i.e., a graph), with salient landmarks serving as nodes and the routes that connect them serving as edges. The impact of working memory, landmarks, learning modality, and exploration strategies on how we learn and recall spatial information suggests a high possibility of heuristics or mental shortcuts inherent in how we represent space, which would be consistent with the use of cognitive graphs (He et al., 2021; Starrett et al., 2019, 2023; Zuo et al., 2009). Landmarks, in particular, serve as essential reference points, helping us orient ourselves within an environment. However, little is known about how the qualitative and quantitative properties of individual routes may impact navigational decisions. For example, if two routes connecting point A and B are equidistant, a cognitive map representation should lead to an equal probability of selecting either route.

Much of the research supporting cognitive graphs has relied on experimental techniques that are not feasible in real-world settings, such as visual illusions or “wormholes” in virtual environments (Du et al., 2023; Warren et al., 2017). The impact of plausibly observable factors, like the number of turns, the length of the initial leg of the route, or the amount of space in the environment that is not part of the routes (referred to as “unpaved areas”), on spatial knowledge and navigation remains underexplored.

It is also crucial to consider how different methods of learning spatial information such as through maps or direct-first person navigation can affect spatial understanding and navigation choices in equidistant routes (Richardson et al., 1999; Starrett et al., 2019, 2023; Weisberg and Newcombe, 2016; Zhang et al., 2014). Map views generally provide more survey knowledge and contribute to the formation of more accurate cognitive maps (van der Kuil et al., 2021). In contrast, navigating in a first-person perspective typically enhances route knowledge (Taylor and Tversky, 1996).

In an initial experiment, we tested whether heuristic biases, a distinguishing factor between cognitive graphs and cognitive maps, would be present when participants made decisions about two routes of equal length in first-person immersive virtual reality environments. Because participants were required to choose between multiple routes to reach a goal, the task emphasized decision-making and the use of spatial knowledge such as heuristics, survey representations, or cognitive graphs (Chrastil and Warren, 2014). This contrasts with route learning or following tasks, which focus on memorizing and reproducing a specific path and rely more heavily on sequential memory and egocentric cues (Chrastil and Warren, 2015). We manipulated only qualitative route properties, such as the number of turns, the length of the route before the first turn, and the size of unpaved areas, but kept the total route distance the same for both options. To investigate whether different ways of learning spatial layouts (e.g., through maps versus first-person exploration) might facilitate or encourage decision-making consistent with a cognitive map, we conducted a second experiment, where the same manipulations were tested using a top-down, map-like view of the environments. Based on the previous literature, we hypothesized that participants would prefer routes with fewer turns and shorter initial legs when learning environments from first-person navigation (Experiment 1) and that this preference would be reduced or eliminated when learning from top-down viewpoints (Experiment 2).

2. Experiment 1

Experiment 1 varied structural features of the environment in a first-person fully immersive virtual reality setup. On each trial, participants first explored all the possible routes of the environment and then chose one of two routes that had the same distance but differed in structural features such as the number of turns and the distance of the initial path before reaching the first turn.

2.1. Materials and methods

2.1.1. Participants

A total of 60 healthy adults between the ages of 18 and 35 were enrolled in the study. Participants had normal color vision with acuity of 20/30 or better, were proficient in English, had no current or history of neurologic disease, and had no major psychiatric illness requiring hospitalization or prescribed psychiatric medication. Due to technical issues unrelated to experimental design (e.g., computer crashes), 20 participants were unable to complete at least 70 % of trials and were excluded from analyses, resulting in a final sample size of $N = 40$ (22 females) between the ages of 18 and 34 ($M = 21.53$, $SD = 3.02$). Due to the lack of similar literature, establishing a baseline sample size was challenging. We targeted a final sample size of 40 to ensure adequate statistical power for a within-subjects design and to avoid spurious effects. A post-hoc power analysis was conducted using G*Power (Faul et al., 2007) for a one-sample, two-tailed t-test. With the effect size of 0.51 based on the results of this experiment, an alpha level of 0.05, and a sample size of 40, the analysis determined a statistical power of 0.88, suggesting that the experiment was sufficiently powered. Participants received monetary compensation for their participation in the study. All participants provided informed consent, and all procedures were approved by the University of California, Irvine Institutional Review Board.

2.1.2. Stimuli and equipment

We designed 15 virtual environments (VEs) (14 test VEs and one practice VE) on graph paper before modeling them in Unity 3D (Unity Technologies, San Francisco, CA) using the included ProBuilder package. Each VE was 6 m × 11 m and comprised a middle route bisecting the long axis of the environment and two routes connecting each end of this middle route (Fig. 1). All routes were 1.5 m wide to prevent corner-cutting and ensure that participants traversed the entirety of each route. Furthermore, segments of a route were long enough that the next turn became visible only after the preceding turn was completed, forcing participants to turn. Graphic textures were applied to the walls (red brick) and floors (grass). The sky was procedurally generated and appeared as generally blue with uniform lighting applied and no visible light source (e.g., the sun) which could have been used by participants to orient or identify one route from another. The only orienting features (landmarks) were two picture frames, one on each end of the middle route (see first-person viewpoint in Fig. 2), displaying a distinct color,

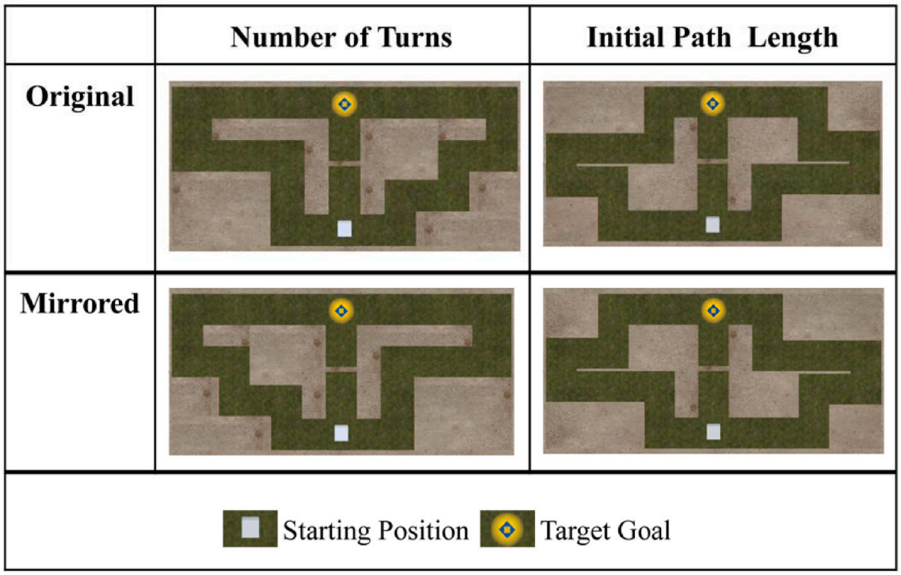

Fig. 1. Experimental design and top-down depiction of the virtual environments. We manipulated either the number of turns (left column) or the length of the first leg (right column). The area of either the inner or outer unpaved region could also differ (for example in the left column), although this factor was not independently manipulated from the other two primary factors. The start location is indicated by the white square and the target by the gem. The central route was blocked during the test as indicated by the gap in the middle of that route. Each of the 13 virtual environments consisted of a mirrored virtual environment along the y-axis, shown in the lower row. In the example shown for the number of turns condition (left column), one route has 4 turns, and the other has 6 turns (i.e., a difference of 2 turns). Participants were fully immersed and could walk in these virtual environments and they never saw these overhead views in Experiment 1.

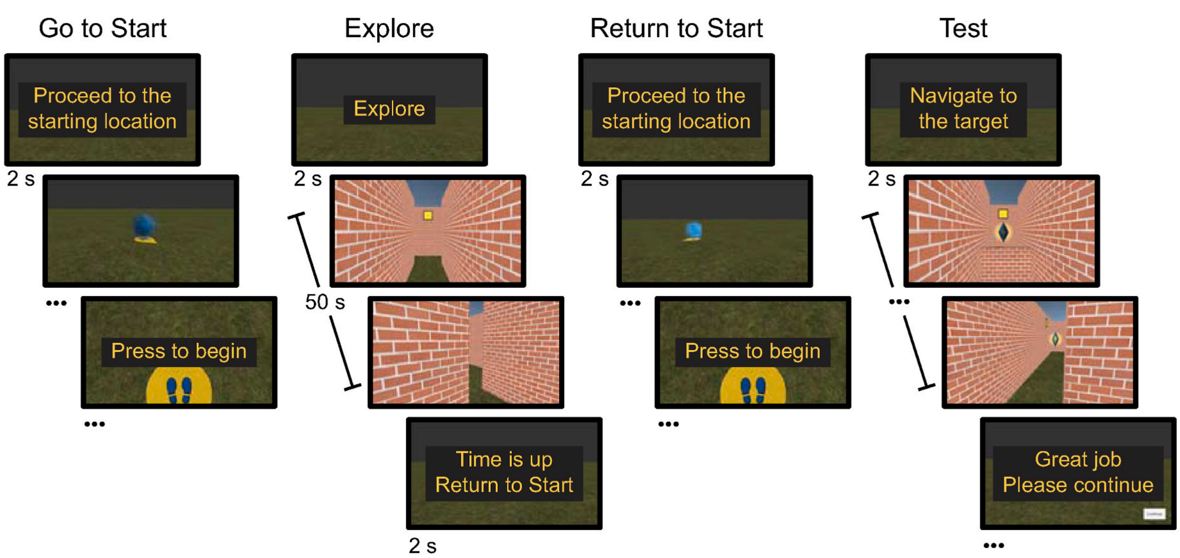

Fig. 2. Trial structure from Experiment 1. Participants began each trial by walking to a starting position (Go to Start) and were instructed to walk around to explore the entirety of the environment within a 50-s timeframe. After exploring for 50 s (Explore), they were then directed to walk back to the starting location to begin the testing phase (Return to Start). During this phase (Test), the middle route was obstructed (Test: second panel), forcing participants to choose either the left or right route to reach the target (gem). For durations, ellipses (…) indicate that participants had no time limit (e.g., reaching the target).

randomly sampled from nine possible colors (adapted from Wong, 2011, with the addition of gray and white); this allowed participants to distinguish one end of the middle route from the other. A mirrored version of each of the 14 test VEs excluding the practice VE (i.e., reflected across the short axis of the environment) was included for counterbalancing and to test for simple left/right biases, resulting in a total of 28 distinct VEs.

