Journal of Experimental Psychology:
Learning, Memory, and Cognition
2015, Vol. 41, No. 4, 1162–1178

0278-7393/15/$12.00 http://dx.doi.org/10.1037/xlm0000082

Active and Passive Spatial Learning in Human Navigation: Acquisition of Graph Knowledge

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It is known that active exploration of a new environment leads to better spatial learning than does passive visual exposure. We ask whether specific components of active learning differentially contribute to particular forms of spatial knowledge—the *exploration-specific learning hypothesis*. Previously, we found that idiothetic information during walking is the primary active contributor to metric survey knowledge (Chrastil & Warren, 2013). In this study, we test the contributions of 3 components to topological graph and route knowledge: visual information, idiothetic information, and cognitive decision making. Four groups of participants learned the locations of 8 objects in a virtual hedge maze by (a) walking or (b) watching a video, crossed with (1) either making decisions about their path or (2) being guided through the maze. Route and graph knowledge were assessed by walking in the maze corridors from a starting object to the remembered location of a test object, with frequent detours. Decision making during exploration significantly contributed to subsequent route finding in the walking condition, whereas idiothetic information did not. Participants took novel routes and the metrically shortest routes on the majority of both direct and barrier trials, indicating that labeled graph knowledge—not merely route knowledge—was acquired. We conclude that, consistent with the exploration-specific learning hypothesis, decision making is the primary component of active learning for the acquisition of topological graph knowledge, whereas idiothetic information is the primary component for metric survey knowledge.

Keywords: navigation, spatial cognition, proprioception, decision making

Imagine the following situation: You have been invited to a party at a house you have never been before, so a friend offers to drive you there. But after a nice evening, you find that your friend has had too much to drink, and now you have to drive home. What should you have done differently to make it easier to find the way back home? Perhaps you should have driven the car to the party while your friend gave you directions or found the route to the party yourself. Or maybe you should have walked instead of driving. It seems obvious that actively navigating in a new environment would facilitate spatial learning. But these scenarios suggest that multiple factors might contribute to active spatial learning and factors may have different roles to play.

In the present article, we investigate the *exploration-specific learning hypothesis*, which posits that specific components of active learning during exploration differentially contribute to particular forms of spatial knowledge. Previously, we found that idiothetic (specifically motor and proprioceptive) information from walking was the primary contributor to metric survey knowledge, whereas decision making during exploration played no role (Chrastil & Warren, 2013). Presently, we examine their contributions to topological graph and route knowledge. Finally, a planned companion article will report on the contribution of active attention to both types of knowledge (Chrastil & Warren, 2014a).

Components of Active Learning

First, consider possible factors that may contribute to passive and active learning as one explores a new environment. Passive learning is based on visual information about the layout of the environment and the path of self-motion that is available at the eye of the observer, such as monocular perspective, binocular disparity, the sequence of views, the pattern of optic flow, and so on. We define *passive viewing* as exposure to such visual information alone.

Active spatial learning might be based on some combination of one or more of the following six components (see Chrastil & Warren, 2012): (a) efferent motor commands that determine the path of locomotion, (b) proprioceptive information about displacement with respect to the substrate (a and b together are known as *podokinetic information*, Weber et al., 1998), (c) vestibular information about head movement in an inertial frame (a–c are collectively referred to as *idiothetic information*, Mittelstaedt & Mittelstaedt, 2001), (d) cognitive decision making about the direction of travel or the selected route, (e) the allocation of attention to relevant spatial properties of the environment, and (f) mental

This article was published Online First November 24, 2014.

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This research was supported by National Science Foundation Awards BCS-0214383 and BCS-0843940. The authors thank Henry Harrison, Michael Fitzgerald, Joost de Nijs, Kurt Spindler, and members of the VENLab for assistance with the research, and Mike Tarr, Rebecca Burwell, and David Badre for their helpful comments. Portions of this article were included as part of Elizabeth R. Chrastil's doctoral dissertation.

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manipulation of spatial information. In this study, we examine the contributions of passive viewing, idiothetic information, and decision making, with the aim of identifying their role in spatial learning. In particular, the type of spatial knowledge that is acquired may depend on which of these components are present during active exploration.

Forms of Spatial Knowledge

Next, consider the forms of spatial knowledge that appear to underlie human navigation. Successful navigation between known locations might involve place recognition, reliance on beacons or landmarks, knowledge of routes or pathways between places, and survey knowledge of their spatial layout (Trullier, Wiener, Berthoz, & Meyer, 1997; Siegel & White, 1975; Wiener, Buchner, & Holscher, 2009). *Beacons* and *landmarks* are prominent features in the environment that act as place markers (beacons) or form a configuration that specifies a location (landmarks). *Route knowledge* consists of a series of place–action associations, detailing a sequence of turns at each identifiable location or decision point (Siegel & White, 1975). *Survey knowledge* is configural map-like knowledge that includes metric distances and directions between locations in an environment. A cognitive map is often thought of as geometrically consistent survey knowledge, such that places are localized in a common coordinate system or "global metric embedding" (Thrun, 2008).

We distinguish *graph knowledge* from both route knowledge, which is somewhat weaker, and survey knowledge, which is somewhat stronger. A topological graph structure consists of a network of nodes linked by edges that have been traveled by a navigator. In a "place graph" of an environment, the nodes correspond to known places (including junctions), and the edges to the known paths between them, so graph knowledge would express the known connectivity of the environment (Byrne, 1979; Chown, Kaplan, & Kortenkamp, 1995; Kuipers, Tecuci, & Stankiewicz, 2003; Meilinger, 2008; Trullier et al., 1997; Werner, Krieg-Bruckner, & Herrmann, 2000). In contrast, route knowledge merely consists of a sequence of place–action associations (Siegel & White, 1975), and unlike a graph does not express multiple paths intersecting at a place or multiple routes between two places. Thus, detours present a challenge for route knowledge but can be negotiated on the basis of graph knowledge by recombining familiar path segments into a novel route. On the other hand, survey knowledge contains metric information about distances and directions between environmental locations, enabling novel shortcuts (Gallistel, 1990), whereas a purely topological graph only represents connectivity. A *labeled graph* may incorporate local metric information about distances between known places (edge weights) and/or angles between known paths (node labels) in this topological structure. Note that such local information can be very rough and biased, and a labeled graph can be globally inconsistent, distinguishing it from survey knowledge with a global metric embedding.