The experimental task was developed in Unity 3D using the Landmarks package (Starrett et al., 2021). The experiment was conducted at the University of California Irvine Center for Ambulatory Virtual Environment Research on Navigation (CAVERN). Participants used an HTC VIVE Pro Eye head-mounted display, and two controllers (HTC Corp., Taoyuan City, Taiwan) at a resolution of 1440 x 1600 pixels per eye, 90 refresh rate, and 98° field of view. The study was run on an Omen 30L Desktop (HP Inc., Palo Alto, CA) with an NVIDIA GeForce RTX 3080 Ti graphics card (NVIDIA Corp., Santa Clara, CA).

2.1.3. Design

This study employed a fully within-subject design, where the primary independent variable was the Condition (number of turns, length of the initial straight path) by which the routes on each side of the environment differed. All participants experienced all 28 distinct testing VEs, and thus each of the route manipulations used. For each of the 14 testing VEs and their mirrored foils (total of 28 trials), the two outer routes were always exactly the same length. We designed the task with two primary variables that we manipulated: number of turns and the length of the first path. Specifically, 14 VEs (50 %, including mirrored versions) featured differences in the number of turns between the two routes, while 6 VEs (21 %, including mirrored versions) varied in the length of the initial path of the route. Additionally, 4 exploratory VEs (14 %, including mirrored versions) manipulated both the turn angle and length of the first path and 4 VEs (14 %, including mirrored versions) combined variations in the number of turns and length of the first path.

After designing the experiment, we recognized an additional factor that could potentially influence participants' decisions: the area of the unpaved regions (brown/gray). Although the inner and outer areas were not directly derived from any predefined theories nor were they part of our initial experimental design, we included additional exploratory analyses related to these other potentially relevant metric properties of the environment. For example, in Fig. 1 the inner unpaved area differs between the left and right routes in the left column, but not in the right column of Fig. 1. Due to the rectangular shape of the room, sometimes both the inner and outer areas differed, but not always. This factor was not independently manipulated from the other two primary factors. In Experiment 1, participants never saw this top-down view, and thus never directly saw either the inner or outer unpaved areas. In Experiment 2, the top-down view is what was presented to the participants, and they could see the inner and outer unpaved areas. Inner blocks were categorized as those connected to the wall blocking the middle route, while outer blocks were defined as disconnected areas on either the left or right, relative to the middle of the short axis of the environment. Due to the rectangular room shape, both the inner and outer unpaved areas sometimes varied but not consistently. Among the 28 VEs, 16 VEs (57 %, including mirrored versions) also featured differences in the inner areas, encompassing the conditions mentioned above, and 18 VEs (64 %, including mirrored versions) exhibited differences in the outer areas, encompassing the same conditions.

The primary dependent measure was whether the route chosen by participants during the test phase had fewer turns or a shorter initial path length, along with secondary observations of preference for a larger inner area, and/or a larger outer area (depending on the feature(s) manipulated in that environment). The mirrored environments allowed us to check for consistency and any non-structural heuristics such as a tendency to favor one direction (e.g., always choosing the right route) or an initial exploration bias (e.g., tendency to select the same route in the exploration and testing phase). Both of these biases could be influenced by factors such as handedness and a lack of knowledge about the environmental layout.

2.1.4. Task procedure

Participants provided informed consent prior to any study procedures. Before beginning the experiment, participant demographics such as age, handedness, sex, native language, ethnicity, history of psychiatric problems or cognitive deficits, history of head trauma, and use of psychoactive drugs were recorded. The experimenter explained the task to participants and instructed them in the use of the HTC Vive Wireless VR system before beginning the experiment using a set of PowerPoint slides and providing answers to any clarification questions. Participants were instructed that the experiment would consist of 28 trials, each including an exploration and a testing phase. They were given 50 s to explore the entire environment before returning to the starting position (Fig. 1, white cube) to begin the testing phase. During the testing phase, the central route was blocked, and their objective was to reach the gem on the other side. To avoid influencing their decisions, words like "choose," "left," "right," "preference," "shorter," or "longer," and their synonyms, were not used during the instructions. Participants were unaware of the specific manipulations or the recorded dependent measures until the study was completed. They were simply told to explore the environment and then a route would be blocked in the testing phase in which their task was to find a way to the gem.

Each trial began with a transitional phase during which participants physically walked to a starting location marked by a set of blue footprints on a featureless grass terrain (Go to Start; Fig. 2). Upon reaching and aligning themselves with the set of blue footprints, participants pressed the trigger on the handheld controller which prompted the appearance of a VE and indicated the beginning of the exploration phase in which participants freely walked and explored the immersive virtual environment (Explore; Fig. 2). After 50 s of free exploration, the environment disappeared, and the transitional environment reappeared, again directing participants to align themselves with a second set of blue footprints (Return to Start; Fig. 2). This phase ensured reorientation to the starting position for the test phase. Researchers observed and ensured that the participants walked the entirety of each environment in the explore phase, and all trials in which participants did not walk the entirety of the environment were excluded from the analysis.

During the test phase (Test; Fig. 2), the environment reappeared with a gem present at the other end of the middle route. However, the middle route was blocked by a low barrier such that participants could see the goal but not traverse the middle route to get there. Participants were thus required to navigate to the goal by selecting either the left or right path. While participants were not explicitly prompted to choose a side or to verbalize their decision, their movement along one of the two available routes served as their response. The order of the 28 trials was randomized for each participant. Participants completed 28 trials, one per VE in a randomized order. Following completion of the VR task, participants completed a survey asking them to rank their preferences for variables such as number of turns and initial path length, as well as to describe strategies they used and whether they noticed any specific properties or differences in the VEs. Lastly, the researcher debriefed participants on the aim and implications of the study, provided compensation, and then dismissed them.

2.1.5. Primary and area analyses

Data was analyzed in R (R Core Team, 2024) via R-Studio (RStudio Team, 2024) using the Tidyverse package (Wickham, 2019). All trials in which participants did not fully explore the environment were excluded from the analysis. Additionally, data from any participant who failed to complete at least 20 of the 28 trials were excluded entirely. For each participant included in the subsequent analyses, we calculated the proportion of trials in which they chose the route with a particular property, relative to the other route (fewer turns, a shorter initial path length). We also calculated the proportion of trials in which participants chose the route with fewer turns, broken down by whether the difference in turns between the left and right route in a VE was one, two, and four. To determine whether parametric or non-parametric tests were appropriate, a Shapiro-Wilk test was used to check for normality and a Levene's test was used to check for equal variance. Based on these results, data were then analyzed using parametric tests (e.g. Analysis of Variance (ANOVA), *t*-test) when appropriate or their non-parametric equivalents (e.g., Friedman Test, Wilcoxon test). Given that inner and outer area of each route was not manipulated independently from the number of turns and initial path length, separate ANOVAs were conducted on each of these factors.

2.1.6. Control & consistency analyses

To confirm that participants were not simply biased for one side or another (e.g. just choosing the route on the right for every environment and its mirror), we conducted several control analyses. For each participant, a directionality-bias score was calculated by dividing how often they initially chose one of three routes in the explore phase (left, middle, right) by the total number of trials completed. We computed the same score for the testing phase by calculating how often participants chose one of two routes (left or right) by the total number of trials in the testing phase.

Consistency was operationalized as the selection of structurally equivalent routes across original and mirrored versions of the same environment. The task included 28 trials, consisting of 14 unique virtual environments, each presented twice: once in its original configuration and once mirrored along the x-axis. For a participant's choice to be considered consistent, they had to select the equivalent route in both the original and mirrored versions. For instance, if a participant chose the right-hand path in the original environment (e.g., the route with fewer turns), consistency required selecting the left-hand path in the mirrored version, as it represents the same structural route following the axis reflection. In contrast, selecting the same directional path (e.g., right in both the original and mirrored versions) would indicate an inconsistent choice, as the mirrored transformation results in different route configurations. Therefore, participants had a 0.5 probability of selecting either route in each environment.

To test how consistent participants were across the original and mirrored versions of each trial (i.e., even if participants did not have preferences for the manipulated conditions, whether they consistent in their choices when faced with almost the exact same trial), we checked how often a participant took the same route in both the mirrored and original virtual environments. This was calculated by dividing the number of times participants followed the route with the same structural properties in both the original and mirrored versions by the total number of distinct environments they explored, categorized by virtual environment type (e.g., number of turns, initial path distance, or area). For example, if a participant chose the route with the same set of identical structural properties in both the *original* and *mirrored* trials for 6 out of 8 total pairs of VEs in which the number of turns varied, the participant would get a consistency score of 0.75.

Different from the consistency score, we calculated how much initial experience influenced later decisions by seeing how often participants chose the same route in the *testing phase* as they did initially during *exploration*. This score was determined by dividing the number of matching route choices between exploration and testing by the total number of trials. For example, an individual may have taken the same initial route in exploration and testing phase 4 of the 8 VEs, meaning that would receive a first impression score of 0.5.

2.2. Results

All data and analysis code for both experiments are available on Open Science Framework [https://osf.io/9zsde/?view_only=fccd4dfff41d4cf98c784a736317200b]

2.2.1. Differences in number of turns

A one-sample *t*-test showed that participants chose the route with fewer turns ($M = 0.59$, $SD = 0.19$) significantly more often than chance (Fig. 3A) ($t(39) = 3.21$, $p = .003$, $d = 0.51$). Further, a one-sample *t*-test also indicated that participants were significantly more consistent ($M = 0.58$, $SD = 0.21$) in choosing the route with identical structural properties between the original and the mirrored version compared to chance, ($t(39) = 2.59$, $p = .014$, $d = 0.41$), for trials that manipulated the number of turns (Fig. 3B). Qualitatively, as the difference in the number of turns between the two routes increased, the general preference for choosing routes with fewer turns was attenuated, and greater variability in route preference was seen (Fig. 3C). To explore the effect of the number of turns and assess whether this preference was static across

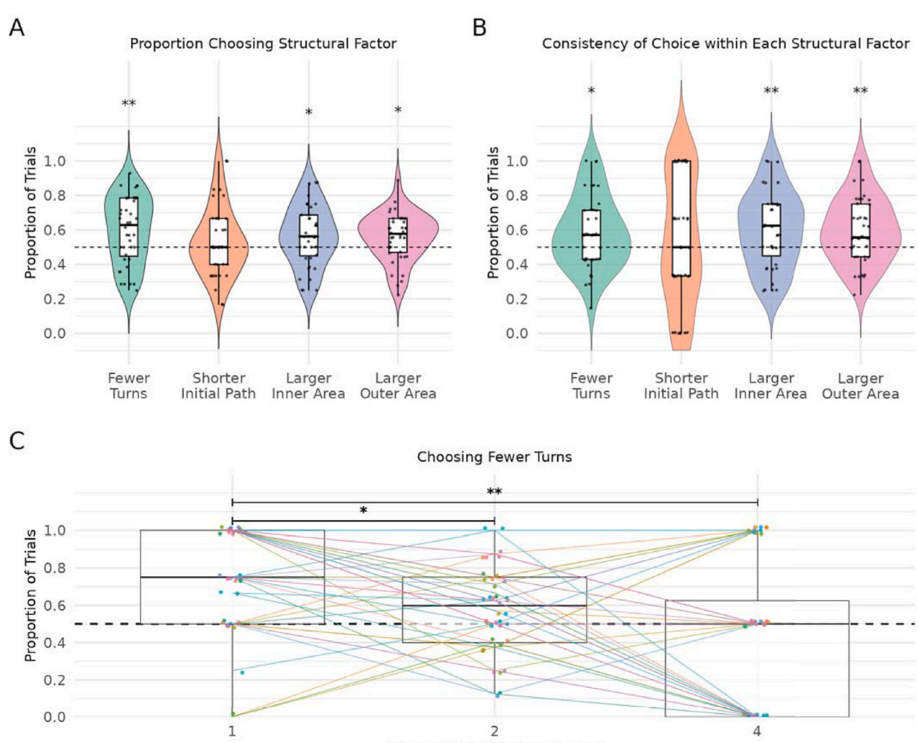

Fig. 3. Experiment 1 Results. People chose fewer turns, larger inner area, and larger outer area more often than chance and were consistent. (A) Proportion of trials reflects the frequency with which participants selected routes based on structural factors - fewer turns, shorter initial path, larger inner areas, and larger outer areas - across the four conditions. Violin plots show the distribution, with boxplots indicating the median and interquartile ranges. Black dots represent individual participants' proportion of choosing routes for each condition. Asterisks indicate statistical significance compared to chance (0.5; dashed line). (B) Proportion of trials where participants chose the route with identical structural properties in both original and mirrored environments (consistency) across the conditions in (A). Asterisks indicate statistical significance compared to chance (0.5; dashed line). (C) A greater proportion of trials on the vertical axis indicates a higher proportion of participants choosing the route with fewer turns, plotted as a function of the difference in the number of turns between the two routes. Lines show individual tendencies to choose routes with fewer turns, with box plots summarizing overall trends. Boxes represent the interquartile range (IQR), medians are marked by the central bolded line, whiskers extend 1.5 times the IQR, and circles indicate trial proportions for turn differences of 1, 2, and 4. Asterisks indicate degree of statistical difference from 0.50: *$p < .05$, **$p < .01$.

multiple-turn trials, a Friedman test (a non-parametric ANOVA) was conducted. The test revealed a significant change in preferences across different turn differences ($\chi^2(2) = 15.47$, $p < .001$). As a follow-up, pairwise Wilcoxon signed rank-sum tests were conducted, with Bonferroni adjustment for multiple comparisons. There was a significant difference in preference between environments with a 1-turn ($M = 0.73$, $SD = 0.30$) versus 2-turn ($M = 0.58$, $SD = 0.22$) difference ($V = 568.0$, $p = .013$), and between a 1-turn versus 4-turn ($M = 0.42$, $SD = 0.38$) difference ($V = 472.0$, $p = .002$), while the difference between a 2-turn and 4-turn environment did not reach significance ($V = 483.5$, $p = .055$).

A possible confounding factor unrelated to the VE structure is a general bias to prefer a certain direction (e.g., right, left, or forward). Two one-sample *t*-tests and one Wilcoxon-test were used to assess whether participants showed any significant directional bias during the exploration phase in VEs manipulating the number of turns. Participants did not show any significant directional bias during the exploration phase. Their choices for each direction - Right ($M = 0.40$, $SD = 0.26$, $t(39) = 1.622$, $p = .113$), Left ($M = 0.31$, $SD = 0.23$, $t(39) = -0.56$, $p = .581$), and Forward ($Med = 0.22$, $SD = 0.25$), $V = 287.5$, $p = .154$) - did not significantly differ from chance levels (0.33). Similarly, in the testing phase, no directional bias (e.g. always going to the right or the left) was observed in the VEs that manipulated the number of turns ($M = 0.51$, $SD = 0.14$, $t(39) = 0.56$, $p = .580$).

Another potential confounding factor may have been a bias toward first impressions, or a tendency to stick with the first route chosen in the exploration phase for the testing phase. Again, participants showed no significant first impression bias for VEs manipulating the number of turns ($M = 0.53$, $SD = 0.22$, $t(39) = 0.930$, $p = .358$), indicating that they did not choose the same route in both exploration and test more than chance.

2.2.2. Differences in length of the first path

In contrast to the result for the number of turns, a one-sample *t*-test revealed that participants' proportion of trials choosing the route with a shorter initial path ($M = 0.53$, $SD = 0.20$) was not significantly different from chance, (Fig. 3A; $t(39) = 0.86$, $p = .393$, $d = 0.14$). Furthermore, participants showed no consistency between the original and mirrored versions of the VEs manipulating the initial path lengths, as indicated by a Wilcoxon signed-rank test ($Med = 0.50$, $SD = 0.36$, $V = 330.5$, $p = 0.974$) (Fig. 3B).

Despite not having a preference during the test phase, participants significantly preferred to explore the route with the shorter initial path before reaching the first turn in their initial decision during the exploration phase. A one-sample *t*-test supported that this preference was significantly different from chance ($M = 0.58$, $SD = 0.23$, $t(39) = 6.91$, $p < .001$), compared to the expected probability of 0.33.

During the explore phase, participants were more likely to choose either the left or right directions over the forward direction. A one-sample *t*-test revealed that participants chose the right direction significantly more than chance ($M = 0.43$, $SD = 0.27$, $t(39) = 2.27$, $p = .029$, $d = 0.36$). Similarly, a Wilcoxon signed-rank test showed that leftward choices were significantly favored and different from chance ($Med = 0.45$, $SD = 0.26$, $V = 464$, $p = .001$, $d = -0.01$), as well. Forward choices were significantly below chance, as indicated by a Wilcoxon signed-rank test ($M = 0$, $SD = 0.16$, $V = 19.0$, $p < .001$, $d = -0.28$). However, in the testing phase, no directional bias for taking the left or right route was observed in the VEs manipulating the initial path lengths, as a one-sample *t*-test showed no significant difference from chance ($M = 0.55$, $SD = 0.25$, $t(39) = 1.18$, $p = .245$, $d = 0.19$).

Another potential influence, unrelated to the environment's structure, may have been the bias toward first impressions, that is, taking the same route during the test that participants took during exploration. However, a one-sample *t*-test confirmed that first impressions had no significant influence on participants' choices ($M = 0.50$, $SD = 0.24$, $t(39) = 0.14$, $p = .887$).

2.2.3. Differences in area

A one-sample *t*-test was conducted to determine whether participants preferred routes with a larger inner area, and their choices were significantly different from chance ($M = 0.56$, $SD = 0.17$, $t(39) = 2.35$, $p = .024$). Another one-sample *t*-test examined if participants preferred routes with a larger outer area, which also showed significant difference from chance ($M = 0.56$, $SD = 0.14$, $t(39) = 2.58$, $p = .014$). Interestingly, participants did tend to initially select the route with the larger inner area in the exploration phase ($M = 0.40$, $SD = 0.15$, $t(39) = 2.65$, $p = .011$), and continued to utilize this heuristic in the testing phase.