To illustrate the distinctions between these levels of knowledge, consider Figure 1, which shows the layout of the maze used in the present experiment. Suppose that during the course of exploration, a navigator had only ever traveled from the sink to the well by going down the hallway on the right of the figure, past the clock. If, when asked to go directly from the sink to the well, the

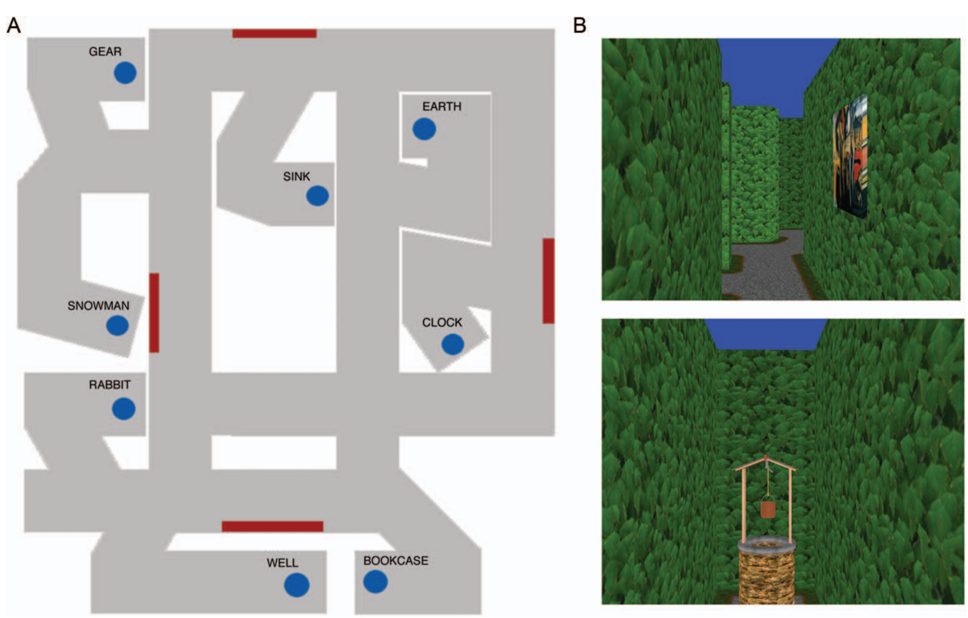

Figure 1. A: Outline of the maze used in the experiment. The maze included eight objects (circles, clockwise from lower right): bookcase, well, rabbit, snowman, gear, sink, earth, clock. There were also four paintings (rectangles) in the hallways that acted as landmarks. Participants never saw this overhead view of the maze. B: Views from inside the maze, from the participant's perspective. Top panel: View of one of the hallways, including a painting. Bottom panel: View of one of the objects in the maze, the well. See the online article for the color version of this figure.

navigator followed the same path again, then they would be displaying route knowledge. However, if the navigator had learned the connections between locations in the maze during exploration, they might take a novel route to the well by traveling down the hallway on the left, past the gear and snowman. This would imply they had acquired graph knowledge of the maze. Finally, if the navigator was able to make an accurate straight-line shortcut through the hedges from the sink to the well, that would be evidence of survey knowledge.

Survey, graph, route, and landmark knowledge form a logical hierarchy, in which each level encompasses the levels below it. Thus, with complete survey knowledge of the places and paths in the environment, a navigator could also exhibit behavior consistent with graph, route, or landmark knowledge, whereas the converse does not necessarily hold. However, a labeled graph would not only support efficient route-finding and novel detours, but would also permit approximate shortcuts via integration of local information, without the difficulties of forming a consistent global metric embedding. Recent evidence suggests that much of human navigation may rely on knowledge consistent with a labeled graph (Chrastil & Warren, 2014b); presently, we focus on the basis for learning route and graph knowledge during exploration of a new environment.

The Exploration-Specific Learning Hypothesis

There are good reasons to expect that the components of active learning during exploration may differentially affect the acquisition of these forms of spatial knowledge. For example, survey knowledge depends on information about metric distances and directions. The idiothetic systems register information related to distances traveled and angles turned along a traversed path (Israel & Warren, 2005), which could be used to build up such survey knowledge (Gallistel, 1990; McNaughton, Battaglia, Jensen, Moser, & Moser, 2006). Indeed, previous evidence supports a role for idiothetic information in survey learning, particularly in large or complex environments (Chance, Gaunet, Beall, & Loomis, 1998; Ruddle, Volkova, & Bülthoff, 2011a; Waller & Greenauer, 2007; Waller, Loomis, & Haun, 2004). We recently found that idiothetic information, specifically podokinetic (motor/proprioceptive) information during walking, significantly contributes to survey knowledge, whereas decision making about one's route does not (Chrastil & Warren, 2013). The purpose of the present experiment was to examine the contributions of idiothetic information and decision making to route and graph knowledge.

Our first hypothesis is that active decision making about one's path of travel during exploration should significantly contribute to route and graph knowledge, over and above passive visual exposure. Given that route knowledge is believed to consist of a sequence of turns at recognized locations, making decisions about where and how to turn should facilitate the formation of such place–action associations. Further, given that graph knowledge consists of a network of paths connecting places, making decisions about one's path of travel should help build up such a graph.

One possible mechanism for the influence of decision making is that it directs the navigator's attention to the relevant aspects of the environment, facilitating learning. Another possible mechanism is prediction learning. On this account, a decision to turn during exploration generates an expectation about the outcome of the action, based on a forward model (e.g., a place–action sequence or graph); the expected and actual outcomes are compared, and the prediction error either reinforces or revises the model. Structures within the medial temporal lobe have been implicated both in spatial navigation and in prospective memory, such that memory of previous events yields better prediction of future events (Bar, 2007; Buckner, 2010; Schacter, Addis, & Buckner, 2007), which could contribute to graph learning. Prediction learning might also extend to survey knowledge, whereby predictions about the distance and direction between locations are compared with the resulting idiothetic information, reinforcing metric survey knowledge. However, we found no experimental support for a contribution of decision making to survey learning (Chrastil & Warren, 2013).

Our second hypothesis is that, although idiothetic information plays a significant role in the acquisition of survey knowledge, it is not necessary for the acquisition of route or graph knowledge. Given that a purely topological graph contains only connectivity relations, without metric distances and directions, there is no reason to expect that idiothetic information is needed to build up graph knowledge. On the other hand, one can see how idiothetic information might augment such route or graph knowledge. Place–action associations could incorporate information about the angle to turn and the distance to the next place. A labeled graph could incorporate node labels derived from idiothetic information about angles turned and edge weights derived from idiothetic information about distances traveled. Passive vision might also provide local metric information about distances and angles (Bertin, Israel, & Lappe, 2000; Frenz, Bremmer, & Lappe, 2003), although visual space perception is subject to significant affine distortions (Koenderink, van Doorn, & Lappin, 2000; Loomis, Da Silva, Fujita, & Fukusima, 1992; Norman, Crabtree, Clayton, & Norman, 2005). A labeled graph, even with rough local metric information, would be sufficient for the selection of shorter routes, as well as for approximate shortcuts, without a global metric embedding. We thus investigate whether idiothetic information and decision making contribute to route and graph learning, over and above passive visual information.

Active and Passive Graph Learning

Previous research on active and passive spatial learning has yielded highly inconsistent results. First, most previous research has focused on the acquisition of survey knowledge, not route or graph knowledge, and experiments that examined the latter have primarily focused on the role of sensory information, not decision making or attention. Thus, the relevant research is quite limited. Second, the research that has investigated decision making has tended to use a desktop virtual reality (VR) paradigm, which removes normal idiothetic information. As reviewed in more detail in Chrastil and Warren (2012), some experiments suggest that making decisions contributes to graph learning, whereas some find that idiothetic information is important for route learning, whereas other research has yielded mixed results.

Initial efforts to distinguish active and passive graph learning in desktop VR were inconclusive. On the one hand, Péruch, Vercher, and Gauthier (1995; see also Tan, Gergle, Scupelli, & Pausch, 2006) reported better performance navigating between learned places after active exploration with a joystick than after passive viewing of a video. In contrast, Wilson, Foreman, Gillett, and Stanton (1997; see also Wilson, 1999) reported no active advantage for either joystick control or decision making during exploration, using the same navigation task. When Wilson and Péruch (2002) teamed up to reconcile their differences, they found something else again: Not only was there no active advantage, but passive participants who had watched active participants explore were more accurate than the active participants themselves. Taken together, these results suggest that any effect of active decision making and control on graph knowledge is small and susceptible to minor differences in procedure.

Subsequent research suggests an active contribution to route and graph knowledge in desktop VR. Farrell et al. (2003) reported that participants who made decisions with a keyboard to find a sequence of targets in a virtual environment made fewer errors when transferred to a real environment than control participants with no prior exposure to the environment. In contrast, passively watching a video of the route between targets did not yield such an improvement. However, the video group only viewed the shortest route, whereas the keyboard group explored widely for a significantly longer time, so additional exposure to the environment might have been a contributing factor. Recently, Voss, Gonsalves, Federmeir, Tranel, and Cohen (2011) had participants explore a 2D grid array of hidden objects on a computer screen either by using a mouse to decide which objects to view or by passively watching a video. They reported that volitional control and decision making facilitated later object recognition as well as recall of the spatial location of the objects, but it is unclear whether this finding translates to a navigational context. In sum, there is little evidence of a contribution of decision making to route or graph learning. It is possible, however, that the lack of a consistent active advantage is due to the absence of idiothetic information in desktop VR.

Studies of route or graph learning during actual walking are surprisingly rare. Hazen (1982) reported that children who freely explored a real playhouse were better at reversing routes and finding novel shortcuts than children who were led around or carried by their parents. This result suggests that making decisions during exploration improves children's route and survey learning, at least when accompanied by idiothetic information. In contrast, it implies that idiothetic information by itself does not significantly contribute to either.

Other research suggests that idiothetic information directly contributes to route knowledge. Grant and Magee (1998) guided participants on a prescribed route during learning, eliminating decision making, and subsequently tested them in a real environment. Participants who walked through the real environment during learning were faster to find locations than participants who walked in place in a matched virtual environment, as well as those who used a joystick in the virtual environment. Walking in place yielded shorter paths during the test than did the joystick alone. These results imply that idiothetic information plays a role in graph learning, but the real-environment group also had a larger field of view and free head movements, which might have contributed to their better performance. Von Stülpnagel and Steffens (2013) also found evidence for a motor contribution to route learning in desktop VR; participants who controlled a mouse and keyboard while following verbal directions for a route were better able to retrace the route than participants who passively observed the keyboard movements and the video.

In work closely related to the present research, Ruddle and his colleagues investigated the contribution of idiothetic information to route, graph, and survey knowledge, using a virtual marketplace laid out on a grid plan and presented in a (HMD). First, in a study of route learning, Ruddle, Volkova, Mohler, and Bülthoff (2011b) found that participants who walked a route in a small environment (10m × 14m) had fewer errors retracing and repeating the route than participants who rotated on foot but used a joystick to translate. This result suggests that idiothetic information about distance contributes to route knowledge. Second, in a study of graph and survey learning, Ruddle et al. (2011a) had participants learn the locations of four target objects during free exploration, then walk to each target and estimate the distances and directions to the others during the test phase. Participants who walked during exploration traveled shorter routes during test than did groups who used various combinations of walking and joystick control during exploration—at least in a small environment (10m × 7m), but not in a large environment (45m × 25m). In contrast, distance and direction estimates showed the opposite effect: Idiothetic information contributed more to survey knowledge of the large environment. Taken together, these results suggest that idiothetic information may contribute to route and graph knowledge of small environments but not large environments. However, this research did not dissociate the effects of idiothetic information from those of decision making during free exploration.

In sum, few prior experiments have tested the influence of decision making and idiothetic information on the acquisition of route and graph knowledge, and the existing results are mixed. Early research was inconclusive (Péruch et al., 1995; Wilson & Péruch, 2002; Wilson, 1999; Wilson et al., 1997): Some experiments have found that decision making contributes to graph knowledge, but they did not dissociate idiothetic information (Farrell et al., 2003; Hazen, 1982; von Stülpnagel & Steffens, 2013; Tan, Gergle, Scupelli, & Pausch, 2006), and others have found that idiothetic information contributes to route knowledge, but they did not dissociate decision making (Grant & Magee, 1998; Ruddle et al., 2011a,2011b). There is thus no research on the interaction of decision making and idiothetic information in the acquisition of route and graph knowledge.

The Present Study

Our purpose is to investigate the exploration-specific learning hypothesis by testing whether these components of active exploration differentially contribute to particular types of spatial knowledge. As described above, we previously found that podokinetic information, but not decision making, significantly contributes to survey knowledge (Chrastil & Warren, 2013). The present study tests the role of idiothetic information and decision making in the acquisition of route and graph knowledge.

In this experiment, we crossed two levels of information with two levels of decision making during exploration of a virtual hedge maze in a between-groups design (see Table 1). In the walking condition, participants had full access to visual and idiothetic information, whereas in the video condition only visual information was available (including perspective, binocular disparity, and optic flow). These conditions were crossed with the free condition, in which participants made decisions

Table 1
Experimental Design

	Decision	
	Yes	No
Information		
Visual + Idiothetic	Free Walk	Guided Walk
Visual	Free Video	Guided Video

about their route during exploration, and the guided condition, in which they were guided along matched routes. To assess route and graph knowledge, participants were then asked to take the shortest route between two learned locations by walking in the maze corridors; on 40% of the trials, barriers were added to promote novel detours. The route task might be performed by repeating routes that had been traveled during exploration. However, for novel routes or detours, previously traveled routes must be integrated into a graph and their segments recombined; taking the shortest possible path additionally requires local metric knowledge.