Furthermore, a one-sample *t*-test indicated that participants were consistent in choosing the route with identical structural properties in terms of larger/smaller inner area on mirror trials ($M = 0.61$, $SD = 0.22$, $t(39) = 3.09$, $p = .004$). Similarly, an additional one-sample *t*-test found that participants were also consistent in choosing the route with identical structural properties on mirror trials for VEs manipulating the outer area; ($M = 0.59$, $SD = 0.19$, $t(39) = 3.28$, $p = .002$).

To determine whether other factors influenced the preference for inner and outer areas, a Wilcoxon signed-rank test was conducted. This test examined whether routes with a larger inner or outer area were significantly associated with having fewer turns, which we found participants did have a preference for (see section 2.2.1). The goal of this analysis was to see whether the observed preference for larger inner or outer areas was driven by a tendency to choose routes with fewer turns and vice versa. Among the 14 environments where the number of turns varied (including mirrored versions), 8 had a route with fewer turns and a larger inner area. The results showed no significant link between choosing a route with fewer turns and having a larger inner area ($Med = 0.50$, $SD = 0.51$, $V = 60$, $p = .618$). However, there was a significant association between routes with fewer turns and a larger outer area of the 14 environments; 12 had a route with fewer turns and a larger outer area. A Wilcoxon signed-rank test confirmed this association ($Med = 1.0$, $SD = 0.36$, $V = 90$, $p < .001$). We examined whether participants' choices were influenced by a bias toward first impressions. In VEs manipulating the inner area, a one-sample *t*-test showed no significant first impression bias ($M = 0.54$, $SD = 0.15$, $t(39) = 1.54$, $p = .113$). Similarly, when the outer area was manipulated, no significant first impression bias was found, ($M = 0.53$, $SD = 0.15$, $t(39) = 1.46$, $p = .153$).

Furthermore, we also examined whether participants exhibited a directional bias during exploration in VEs manipulating the inner area, which is a tendency to favor turning right, left, or going forward at the beginning of exploration. This was assessed using a one-sample *t*-test and two Wilcoxon tests. In the condition involving the inner area, participants' choices showed a significant bias: they chose the right direction more frequently than the chance level (0.33), ($M = 0.43$, $SD = 0.25$, $t(39) = 2.40$, $p = .021$). In contrast, the forward direction was chosen significantly less frequently than chance, ($Med = 0.18$, $SD = 0.25$, $V = 154$, $p = .002$), while the frequency of left turns, ($M = 0.32$, $SD = 0.23$, $V = 412$, $p = .581$), did not differ significantly from the expected chance level. No directional bias (right or left) was observed during the testing phase, ($M = 0.50$, $SD = 0.12$, $t(39) = 0.02$, $p = .985$).

For the condition involving the outer area, no significant directional bias was detected during exploration for any of the directions: rightward choices with Wilcoxon signed-rank test, ($Med = 0.37$, $SD = 0.24$, $V = 455$, $p = .223$); leftward choices with one-sample *t*-test ($M = 0.33$, $SD = 0.22$, $t(39) = -0.07$, $p = .945$); forward choices with Wilcoxon signed-rank test, ($Med = 0.19$, $SD = 0.23$, $V = 251$, $p = .084$). Moreover, participants did not demonstrate a significant preference for the route with the larger outer area in the exploration phase, ($M = 0.36$, $SD = 0.15$, $t(39) = 1.33$, $p = .193$). During the testing phase, there was no evidence of a directional bias (choosing right or left) either. The proportion of rightward route selections was not significantly different from chance ($M = 0.51$, $SD = 0.12$, $t(39) = 0.557$, $p = .580$).

2.3. Experiment 1: Discussion

Participants in this study explored 14 unique testing virtual environments and their mirrored versions, with access to visual, vestibular, proprioceptive, and somatosensory information to navigate. They tended to prefer routes with fewer turns as well as larger inner and outer areas despite the routes being of equal length. This suggests that instead of forming detailed mental maps of the environments, participants relied on non-metric graph-like properties heuristics to aid in decision-making. For the number of turns, this preference tended to shift as the difference in the number of turns increased between route choices. Participants were consistent in their choices for the number of turns, inner area, and outer area. However, participants had no biases for the length of the first turn and were inconsistent in choosing the same route.

The preference for routes with fewer turns aligns well with the cognitive graph framework, which proposes that spatial understanding is built from general, approximate information. To make sense of incomplete details, the use of mental shortcuts (heuristics) is required, rather than relying on exact spatial details like metric distance. The consistency in route choices across the original and mirrored environments shows that heuristics are not only present but also follow clear and consistent patterns that guide decision-making, indicative of an underlying cognitive graph framework. Alternatively, without relying on biases they might have been attempting to use a highly detailed spatial representation for distance. Because both routes were the same length, such an attempt would produce random decision-making; however, participants differed from random chance in their preferences. Previous studies have shown that routes with major bends or multiple direction changes (e.g., two to four turns) are often perceived as longer than they are (Byrne, 1979). Furthermore, increasing the number of turns reduces the degree of underestimation (Bonasia et al., 2016). These findings align with our observation that participants preferred routes with fewer turns, since more turns can distort distance estimates for routes of equal length.

A larger discrepancy between the routes in the number of turns would, intuitively, make the fewer-turn route more appealing; however, this was not consistently observed in our data. One possible explanation is that with every additional turn, the segments of the route may rotate more toward the goal, which could bias participants toward selecting them. This aligns with the least-angle heuristic, wherein navigators tend to prefer routes that appear to head more directly toward the destination. Therefore, some virtual environments may be structured such that routes with more turns are perceived as more goal-aligned, even when all routes are equal in path distance.

In contrast, in trials that manipulated the initial path length, participants demonstrated no clear preference or consistency, indicating that decisions in these scenarios were likely made at random. This finding suggests a weak or non-existent influence of this particular route property on navigational behavior, perhaps reflecting the existence of a cognitive map. Furthermore, this lack of preference for shorter or longer initial path challenges earlier studies that identified a preference for longer initial paths, a phenomenon known as the Initial Segment Strategy (ISS) ((Bailenson et al., 1998, 2000; Brunyé et al., 2015; Christenfeld, 1995; Golledge, 1995).These studies were all conducted using top-down map views of the environment, which differed from our first-person perspective. We note that our paths are oblique to the direct line to the target, and it is possible that the routes might need to be somewhat directed toward the target to be effective (e.g. Christenfeld, 1995). This open theoretical question should be pursued in future work. Furthermore, participants may have also used other strategies, such as the "least-angle strategy," which favors routes that deviate the least from the target destination (Bongiorno et al., 2021; Hochmair and Frank, 2002). Additionally, Bongiorno et al. (2021) found that for longer journeys, participants are more likely to head in the general direction of their destination rather than evaluating every possible route to find the shortest one. They rely on simpler strategies to manage the increased complexity of longer routes. Therefore, in our study, since the environment was small and relatively simple, the initial path length may not have significantly influenced decision-making.

In contrast to the Initial Segment Strategy - a preference for longer initial paths - our results align with those of Hochmair and Karlsson (2005) who observed a preference for shorter initial paths without prior exploration. Interestingly, their study utilized a similar first-person perspective within a desktop virtual environment that provided a limited view of the scene at the starting point. Consistent with their findings, we observed that participants chose the route with the shorter initial path when first exploring. However, a key difference between our study and Hochmair & Karlsson's is that the preference for shorter initial paths disappeared during the testing phase in our study, after participants had fully explored the environment. This finding suggests that the length of the first path does have an influence on that very first navigational decision of where to explore, although not later on, such that the use of heuristics, including favoring shorter initial paths, may depend on the type and amount of spatial information available.

Although the conditions of the inner area and outer area were a secondary condition derived from creating maps for the other conditions, it still reveals that there is a preference for routes with a larger inner area or larger outer area. There was no association of fewer turns and larger inner area, therefore the preferences for inner area was not an artifact of fewer turns, although the outer area was not independent of turns. We do not know of other studies that have examined this factor before. This exploratory analysis should motivate future research to directly manipulate these areas to produce a stronger argument for the preference of larger and inner areas.

Although we think it likely that these results are best explained by heuristics from cognitive graphs, path integration demands, cognitive load, and stress can also readily influence route selection. Participants may have preferred routes with fewer turns not because of graph-based representations, but because such routes were less computationally demanding to integrate the rotations, reflecting a non-graph heuristic. Although some routes in our study featured more turns, thereby increasing the demands of path integration, the overall task was computationally straightforward and likely minimized the potential for path integration errors. In addition, previous research suggests that under stress, individuals tend to revert to simpler, fewer-turn routes based on non-graph reactive heuristics (Schwabe et al., 2007; Schwabe and Wolf, 2009, 2010). This shift is thought to reflect stress-related impairments in prefrontal cortex function, which plays a key role in complex decision-making and executive control (Arnsten, 2009; Liston et al., 2009). In contrast, under low-stress conditions, individuals are less likely to rely on such heuristics and are more likely to engage in higher-order spatial reasoning, including graph-based evaluations of route structure. In our study, participants had ample time to freely explore each environment before testing, and the test phase consisted of untimed, forced-choice decisions. These minimal-stress conditions reduce the likelihood that reactive heuristics influenced behavior.

In conclusion, results from Experiment 1 suggest that, even in simple environments learned through active first-person exploration, participants rely on graph-like properties absent any differences in metric distance. Their choices and preferences were influenced by heuristics, such as minimizing the number of turns. These findings align with the idea that, at least in some contexts, spatial information is not processed in the form of a cognitive map, but in a less metrically accurate manner consistent with a cognitive graph.