On the basis of the preceding theoretical and empirical considerations, we can make several predictions. First, we predict that decision making will play a significant role in route and graph learning, in contrast to survey learning. The decisions made during exploration are likely to facilitate the formation of place–action associations as well as the formation of edges and nodes in a place graph, possibly via the allocation of attentional resources or prediction learning. Thus, we expect that participants in the free condition will be more successful in the route test than those in the guided condition.

Second, idiothetic information may interact with decision making. Acquiring a topological graph or route does not require information about metric distances and directions, so participants should show evidence of graph learning without idiothetic information (in the free video condition). On the other hand, such local metric information might be incorporated into a labeled graph. In this case, participants should exhibit shorter and more accurate paths when idiothetic information is present during learning (in the free walking condition). Third, we expect that participants will acquire not merely route knowledge but graph knowledge, displaying evidence of novel routes and detours during the test phase.

The results demonstrate that decision making during exploration makes a significant contribution to graph knowledge, at least in combination with idiothetic information. Participants who made decisions during the learning phase when idiothetic information was available (free walking condition) displayed the greatest route and graph knowledge. In addition, participants took novel routes and detours on the majority of trials—indicative of graph knowledge, not merely route knowledge—and frequently chose the shortest path. The results are consistent with the acquisition of a labeled graph of the environment. Together with our previous work (Chrastil & Warren, 2013), the findings support the exploration-specific learning hypothesis; whereas idiothetic information is the primary contributor to survey knowledge, decision making is the primary contributor to graph knowledge.

Method

Participants

Participants were 125 (85 female, 40 male) volunteers who were paid for their time. Ninety-six participants (sex: 48 female, 48 male; age: $M = 23.23$, $SD = 7.64$) completed the experiment. Eighteen (12 female, 6 male) withdrew because of symptoms of simulator sickness, 6 (4 female, 2 male) were excluded for failure to find all of the objects during exploration, and 5 (3 female, 2 male) were excluded for experimenter error or technical problems. Attrition for each experimental group as a result of symptoms of simulator sickness (or failure to find all objects) was as follows: free walk, 1 (1); guided walk, 3 (0); free video, 5 (5); guided video, 9 (0). To avoid confounding by documented sex differences (e.g., Moffat, Hampson, & Hatzipantelis, 1998; Waller, 2000; Wolbers & Hegarty, 2010), the final experimental groups had equal numbers of men and women. All participants read and signed forms indicating their informed consent to participate in the experiment, in accordance with a protocol approved by the Brown University Institutional Review Board.

Equipment

This experiment was conducted in the VENLab, a 12 m × 14 m ambulatory VR facility. All participants viewed stereoscopic images presented in a Rockwell-Collins SR80A (Cedar Rapids, IA) HMD (63° H × 53° V field of view, 1280 × 1024 pixels, complete binocular overlap, 60 Hz frame rate). An InterSense IS900 (Billerica, MA) tracking system (60 Hz sampling rate, 1.5 mm RMS and 0.1° RMS error) recorded head position and orientation, which was used to update the display (50 ms latency). Participants responded by walking to target locations and pressing a button on a radio mouse. The virtual environment was generated and rendered on a Dell XPS graphics PC (Round Rock, TX) using Vizard software (WorldViz, Santa Barbara, CA). Naturalistic evening sounds were presented over headphones to interfere with any auditory location or orientation cues.

Displays

The 11 m × 12 m virtual maze environment (see Figure 1) contained eight objects located in the terminal segment of branch hallways, so they were not visible from the main corridors. They were models of common objects, such as a sink or bookcase, scaled to be easily visible at eye height. In addition, four landmarks—familiar paintings by Monet, Dali, Magritte, Van Gogh—appeared in a constant location on the walls of the maze in main corridors to aid orientation. The ground in each corridor was a random grayscale gravel texture with a brown earthen and green grassy border.

Design

Four groups of participants were tested in a 2 × 2 (Information × Decision) design, yielding four exploration conditions (see Table 1): (1) free walking, (2) guided walking, (3) free video, and (4) guided video. Each group consisted of 16 randomly assigned participants, with the restriction that the groups were evenly divided between males and females, making 64 participants in the initial experiment. On the basis of a preliminary analysis, 16 participants were added to each of the two walking groups (free walking and guided walking), for a total of 96 participants.

Procedure

Participants were informed that they would be traveling through hallways in a virtual hedge maze, and that the task was to find all of the objects and learn their locations. To equate eyeheight-scaled perspective information, participants in the video condition sat in an adjustable chair at approximately their measured standing height, and the virtual eye height was set to their measured standing eye height; eye height in the walking condition corresponded to the participant's actual eye height as measured by the head tracker.

Practice. Participants were given several minutes in a practice maze with a different layout and different objects from the test maze, in their assigned exploration condition. This procedure allowed them to become familiar with VR and, in the Free Video condition, to practice using the keyboard.

Learning phase. In the learning phase, participants were informed that they had 10 min to explore the environment and learn the locations of all the objects. They were not told how many objects were in the maze. They were then guided to one of six start locations, and the experimental maze appeared to start the learning phase. Participants in the free walking condition were instructed to explore the virtual environment by walking freely, with normal visual and idiothetic information and decision making about the path of exploration. In the guided walking condition, each participant was guided by the arm along the same path as taken by a participant in the free walking group, giving them matched visual and idiothetic information without the decision-making component. In the free video condition, seated participants pressed the four arrow keys on a keyboard to turn during exploration, analogous to desktop VR. The keys provided continuous movement when pressed, with a fixed translation speed of 1.0 m/s and rotation speed of 90°/s, similar to walking speed. Participants could press two buttons at once to enable smooth curved movement. Thus, only visual information was available, together with decision making. In the guided video condition, each participant viewed a video replay of exploration from a matched participant in the free walking group, without making decisions. Head position was recorded throughout the exploration period.

Given that the experiment was designed to test the effect of removing active components from normal walking, the paths in both of the guided conditions were matched to paths from the free walking group, rather than the free video group. The paths in the two free conditions could not be matched, so any differences between those groups might be attributable to differences between the exploration paths not only to differences in idiothetic information. To match the two free conditions as closely as possible, the display speed in the free video condition was matched to the mean free walking speed. Exploration paths were also analyzed to check for significant differences between conditions (see the discussion of the dependent measures).