Previous work has shown differences in the degree to which map-learning and wayfinding contribute to route and survey knowledge (Richardson et al., 1999; Starrett et al., 2019, 2023; Weisberg and Newcombe, 2016; Zhang et al., 2014). Thus, it is possible that map-learning or viewing environments from an aerial perspective may provide more salient access to information about the metric length of each route and potentially override or negate the influence of graph-based heuristics. To address this, we conducted a second experiment in which the first-person exploration and test phases were replaced with top-down viewing of the environments.

3. Experiment 2

Experiment 2 used the same environments and paradigms as Experiment 1, but instead of learning the environments from the first-person perspective, participants were shown overhead views of the entire environment, similar to some previous paradigms (e.g. Bailenson et al., 1998; Brunyé et al., 2015). We hypothesized that any preferences for differences in turns or initial path lengths would be substantially weaker in Experiment 2, relative to Experiment 1, or absent completely because participants would gain better survey knowledge of the environment from the map view, helping them form more accurate mental maps. In turn, participants will have more accurate distance information and might rely less on simple shortcuts or heuristics, resulting in no strong preference for any specific route.

To test this hypothesis, we conducted a two-alternative forced-choice task in which participants viewed 28 top-down environments from Experiment 1, along with 12 new environments - with half of those being mirrored environments - added for Experiment 2, making a total of 40 environments. All 40 environments were presented in each block in a random order, and the task consisted of 4 blocks in total. Six new virtual environments were added for exploratory and pilot data: three varied the number of turns, one varied inner and outer areas, one varied the first-turn angle, and one varied number of turns, first-turn angle, initial path length, and inner/outer areas. To ensure a fair comparison between Experiment 1 and Experiment 2, the six new environments were excluded from the analysis since their main purpose was for pilot/exploratory data analysis. Additionally, one of the exploratory environments from Experiment 1 - designed to manipulate both initial path length and turn angle - was mistakenly uploaded twice, replacing another exploratory environment with similar manipulations. However, neither of these environments was included in the final analysis, as they were intended solely for piloting and did not incorporate differences between inner or outer areas necessary for the study's main comparisons.

3.1. Materials and methods

The hypotheses, design plan, sampling plan, methods, and analysis plan for Experiment 2 were pre-registered on Open Science Framework (https://osf.io/jqpx9).

3.1.1. Participants

We used the results of Experiment 1 to generate a power analysis for Experiment 2. Specifically, we aimed to collect a sample sufficient to replicate the group-level effect for preferring routes with fewer turns ($d = 0.48$).[3] The power analysis was performed using G*Power (Faul et al., 2007) and estimated that 41 participants were needed to detect an effect size of 0.48 at 85 % power at an alpha level of 0.05. A total of 44 healthy adults aged 18 to 35 with normal color vision were enrolled in the study. Three participants had previously completed the initial experiment and were excluded from the analysis, resulting in a final sample size of $N = 41$ (25 females) aged 18 to 34 ($M = 21.29$, $SD = 3.94$). All participants provided informed consent and all procedures were approved by the University of California, Irvine Institutional Review Board. Participants were paid for their time.

3.1.2. Stimuli and equipment

The same environments from Experiment 1 were utilized in Experiment 2. However, in Experiment 2, the stimuli were top-down images of the environments created in Unity (Fig. 4). Participants could view the concrete walls/blocks and grass routes clearly with the addition of the goal object, the white cube, and the wall blocking the middle route. All environments were dimensionally identical. Due to the top-down perspective, the paintings were not visible, as in Experiment 1. On the display viewed by participants, each environment image was 18 inches wide by 7 inches tall.

The study was conducted on a Victus by HP 15L Gaming Desktop equipped with a 13th Gen Intel Core i5-13500 processor running at 2.50 GHz. The system operated on Windows 11 Home, Version 23H2, and used an LG 27MQ450-B display powered by Intel Arc A380 graphics. The display was 24 inches wide by 10 inches tall (26 inches diagonally) with a resolution of 1920 x 1080, a refresh rate of 60 Hz, and an 8-bit

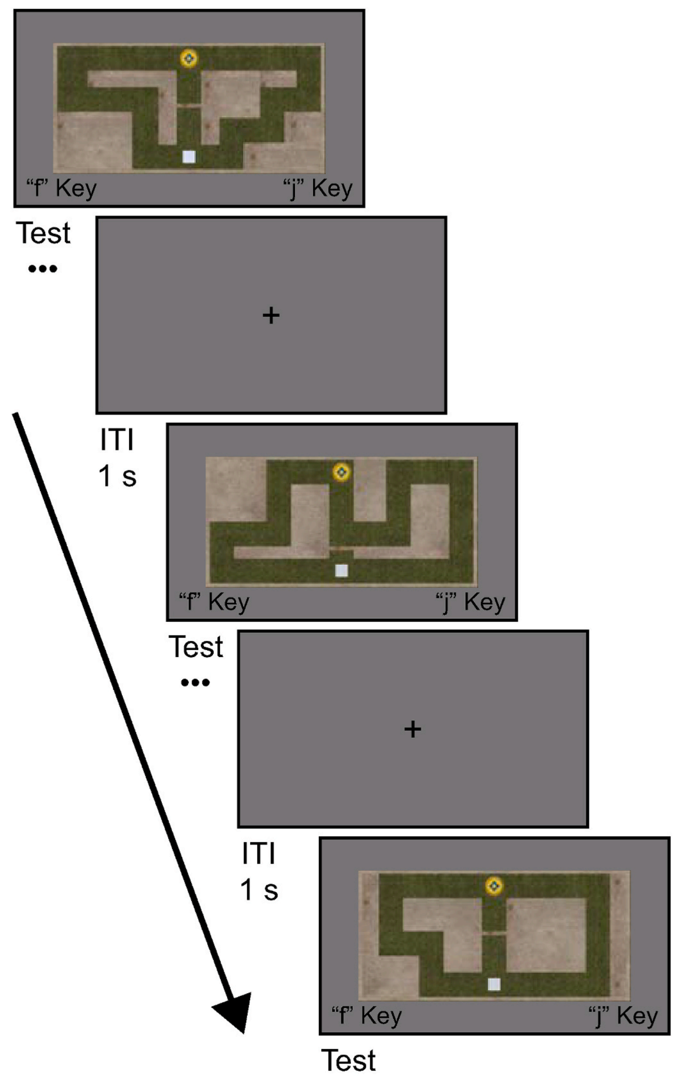

Fig. 4. Experiment 2 Methods. Participants used the "f" or "j" key to indicate which route participants would take to go from the starting position (white cube) to reach the final destination (gem in "Test" panels) in each virtual environment. Test trials were separated by a 1-s inter-trial interval (ITI), during which only a fixation cross was shown. For durations, ellipses (…) indicate that participants had no time limit.

[3] Notably, our preliminary analysis revealed an effect size of 0.48 for a two-tailed *t*-test on the preference for routes with fewer turns, as pre-registered on the Open Science Framework (OSF). However, a thorough review of the analysis revealed a coding error that inadvertently included exploratory trials, leading to an inaccurate effect size calculation. The corrected effect size was 0.51. After discussion, we decided to adhere to the pre-registered effect size of 0.48 when determining the required sample size, resulting in a target of 41 participants instead of the 37 that would be needed for a 0.51 effect size.

color depth. Trial presentation code was created using E-Prime version 3.0.3.214 (Psychology Software Tools, Inc, Pittsburg, PA). Due to the nature of the task, trial duration was shorter than in Experiment 1 (on the order of seconds rather than minutes). In addition to an initial block, which comprised a single exposure to each environment and mirror version (40 total), participants completed three additional blocks (four total).

3.1.3. Procedure

Before the experiment, participant demographics such as age, handedness, sex, native language, ethnicity, history of psychiatric or cognitive deficits, history of head trauma, and use of psychoactive drugs were recorded. Within each block, each of the 40 environments were presented in a randomized order. The study began with a practice trial (identical to the practice VE in Experiment 1) to help participants understand the procedure. In each trial, they viewed a top-down image of an environment that included a starting position, represented by a white cube, and a target position, marked by a top-down view of the same blue gem used in Experiment 1. Participants were asked to press either the "f" or "j" key to indicate the direction the white cube should move to arrive at the gem. There was no time limit, making the task a two-alternative forced-choice paradigm. Each response was followed by a 1 s inter-trial interval (ITI) displaying a fixation cross (+) before the next environment was displayed (Fig. 4).

3.1.4. Primary analyses

The primary analyses from Experiment 1 were repeated in Experiment 2. Additionally, reaction times - the duration in milliseconds from the appearance of a VE to the participant's inputted response - were recorded in Experiment 2. Because Experiment 2 uniquely included four blocks, unlike Experiment 1, which consisted of a single block, a 2 (Condition: number of turns, length of the first path) x 4 (Block: 1–4) ANOVA was conducted to examine the relationship of reaction time between the four experimental conditions across repeated exposures. Separate, exploratory one-way (Block: 1–4) ANOVAs were conducted for inner area and outer area. All control analyses from Experiment 1 were repeated in Experiment 2, except for directionality bias during the exploration phase, which was not possible in the top-down paradigm used. Participants were excluded if more than 25 % of their trials had reaction times below 150 ms. Additionally, all individual trials with reaction times under 150 ms were excluded from analysis. Furthermore, we excluded trials that fell outside three standard deviations from each participant's mean reaction time.