Test phase. Route and graph knowledge were tested using a shortest route task, in which the participant walked through the corridors of the maze from a starting object to the remembered location of a target object. Prerecorded instructions were presented to the participants over the headphones and then repeated by the experimenter. Participants then completed two practice trials with object pairs not used during the test phase, followed by 40 test trials. Each trial began by wheeling the participant in a wheelchair through a virtual desert environment to the location of the entrance of the branch hallway (where the branch hallway met the main hallway) containing the start object, approximately 1 m from the object; the participant stood up, clicked the mouse, whereupon the maze and start object appeared. This procedure oriented participants within the maze while limiting spatial learning during the test phase. The participant was instructed to walk to the start object, at which point the target object was named over the headphones. All objects were replaced with red blocks after the target was named to avoid providing feedback (Figure 2A); the four landmark paintings remained visible. The participant was then given 30 s to walk to the location of the target object and click the mouse, taking the shortest route possible in the maze corridors. The trial ended when the participant clicked the mouse or the 30 s elapsed. The maze then disappeared, and the experimenter wheeled the participant to the starting location of the next trial, taking a circuitous route in the desert environment to prevent path integration between trials. Participants were not given explicit feedback regarding whether they reached the correct target location. Head position and orientation were recorded between the initial and final mouse click, which served as the trial endpoint. This task allowed us to evaluate route and graph knowledge by comparing the paths taken during test with the routes traveled during exploration.

On 40% of the test trials, one of the shortest paths was blocked with a barrier and participants were instructed to take a different route to the target object if they encountered the barrier (Figure 2B and 2C). These barrier trials probed graph knowledge because they led participants to quickly synthesize novel routes through the maze. Because detour paths often required additional time and distance, participants were given 15 additional seconds for these trials, although they were not informed of the additional time. Note that participants did not necessarily encounter the barriers, but they frequently led to detours.

Participants were tested on eight pairs of start and target objects (henceforth "targets"), with five trials for each start-target pair (three direct and two barrier trials), for a total of 40 test trials. All trials were presented in a random order with the exception that targets did not repeat back-to-back. Although the experimental groups received differing levels of information during the learning phase, they all walked with full visual and idiothetic information in the test phase, to avoid differences in the testing conditions that could yield differences in performance.

Follow-up tests. Finally, participants performed several additional tests to evaluate whether the experimental groups differed in spatial ability. First, participants drew a sketch map of the maze. Participants were presented with a list of the names of the objects and paintings in the virtual maze and were asked to draw a map of the maze freehand, using a pen on a sheet of paper. The maps were scored on a 10-point scale by a double-blind rater for general accuracy of spatial layout (cf. Figure 1), with most importance given to the locations of the hallways and the relative positions of the objects and paintings. Next, they answered questions prompt-

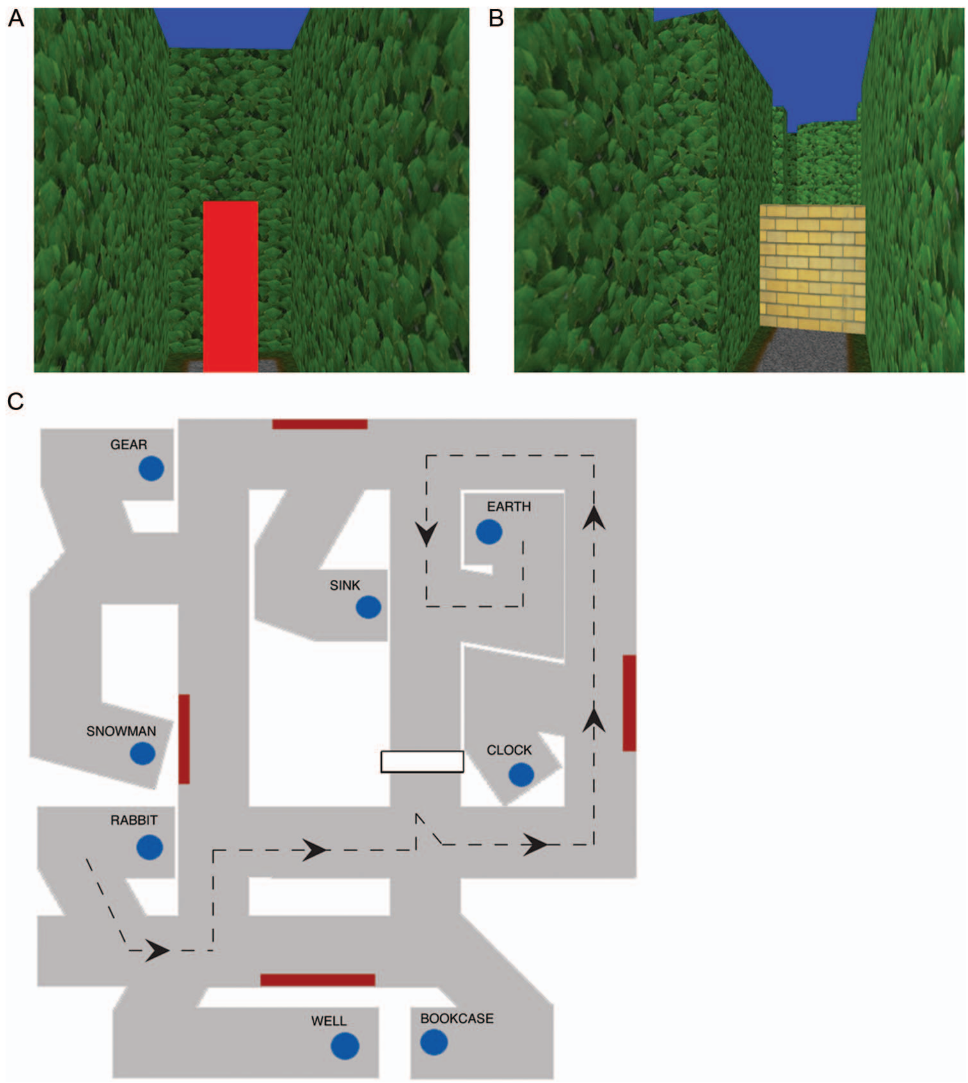

Figure 2. Views of the test phase. A: Red blocks replaced the objects during the test trials. B: A wall was placed in a hallway during barrier trials. C: Overhead view of the maze with an example of a barrier trial, from the rabbit to the earth (white rectangle is barrier). A participant taking the correct path would walk toward the earth, encounter the wall, and then take a new path to reach the target location. See the online article for the color version of this figure.

ing self-report of the strategies used during the both the exploration and the test phases. They also completed the Santa Barbara Sense of Direction Scale (SBSOD; Hegarty, Richardson, Montello, Lovelace, & Subbiah, 2002) and a questionnaire including report of current and past video game use and ratings of nausea and sense of immersion during the experiment. We note that video game experience has been shown to be a factor in virtual navigation (Richardson, Powers, & Bousquet, 2011). They were also given the Road Map Test (Money & Alexander, 1966; Zacks, Mires, Tversky, & Hazeltine, 2000), in which participants report the direction of each turn in a route pre-drawn on a city map, modified to have a 20-s time limit. Finally, participants performed the Perspective-Taking Test (PTSOT; Kozhevnikov & Hegarty, 2001), in which they view a 2D array of objects on a page and indicate their directions from different imagined viewpoints. The Road Map Test and Perspective-Taking Tests gauge a navigator's ability to process location and direction information from different perspectives, which could be important for acquiring graph knowledge during exploration or for orienting within the maze during the test phase.