3.2. Results

3.2.1. Differences in number of turns

A one-sample *t*-test showed that participants were significantly more likely to choose the route with fewer turns compared to chance ($M = 0.69$, $SD = 0.20$, $t(40) = 21.67$, $p < .001$) (Fig. 5A). Similar to Experiment 1, participants' preference for routes with fewer turns decreased as the difference in the number of turns increased (Fig. 5C). This trend also revealed greater variability in participants' choices. To further analyze the effect of the number of turns, a Friedman test was conducted, revealing a significant change in preferences across turn differences, ($\chi^2(2) = 15.47$, $p < .001$). As a follow-up, pairwise Wilcoxon signed rank-sum tests were conducted, with Bonferroni adjustment for multiple comparisons ($p < .017$ for three comparisons), to examine how the

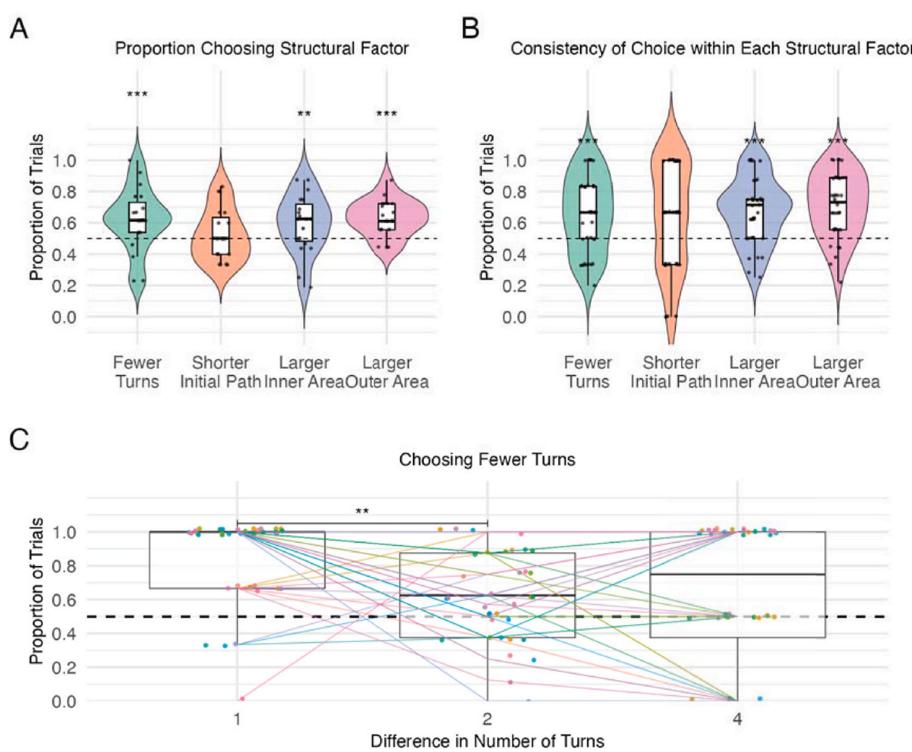

Fig. 5. Experiment 2 Results. People chose fewer turns, larger inner area, and larger outer area more often than chance and were consistent. (A) Proportion of trials reflects the frequency with which participants selected routes based on structural factors - fewer turns, shorter initial path lengths, larger inner areas, and larger outer areas. Violin plots show the distribution, with boxplots indicating the median and interquartile ranges. Black dots represent individual participants' choices. Asterisks indicate statistical significance compared to chance (0.5; dashed line). (B) Proportion of trials where participants chose the same route in both original and mirrored environments (consistency) across the conditions in (A). Asterisks indicate statistical significance compared to chance (0.5; dashed line). (C) A greater proportion of trials on the vertical axis indicates a higher proportion of participants choosing the route with fewer turns, plotted as a function of the difference in the number of turns between the left and right route. Lines show individual tendencies to choose routes with fewer turns, with box plots summarizing overall trends. Boxes represent the interquartile range (IQR), medians are marked by the central bolded line, whiskers extend 1.5 times the IQR, and circles indicate trial proportions for turn differences of 1, 2, and 4. Asterisk indicates the degree of statistical difference from 0.5 between the conditions: $^{**}p < .01$, $^{***}p < .001$.

difference in the number of turns affected the likelihood of selecting the route with fewer turns. For routes with a one-turn difference, participants preferred the route with fewer turns ($M = 0.85$, $SD = 0.26$), and this preference was significantly higher than for routes with a two-turn difference ($M = 0.61$, $SD = 0.26$, $V = 498.50$, $p < .001$) or a four-turn difference ($M = 0.63$, $SD = 0.42$, $V = 243.00$ $p = .030$), although the latter did not survive multiple comparison correction. However, there was no significant difference in preference between the two-turn and four-turn differences ($V = 191.50$, $p > .250$).

A Wilcoxon signed-rank test revealed that participants were consistent in their choices between the original and mirrored versions ($Med = 0.67$, $SD = 0.24$, $V = 522$, $p < .001$) (Fig. 5B). A possible confounding variable unrelated to the structure of the environment is the bias to prefer a direction (e.g., choosing the right route on all trials) regardless of the structure of the environment. A bias for choosing the right side or 'j' key was seen in this condition ($Med = 0.54$, $SD = 0.13$, $V = 579.5$, $p = .022$).

3.2.2. *Differences in length of the first path*

Participants did not show a significant preference for the route with a shorter initial path, with their choices ($Med = 0.50$, $SD = 0.17$) being no different from random chance, ($V = 81$, $p = 0.140$) (Fig. 5A). Furthermore, participants were not consistent in their choice between the original and mirrored version ($Med = 0.67$, $SD = 0.33$, $V = 553.50$, $p = .107$) (Fig. 5B). However, no directionality bias was seen in this condition ($Med = 0.67$, $SD = 0.32$, $V = 380$, $p = .461$) with a Wilcoxen signed rank *t*-test.

3.2.3. *Differences in area*

A one-sample *t*-test was conducted to determine whether participants preferred routes with a larger inner area, and their choices were significantly different from chance ($M = 0.57$, $SD = 0.15$, $t(40) = 3.23$, $p = .003$) (Fig. 5A). A one-sample *t*-test examined whether participants preferred routes with a larger outer area, which also showed significant difference from chance ($M = 0.57$, $SD = 0.07$, $t(40) = 6.34$, $p < .001$) (Fig. 5A).

An additional Wilcoxen signed rank test showed that participants were consistent in choosing the same route associated with the inner area ($Med = 0.75$, $SD = 0.21$, $V = 861$, $p < .001$) (Fig. 5B). Similarly, participants consistently chose the same route associated with the outer area as well ($M = 0.73$, $SD = 0.20$, $V = 552.50$, $p < .001$) (Fig. 5B).

No directionality biases were seen in either the condition which manipulated the inner area ($M = 0.52$, $SD = 0.12$, $t(40) = 0.94$, $p = .351$) or the outer area ($M = 0.51$, $SD = 0.11$, $t(40) = 0.59$, $p = .559$), using one-sample *t*-tests.

3.2.4. *Reaction time across blocks*

Due to technical issues, only the last 19 participants (of the 41 total) had a record of reaction times for all four blocks.

A 2 (Condition: number of turns, length of the initial path) x 4 ANOVA (Block: 1–4) was conducted on reaction time data, using Greenhouse-Geisser sphericity correction. The results revealed a significant main effect of block ($F(1.34, 17.43) = 5.68$, $p = .021$), indicating that reaction time was significantly faster across repeated exposure to the environments (Fig. 6A). Similarly, a significant main effect of condition was observed ($F(1, 13) = 10.31$, $p = .007$). However, no interaction effect was observed ($F(2.68, 34.84) = 0.56$, $p = .627$). Reaction time differed between number of turns ($M = 2338$ ms, $SD = 2346$ ms) and length of the initial path ($M = 2774$ ms, $SD = 2595$ ms) ($V = 238845.5$, $p < .001$. The Greenhouse-Geisser corrected one-way ANOVA for inner area revealed significant changes over the course of the four experimental blocks ($F(1.58, 20.58) = 6.67$, $p = .009$; Fig. 6B), and significant change over blocks was also observed for outer area ($F(1.65, 21.45) = 5.20$, $p = .019$; Fig. 6C).

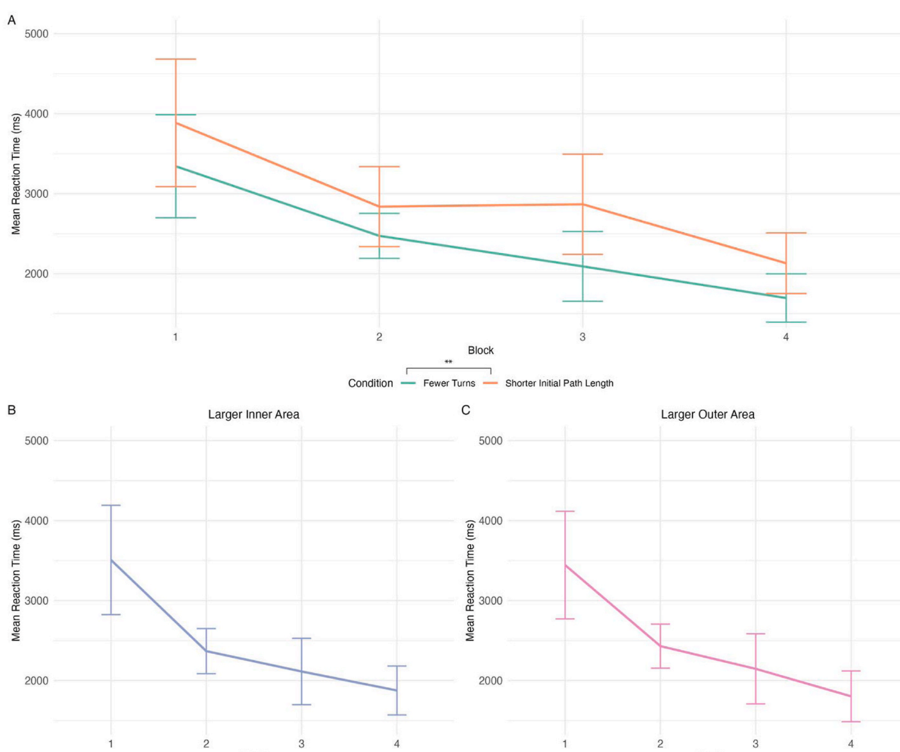

Fig. 6. Reaction Time by Condition and Block in Experiment 2. The y-axis represents the mean reaction time (in milliseconds) for participants to input a response, categorized by block and condition. Error bars indicate standard error. Each condition is represented by a unique color. Panel A: A 2 (condition) x 4 (block) ANOVA for the original design conditions found a main effect of block ($p = .021$), with participants responding faster over time, and a main effect of condition ($p = .007$), with people responding faster in the number of turns condition. Panel B and C: A main effect of block was observed for inner area ($p = .009$), and for the outer area ($p = .019$).

3.2.5. Preferences across blocks

As with the reaction time data, a 2 x 4 ANOVA was conducted to compare turn number and initial path length across blocks and separate 1 x 4 ANOVAs were conducted to compare inner and outer area across blocks, respectively. For each of these tests, variance was computed separately for groups to account for inhomogeneity and Greenhouse-Geisser sphericity correction was applied. The 2 x 4 ANOVA revealed that participants preferred routes with fewer turns significantly more than routes with shorter initial path length ($F(1, 34) = 19.79, p < .001$). There was no main effect of Block ($F(2.62, 89.60) = 0.71, p = .530$) suggesting that preferences did not change after repeated exposure. The main effect of Block did not reach significance for either inner area ($F(2.20, 74.96) = 0.29, p = .769$) or outer area ($F(2.91, 99.07) = 0.80, p = .492$).

3.3. Experiment 2: Discussion

In this study, participants viewed 40 unique map-style environments (20 environments and their mirror images) in a top-down view on a desktop. Of the 40 environments, the results showed that participants preferred routes with fewer turns and larger inner and outer areas but did not have a preference for a shorter length of the first path. Contrary to our hypothesis that a clear and complete overview of the environment would be more conducive to forming a metric cognitive map for decision making, participants still displayed preferences based on differences in turns and unpaved areas (Meneghetti and Pazzaglia, 2021). This suggests that the results obtained in Experiment 1 were not simply due to path integration, since participants in Experiment 2 never actually traversed the routes (neither by walking nor by moving an avatar on the computer screen). Our interpretation that participants instead relied on cognitive graphs, along with several alternatives, is addressed in the General Discussion.

4. Comparison Between Experiments 1 and 2

We compared Experiment 1 and Experiment 2 to examine differences in navigational behavior between first-person active VR and top-down views of identical environments. Depending on data normality and variance equality, we used either a two-sample t-test, Wilcoxon rank-sum test, or Welch's t-test to analyze the proportion of trials where participants preferred routes with fewer turns, shorter initial paths, or larger inner or outer areas. We also assessed their consistency across conditions in both experiments using the same parameters based on data normality and variance equality for statistical testing. Nonparametric statistical tests were reported with median differences, while the two-sample t-test was reported with mean differences.

Statistical results are reported in Table 1. In both Experiment 1 and 2, participants generally preferred routes with fewer turns. Participants chose routes with fewer turns more often in Experiment 2 than in Experiment 1, but this did not reach statistical significance. For the initial path length condition, there was no significant difference in their preference across Experiments. Similarly, no clear differences in preference emerged in the inner area or outer area condition (Table 1). However, participants were more consistent in Experiment 2 compared to Experiment 1. For routes with fewer turns, participants exhibited a significantly stronger consistency in Experiment 2.

The post-study survey included eight questions assessing participants' experience with the VR/desktop system and task difficulty. Participants rated task difficulty, ease of using the VR headset and controller (Experiment 1), acclimation speed, motion sickness, and its impact on performance. They also ranked factors influencing daily route selection. Survey results from both experiments showed that the number of alternative routes (overall $M = 2.41$, SD $= 1.31$) and estimated travel time (overall $M = 2.46$, SD $= 1.23$) were rated least important, while route complexity (overall $M = 2.57$, SD $= 1.09$) and total distance (overall $M = 2.57$, SD $= 0.78$) were most influential (scale: 1 = least, 4 = most important). A mixed 2×4 ANOVA found no significant differences between VR (Experiment 1) and Desktop (Experiment 2) groups ($F(1, 59) = 1.26, p = .265$), between the four measures ($F(3, 177) = 0.16, p = .921$), or in the interaction between experiment and measure ($F(3, 177) = 0.59, p = .621$).

5. General Discussion

In two experiments, participants took selected routes to a goal, which were equal in overall length but differed in several structural features of the environment. We found that participants chose routes that had fewer turns in both experiments, and were consistent in their choices for most conditions. Although participants tended to choose the route with the shorter initial path when they were first exploring from the first-person perspective (Experiment 1), participants did not have a preference when they were later asked to go to the target (Experiment 1) or when they saw an overhead view (Experiment 2). Participants also tended to choose routes that had larger unpaved areas, both on the inside of the routes and the outer region. Together, these findings suggest that participants use structural properties of the environment to make decisions.

Previous research has supported the idea that different learning modalities (map-based vs. first person) can affect acquisition of spatial knowledge where map-based provides a clearer overview of the environment, facilitating the formation of a cognitive map (Qiu et al., 2020; van der Kuil et al., 2021; Zhang et al., 2014). Contrary to our hypothesis - that desktop navigation would show weaker preferences than first-person navigation - participants in the desktop condition exhibited the same degree of preferences. They consistently favored routes with fewer turns and larger areas outside the paths, both the inner and outer regions of the environment, however Experiment 2 revealed a greater consistency in their choices than for Experiment 1. A possible explanation for this is that the additional spatial information - rather than

Table 1

Comparing preferences and consistency across Experiment 1 and Experiment 2. This table summarizes the mean or median differences (*M/Med*), statistical test type (Test), degrees of freedom (*df*), *p*-values (*p*), and effect sizes (*d*) for preference measures across VR (Experiment 1) and Desktop (Experiment 2) conditions. The top row shows the statistics for Experiment 1, and the bottom row shows the statistics for Experiment 2 for each variable. Tests include two-sample t-tests (t), Welch's t-tests (t_{Welch}), and Wilcoxon signed-rank tests (V). Participants were more consistent in Experiment 2 compared to Experiment 1 for choosing fewer turns and larger outer areas, but otherwise there were no differences between the experiments. $^{**}p < .01$, $^{*}p < .05$.

	Preference						Consistency					
	M/Med	SD	Test(df)	STAT	p	d	M/Med	SD	Test(df)	STAT	p	d
Fewer Turns	0.59	0.19	$t(79)$	−1.52	0.132	−0.338	$0.57^{\dagger}$	0.21	V	597	0.035*	−0.393
	0.66	0.20					$0.67^{\dagger}$	0.24				
Initial Path Length	$0.50^{\dagger}$	0.20	V	3700.5	0.172	0.294	$0.50^{\dagger}$	0.36	V	666.5	0.186	−0.31
	$0.50^{\dagger}$	0.21					$0.67^{\dagger}$	0.33				
Larger Inner Area	0.56	0.17	$t(79)$	−2.80	0.780	−0.063	$0.63^{\dagger}$	0.22	V	647	0.100	−0.39
	0.57	0.15					$0.75^{\dagger}$	0.21				
Larger Outer Area	0.56	0.14	t_{Welch} (59)	−0.67	0.508	−0.149	$0.56^{\dagger}$	0.19	V	521	0.004**	−0.64
	0.57	0.07					$0.75^{\dagger}$	0.20				

enhancing participants' survey knowledge and reducing their reliance on heuristics - amplified the visual information and the influence of heuristics during decision-making. One of these major heuristics may be derived from a theory that suggests when making decisions in spatial tasks, participants prioritize the number of turns (topological relationships) over exact distances (Baumann and Mallot, 2023). As a result, participants preferred routes with fewer turns or fewer decision points, even when both routes covered the same distance. Participants consistently selected routes with fewer turns, regardless of the spatial details provided, inconsistent with the use of cognitive maps. Across both studies, this preference for fewer turns decreased as the difference in number of turns between the route choices increased. Participants had similar preference for number of turns, inner unpaved area, and outer unpaved area across the two experiments.

A possible explanation for the preference of routes with fewer turns in Experiment 1 may be that routes with fewer turns require less physical effort to navigate, potentially resulting in shorter average navigation times; this could be an indirect consequence of the structural features of the environment that may have influenced participants' route preferences. However, temporal and path integration factors were absent in Experiment 2, when participants viewed a top-down map of the environment and made decisions without engaging in active navigation. Despite this difference, participants demonstrated similar preferences across all variables, suggesting that, even if routes with more turns in Experiment 1 required slightly more time to traverse, navigation time was not a confounding factor influencing route choice.

The inner and outer unpaved areas emerged as a new heuristic identified in this study. While this heuristic may be specific to the closed-loop environments tested, it is useful in understanding the kinds of things that drive navigational decisions. Although the inner and outer areas were part of a post-hoc exploratory analysis and not included in the original experimental design, we found that this factor had a strong influence on route choice. Experiment 1 interestingly provided little to no explicit spatial information about these areas, however participants had similar preferences in Experiment 2. Nevertheless, the inner area could have been implicitly inferred in Experiment 1. Similarly, Meilinger (2008) showed that through first-person free exploration people could infer allocentric spatial knowledge. Ekstrom and Isham (2017) supported the idea that relational spatial knowledge between nodes can gradually form from a first-person perspective over time, allowing individuals to develop a rough sense of spatial relationships based on boundaries or movement patterns, as was the case in our study. Moreover, the virtual environments in our study were intentionally simple, which could facilitate inference of the inner area. On the other hand, the outer area was shown to be associated with the route with fewer turns and could not be inferred without knowledge of the room, and so we believe that in Experiment 1 at least, is likely related to other structural factors.