Dependent Measures and Analysis

Multiple dependent measures were taken, but a number of them were redundant and yielded very similar results. We thus report only the following measures: *Proportion of correct trials* (accuracy), where a trial was considered correct if the participant ended anywhere in the branch hallway containing the target object. The chance level was defined as the probability of randomly ending at any one of the eight object locations, or $1/8 = 0.125$ (participants did occasionally end up at the starting location). Measures of response consistency, travel time, and final distance from target yielded similar results to proportion correct and are not reported here. *Proportion of novel routes*, which is the proportion of correct test trials on which the observed route was not previously taken during free exploration. Specifically, the sequence of junctions through which a participant passed on each test trial was compared against all such sequences during their free exploration phase. If the sequence was previously observed, in either the forward or backward direction, the route was counted as familiar; if not, it was counted as novel. *Proportion of shortest paths* is the proportion of correct test trials in which the participant took the shortest-length path in the maze between the start and target locations, as measured in meters (*metric distance*). *Sketch map rating*, which is the rating, out of a maximum possible of 10, for the sketch map drawn during the follow-up tests. *Exploration behavior,* including total distance traveled, total angular rotation, and mean number of visits per object during the 10 min exploration phase; the standard deviation and range of the number of visits per object reflect how evenly a participant explored the environment. Most analyses were performed on participant means using a 2 × 2 × 2 (Information × Decision × Sex) unequal sample size analysis of variance (ANOVA).[1] Separate item analyses and analyses of direct and barrier trials were also performed.

Preliminary analysis. A preliminary analysis was performed on data from 16 participants per group. Mean proportion correct in each group was as follows: free walking ($M = 0.607$, $SD = 0.292$); guided walking ($M = 0.459$, $SD = 0.323$); free video ($M = 0.479$, $SD = 0.311$); guided video ($M = 0.384$, $SD = 0.248$). A 2 × 2 × 2 (Information × Decision × Sex) ANOVA yielded a marginal main effect of decision making, $F(1, 62) = 2.794$, $p = .100$, $\eta_p^2 = 0.048$, such that the free groups performed better than the guided groups, but no effect of information, $F(1, 62) = 1.960$, $p = .167$, $\eta_p^2 = 0.034$, and no interactions. There was also a significant effect of sex, $F(1, 62) = 4.949$, $p = .030$, $\eta_p^2 = 0.081$. An analysis of effect size revealed that the main effect of decision making stabilized around a moderate value ($\eta_p^2 = 0.05$; $n = 12$), whereas the effect size of information remained small (stabilizing around $\eta_p^2 = 0.025$). Given the large interindividual variability (standard deviations on the order of 0.3), this result justified an increase in power to further investigate the possible effect of decision making. Consequently, 16 additional participants were added to both the free and guided walking groups. Thus, the final analyses included ANOVAs for unequal sample size on data from 32 participants in each of the free and guided walking groups, and 16 participants in each of the free video and guided video groups, for a total of 96 participants. We note that proceeding with a fixed sample stopping rule after conducting preliminary analysis with a sequential stopping rule can affect Type I error (Frick, 1998).

Results

Proportion Correct

We begin by analyzing the proportion of correct test trials in each condition, which appears in Figure 3. Performance in all groups was significantly above the chance level (0.125, indicated by the dashed line), as determined by one-sample t tests (Free Walking: $t_{31} = 8.235$, $p < .001$; Guided Walking: $t_{31} = 5.008$, $p < .001$; Free Video: $t_{15} = 4.550$, $p < .001$; Guided Video: $t_{15} = 4.177$, $p = .001$). This result indicates that visual information alone is sufficient for significant route and graph learning, as we previously observed for survey learning (Chrastil & Warren, 2013).

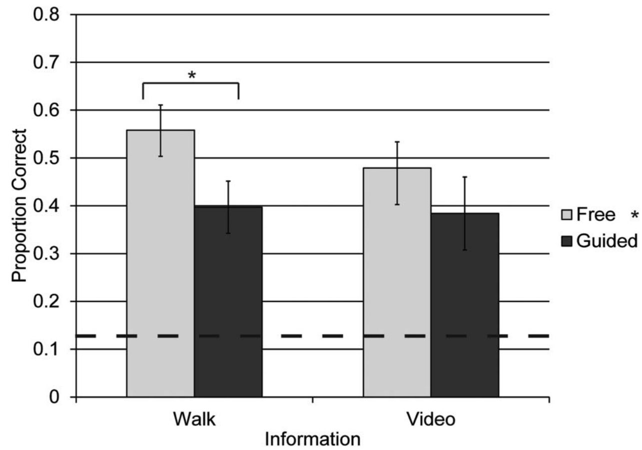

Figure 3. Proportion of trials ended at the correct object location for the four experimental groups. Dashed line indicates chance level. Error bars indicate between-subjects standard error. Significant effects are indicated by asterisks.

A three-way ANOVA for unequal sample size (2 Information × 2 Decision × 2 Sex) on the proportion of correct trials revealed a main effect of decision making, $F(1, 94) = 4.157$, $p = .044$, $\eta_p^2 = 0.045$, such that participants who made decisions during exploration had a higher proportion correct than those who were guided. In contrast, there was no main effect of information, $F(1, 94) = 0.548$, $p = .461$, $\eta_p^2 = 0.006$, indicating the absence of an idiothetic advantage, and no Information × Decision interaction, $F(1, 94) = 0.276$, $p = .601$, $\eta_p^2 = 0.003$. There was also a main effect of sex, $F(1, 94) = 4.609$, $p = .035$, $\eta_p^2 = 0.050$, such that men performed better overall than women, but no interaction was found between sex and information, $F(1, 94) = 1.739$, $p = .191$, $\eta_p^2 = 0.019$, or between sex and decision making, $F(1, 94) = 2.132$, $p = .148$, $\eta_p^2 = 0.024$, neither was there a three-way interaction, $F(1, 94) = 0.092$, $p = .762$, $\eta_p^2 = 0.001$.

We also computed Bayesian factors for models alternative to the null model by taking the ratio of the likelihood of the null model to the likelihood of the alternative model (likelihood null model/likelihood alternative model), with smaller numbers indicating greater support for the alternative model. Proceeding incrementally, the first alternative model included only the factor of information. This analysis yielded a Bayesian factor of 0.772, indicating that the probability of the null model given the data is approximately 77.2% of the probability of the data given this alternative model. In contrast, the Bayesian factor for the factor of decision making alone was 0.070, indicating that the null model is only 7.0% as likely as the model with just decision making added.

[1] Analyses of proportion data were also performed following an arcsine transformation, however there were no substantial differences between those analyses and those of the untransformed data. Thus, analyses of the untransformed data are reported here.