Previous studies have compared how participants learn the layout of an environment using different methods, such as studying a map or actively exploring in first-person view. These studies found that both groups performed similarly when estimating the length of a traveled path However, map learners were significantly better at judging the absolute distance between two points. In contrast, those who learned through first-person exploration were less accurate with straight-line distances, likely because this method requires a broader, more global understanding of the layout (Richardson et al., 1999). This finding may help explain why Experiment 2 (top-down) showed a stronger consistency for the outer area. Map learners were more accurate in assessing the absolute distance between two points that passed through unpaved areas. This inadvertently suggests that participants in Experiment 2 had better awareness and spatial judgment related to unpaved areas compared to those in Experiment 1, using this additional spatial information to strengthen the consistency of their route choices. Meanwhile, first-person explorers, who tend to be less accurate in absolute distance judgments, likely had a weaker representation of unpaved areas, limiting their ability to use unpaved areas as a factor for route choice. Further study on this question is needed to fully understand the contribution of area to route choice.

Additionally, not all participants had the same preferences, highlighting individual variations in the experiment. For example, Figs. 3 and 5 illustrate that some participants shifted from preferring fewer turns to preferring more turns when the difference in the number of turns between the two routes became larger. In contrast, others did not change, or even showed opposite preferences. Possible factors like working memory, exploration strategies, and spatial knowledge acquisition may have contributed to variability in route preferences (Ishikawa and Montello, 2006). Despite these differences, the majority of participants demonstrated some preference for routes, regardless of whether they had more or fewer turns, challenging the traditional concept of cognitive maps, which assume accurate spatial representations.

The behavioral results agree with neurocognitive models of spatial learning. Work has demonstrated the role of the retrosplenial cortex in integrating egocentric spatial cues and self-motion signals into allocentric, map-like representations (Wolbers and Büchel, 2005). This finding suggests that retrosplenial cortex could be involved in making some of the spatial decisions presented here. In addition, the right posterior hippocampus is involved in tracking local connectivity, whereas the anterior hippocampus responds to global spatial properties, showing the capability of participants engaged in internal simulations of paths and selected routes based on a combination of local and global features (Javadi et al., 2017), and in general the hippocampus tracks distance information (Chrastil et al., 2015; Sherrill et al., 2013). The posterior hippocampus tracks cumulative path distance, while the anterior hippocampus and entorhinal cortex encode goal direction and Euclidean distance at decision points (Howard et al., 2014). However, in our study, the routes were equally long and equally direct from the goal at the starting position. This symmetry may have limited the anterior and posterior hippocampal dissociation from influencing route selection, and instead encouraged reliance on alternative strategies. We theorize that when default hippocampal mechanisms such as the posterior and anterior goal-vector representations described by Howard et al. (2014) do not favor one route over another due to equivalent distances, participants may default to heuristics. This raises a broader question about whether such heuristics function independently of hippocampal processes or reflect alternative neural mechanisms.

According to the Peer et al. (2021) model, cognitive graphs are supported by hippocampus, retrosplenial cortex, and medial parietal areas (e.g., precuneus), rather than the hippocampus and entorhinal cortex alone, which are more strongly associated with metric cognitive maps. Using this model framework, we would hypothesize that, when participants navigate environments in which they consistently demonstrate preferences for fewer turns when selecting between equidistant routes, retrosplenial cortex should be disproportionately engaged relative to entorhinal cortex, with no difference in hippocampal activity. Additionally, if a lack of consistent preference was due to a more metrically accurate cognitive map guiding route preference, we would expect to observe the reverse. Thus, future neuroimaging research could more definitively adjudicate if and when these different cognitive representations are utilized.

Although our results are consistent with cognitive graph theory, alternative explanations should be considered. Route choice could be influenced by perceptual fluency properties favoring simpler, more symmetric, and less cluttered routes (Undorf et al., 2017). These perceptual tendencies may not conflict with the cognitive graph theory but work together in the form of coarse or relative survey knowledge integrated into a graph-like representation. However, in Experiment 1, participants lacked access to a top-down view and therefore could not rely on visual simplicity or layout fluency in the same way yet still demonstrated similar patterns as in Experiment 2. The consistency of these results across both formats, despite differing spatial inputs and task presentations, implies that participants drew on a stable, underlying spatial representation. Similarly, affordance theory suggests that participants may have a bias toward choosing routes that appear more spacious, explaining the preference for larger areas (Gibson, 2014; Warren and Whang, 1987). However, all routes in our study were uniformly 1.5 m in width, reducing the likelihood of this alternative. Since the gray (inner) and outer buffer zones in our environments were not traversable and participants could not enter, stand on, or cross them, they did not provide any actual locomotor affordances, although it is possible that these regions were perceived as being walkable.

Both perceptual fluency and navigational affordance are generally framed in terms of scene perception (i.e., viewpoint dependent) and would predict different behaviors across first-person (Exp 1) and top-down (Exp 2) views, which is not what we observed. In Experiment 1, the viewpoint from the starting location in any scene where the number of turns was manipulated would be virtually identical because the length of the first hallway was always identical in those trials, which should have resulted in no preference for number of turns under affordance theory or perceptual fluency. Perceptual effects could also be further ruled out with future neuroimaging experiments; for example, we would expect differences in the recruitment of the occipital place area when using navigational affordances versus when using a cognitive graph (Bonner and Epstein, 2017; Gregorians and Spiers, 2022).

It is also possible that the simplicity of the task and environments facilitated these heuristics. Participants may have had full survey knowledge, but without complex navigational challenges or a difficult environment, they did not fully use that knowledge and instead relied on heuristics. We cannot rule out that participants could have more detailed knowledge that they did not use; future studies should test for survey knowledge as well (e.g. through a pointing task). Notably, preferences between metrically equidistant routes were not observed across all conditions. For example, participants consistently showed a preference for routes with fewer turns, yet no significant preference emerged for routes with shorter initial path lengths. If heuristic-based decision-making were merely a consequence of low task demands, we might expect participants to apply similar simplifying rules, like favoring shorter initial legs, however, we do not. Interestingly, such a preference for shorter initial leg did emerge during the initial exploration phase but disappeared after full exposure to the environment, suggesting that once participants had gained complete spatial knowledge, their reliance on that initial heuristic diminished. That finding suggests that participants did not simply apply surface-level heuristics due to low demand throughout the study, but rather adapted their decisions based on an evolving structural representation of space.

Although the findings favor the use of cognitive graph representations over cognitive map representations for decision-making, the study has limitations. Our study did not systematically manipulate the numerical difference in number of turns (e.g., only one environment and its mirror had a difference of four turns and no environments had a difference of three turns), which could provide further clarity on the pattern and trajectory of preferences. Additionally, this study does not differentiate between specific types of cognitive graph knowledge, such as topological graph, labeled graph, or route-based knowledge (Chrastil and Warren, 2014; Peer et al., 2021; Warren, 2019). However, in both Experiment 1 and Experiment 2, participants showed a clear preference for routes with fewer turns, even though the routes were equidistant, which may suggest that a topological graph may play a role in how space is represented. However, we also observed that participants consistently chose the same routes with outer or inner unpaved areas in both experiments. In a purely topological graph, this consistency would not be expected; participants would likely choose the route with fewer nodes, regardless of the size of the unpaved area. These findings suggest that how we represent space, whether from a top-down view or a first-person immersive perspective, involves more than just a simple topological graph. Future research should focus on manipulating variables such as the angle of turns and the positioning of nodes relative to the target destination. This could help uncover the dynamics of heuristics and provide a deeper understanding of how we represent and navigate space.

6. Conclusions

This work provides insights into how graph-like structural factors like the number of turns, initial path length, and unpaved areas influence how participants mentally represent space and make navigation decisions even for equidistant routes. Regardless of whether participants observed a top-down view of environments or an active first-person experiment, the results provide evidence against the use of metrically accurate cognitive maps for decision making. This theory suggests that we rely on stable heuristics to guide our route choices, rather than relying on metric information, which would lead to making random decisions on these equidistant routes. Previous work has relied on physically impossible scenarios to support the cognitive graph model. However, this study has the advantage of providing direct insight into how humans make navigation decisions in everyday life and how cognitive graph principles apply in the real world.

The results of this study, which revealed that some structural factors influenced route preferences while others did not, suggest the need for a more refined cognitive graph model. The consistency across mirrored trials, the disappearance of the initial leg bias following exploration, and the preference for routes with fewer turns across both immersive and map-based conditions all point to a stable underlying structure that incorporates elements of both route and survey knowledge. However, we acknowledge that the cognitive graph framework is not the only plausible explanation. We are confident, however, that our findings do not support a traditional cognitive map. These findings emphasize the importance of understanding how human participants adapt their navigational strategies to simplify decisions, as well as showing the need for more research to explore how these mental shortcuts work in different settings and situations.

CRediT authorship contribution statement

Luke Chi: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Michael J. Starrett:** Writing – review & editing, Software, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Yiwen Rao:** Writing – review & editing, Methodology, Investigation, Formal analysis. **Elizabeth R. Chrastil:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

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Data availability

The data and code supporting this study are publicly available from Open Science Framework at https://osf.io/q52nk/.

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