The combined information and decision-making model (two-factor) had a Bayesian factor of 0.046. Finally, the full three-factor model (information, decision making, and sex) yielded a Bayesian factor of 0.0008.

A planned comparison to test the role of decision making in the walking condition found a significant main effect of decision making, $F(1, 62) = 4.568$, $p = .037$, $\eta_p^2 = 0.071$, with the free walking group having a greater proportion of correct trials than the guided walking group. This result indicates that decision making together with full idiothetic information during exploration significantly improves performance. The planned comparison between the free video and guided video groups did not find an effect of decision making, $F(1, 30) = 1.035$, $p = .318$, $\eta_p^2 = 0.036$. Although this comparison had less power, the effect size had stabilized at a value that was half that of the walking condition. This pattern of results supports the conclusion that decision making significantly contributes to route and graph knowledge, at least in combination with idiothetic information and illuminates previous equivocal results in desktop VR.

Figure 4A illustrates the individual performances in the two walking groups (each $n = 32$). Participants are plotted in rank order by performance, from left to right. All rank-ordered members of the free walking group have a higher proportion correct than their peer in the guided walking group. A Mann–Whitney U test evaluated the rankings of the proportion correct in the two groups, and found that the rankings were significantly different ($U = 341.5$, $p = .022$). The wide performance range in both groups highlights the individual differences commonly observed in navigation tasks. The pattern also suggests that making decisions during exploration did not greatly affect performance at the lowest end of the spectrum, whereas there was a ceiling effect at the highest end, but it increased learning 10% to 20% (by one or two objects) in the broad midrange of spatial performance. In contrast, Figure 4B illustrates the individual performances in the two video groups (each $n = 16$). The only difference between the free and guided groups appears at the high end of the spectrum. A Mann–Whitney U test evaluated the rankings of the proportion correct in the two groups and found that the rankings were not significantly different ($U = 106.0$, $p = .406$). These results reinforce the finding that decision making, in combination with idiothetic information, contributes to route and graph learning.

Direct and barrier trials. The proportion correct in each condition is broken down by direct trials ($M = 0.45$, $SD = 0.30$) and barrier trials ($M = 0.48$, $SD = 0.31$) in Figure 5. The slightly higher accuracy on barrier trials may be due to the extra 15 s allowed for barrier trials.

For direct trials (see Figure 5A), a three-way ANOVA yielded a marginal effect of decision making, with the same effect size as for all trials, $F(1, 94) = 3.855$, $p = .053$, $\eta_p^2 = 0.042$, but no main effect of information, $F(1, 94) = 0.467$, $p = .496$, $\eta_p^2 = 0.005$, or interactions. There was also a main effect of sex, $F(1, 94) = 4.354$, $p = .040$, $\eta_p^2 = 0.047$, with men performing better than women. A separate analysis of barrier trials (see Figure 5B) revealed a significant main effect of decision making, $F(1, 94) = 4.490$, $p = .037$, $\eta_p^2 = 0.049$, and a main effect of sex, $F(1, 94) = 4.365$, $p = .040$, $\eta_p^2 = 0.047$, but no effect of information, $F(1, 94) = 0.667$, $p = .416$, $\eta_p^2 = 0.008$, or interactions. These results imply that decision making during learning improves route finding on both direct paths and barrier trials, but it does not significantly interact with idiothetic information.

Planned comparisons in the walking condition confirmed an advantage of decision making, revealed especially by barrier trials. There was a significant effect of decision making on barrier trials, $F(1, 62) = 6.551$, $p = .013$, $\eta_p^2 = 0.098$, with a greater proportion correct in the free walking than the guided walking group; this effect was marginal on direct trials, $F(1, 62) = 3.147$, $p = .081$, $\eta_p^2 = 0.050$. Thus, finding a novel detour was significantly easier for participants who had made decisions during exploration, supporting the idea that decision making contributes to graph knowledge.

Target difficulty. To compare the difficulty of the eight object pairs, we performed an item analysis. First, one-sample t tests comparing each target to the chance level (0.125) revealed that all targets were located significantly more often than expected by chance (all $ps < .001$). Thus, participants acquired reliable graph knowledge of all object locations in the maze. However, some targets were more difficult to find than others: a repeated-measures ANOVA on the proportion of correct trials with target as a within-

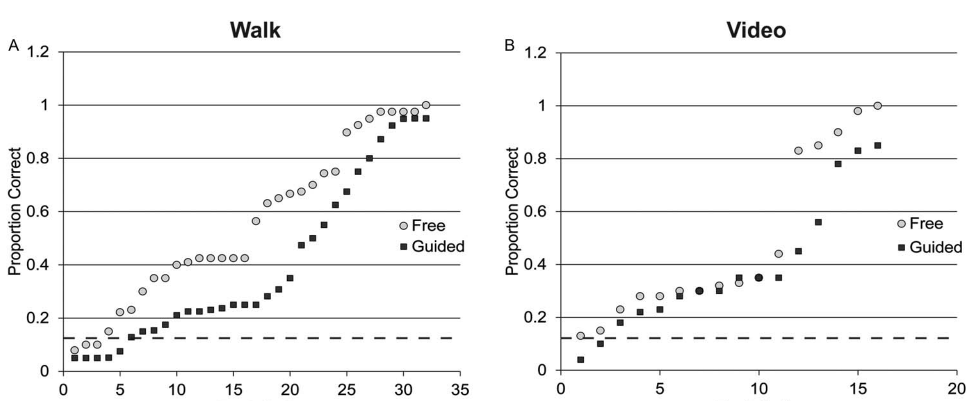

Figure 4. Individual performance. Participants in each group were ordered from least proportion correct to greatest proportion correct. Dashed line indicates chance level, 0.125. A: Walking conditions. B: Video conditions.

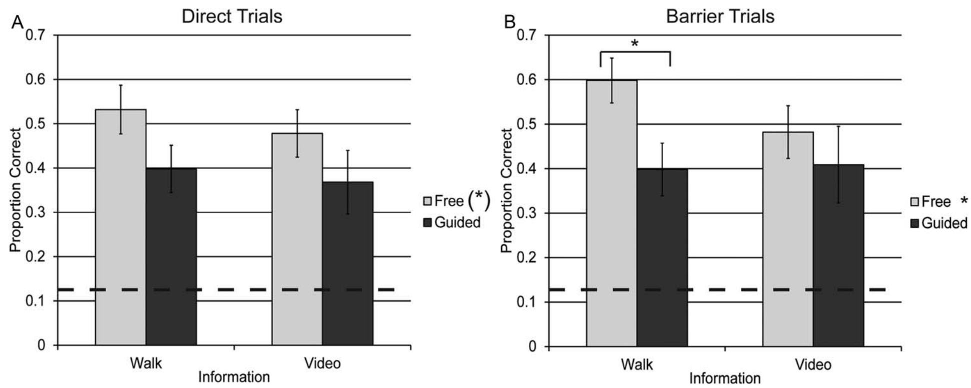

Figure 5. Proportion correct of direct and barrier trials. Dashed line indicates chance level. Error bars indicate between-subjects standard error. Significant effects are indicated by asterisks. A: Proportion correct of the direct trials for the four experimental groups. B: Proportion correct of the barrier trials for the four experimental groups.

subjects factor revealed a main effect of target, $F(7, 665) = 8.237$, $p < .001$, $\eta_p^2 = 0.086$. Referring to Figure 1, post hoc tests found that snowman-to-rabbit was the most difficult pair, with only 37.1% correct, while bookcase-to-well was the easiest, with 61.3% correct.

To investigate factors that affected target difficulty, we computed the Pearson correlation between the mean proportion correct on each of the eight targets (direct trials only) and several measures of the relationship between start and target objects: as-the-crow-flies distance, metric (in m) and topological distance (number of intersections or segments) of the shortest route, and the number of turns on the shortest route (not counting turns within the branch hallways themselves; branch hallways generally all had one turn, thus excluding these does not substantially change the results). Of these potential factors, only the number of turns was statistically significant overall ($r_6 = -0.855$, $p = .007$). Looking at each experimental group, the number of turns was significant in the free walking group ($r_6 = -0.847$, $p = .008$), the guided walking group ($r_6 = -0.869$, $p = .005$), and the free video group ($r_6 = -0.758$, $p = .029$), but not the guided video group ($r_6 = -0.078$, $p = .855$). In contrast, in the guided video group accuracy was only correlated with topological distance ($r_6 = -0.903$, $p = .002$). Finally, in the guided walking group there was also a significant correlation with metric distance in the maze ($r_6 = -0.708$, $p = .049$). It is interesting to note that target accuracy in the guided video group was not correlated with any other group ($p > .50$ for all comparisons), whereas the other three groups were all intercorrelated ($p < .01$ for all comparisons). These results suggest that completely passive learning yields somewhat different graph knowledge than does active learning.

Learning during test. It is possible that learning continued during the 40 test trials, which could have influenced the overall results. A within-subject ANOVA comparing the first and last block of 10 test trials revealed that the proportion correct significantly increased during the test phase, $F(1, 94) = 58.829$, $p < .001$, $\eta_p^2 = 0.401$. However, an analysis of just the first block of 10 trials revealed a marginal effect of decision making, $F(1, 94) = 3.966$, $p = .050$, $\eta_p^2 = 0.043$, but no effect of information, $F(1, 94) = 1.003$, $p = .319$, $\eta_p^2 = 0.011$, and no interaction. A separate analysis of the walking condition demonstrated that the free walking group had a greater proportion correct than the guided walking group in the first block of 10 trials, $F(1, 62) = 5.464$, $p = .023$, $\eta_p^2 = 0.083$. Overall, these results confirm a decision making advantage even in the first 10 test trials.

Novel Routes

Route knowledge would only enable participants to use familiar routes to the target in the test phase, whereas graph knowledge would enable participants to recombine known path segments into novel routes. Thus, to determine whether performance reflected route or graph knowledge, we analyzed the proportion of correct test trials in which participants took routes they had not traveled during exploration. Overall, novel routes were taken on 64.5% of correct direct trials and, even more strikingly, 88.7% of correct barrier trials. Pure route knowledge predicts that a navigator could never take a path that they had not experienced during exploration because they can follow only known routes. Both of these values differ significantly from this pure route knowledge prediction, namely, 0 novel routes ($p < .001$ for both direct and barrier trials, one-sample t test against 0). This result implies that participants did not simply learn specific routes between objects, but they acquired a graph of connections between places by traversing different segments at various times during exploration; they were then able to recombine the segments to generate novel routes during test. There were no differences between conditions in the number of novel paths on direct trials, but for barrier trials there was a marginal effect of information, $F(1, 92) = 3.967$, $p = .050$, $\eta_p^2 = 0.044$, such that the walking groups took more novel routes than the video groups (see Table 2). There was also a three-way interaction, $F(1, 92) = 5.067$, $p = .026$, $\eta_p^2 = 0.056$.

Shortest Routes

Pure graph knowledge would support routes with the shortest topological length (fewest number of intersections or segments), whereas a labeled graph would enable routes with the shortest metric length (in m). To estimate whether performance reflected such local metric knowledge, we measured the proportion of correct trials in which participants took the metrically shortest

Table 2
Percentage (SD) of Correct Trials in Which Novel Routes Were Taken During the Test Phase, for Both Direct and Barrier Trials in the Four Groups

	Decisions			
	Direct trials		Barrier trials	
	Free	Guided	Free	Guided
Information				
Walk	62.64% (22.55)	72.84% (14.59)	90.06% (11.38)	92.49% (19.56)
Video	61.13% (29.86)	66.18% (26.15)	86.37% (17.77)	80.72% (27.50)

available route between the start and test objects. Overall, the percentage of metrically shortest routes was 64.6% on correct direct trials, and 64.0% on correct barrier trials, suggesting that metric information played a role in route selection. For direct trials (see Table 3), a three-way ANOVA on the proportion of shortest path among the correct trials revealed no main effects of information, $F(1, 92) = 0.280$, $p = .598$, $\eta_p^2 = 0.003$, decision making, $F(1, 92) = 0.316$, $p = .575$, $\eta_p^2 = 0.004$, or sex, $F(1, 92) = 1.843$, $p = .178$, $\eta_p^2 = 0.021$, and no interactions. For barrier trials (see Table 3), however, there was a main effect of decision making, $F(1, 92) = 6.012$, $p = .016$, $\eta_p^2 = 0.065$, such that participants who made decisions during exploration had a higher proportion of shortest paths than those who were guided. There was also a marginal effect of information, $F(1, 92) = 3.651$, $p = .059$, $\eta_p^2 = 0.041$, and a main effect of sex, $F(1, 92) = 5.071$, $p = .027$, $\eta_p^2 = 0.056$, such that men took more shortest paths than women. The only interaction was a three-way interaction, $F(1, 92) = 6.055$, $p = .016$, $\eta_p^2 = 0.066$. Participants who had made decisions during exploration were able to take the shortest paths during test, whereas participants who had been guided tended to take longer routes, particularly on barrier trials.

However, the shortest metric and topological routes in the maze were often the same. To dissociate them, we examined cases in which there were alternative routes between the start and target objects that were topologically equivalent to but metrically longer than the shortest route. Of the eight targets, there were two that possessed at least one such alternative route on direct trials and three others that had alternative routes on barrier trials (see Table 4). On four of these five targets, participants took the metrically shortest route more frequently than the topologically equivalent alternatives combined (each $p = .001$ or better, repeated-measures ANOVA); the fifth case was marginally significant in the other direction. This clearly demonstrates that participants generally selected the metrically shortest route to the target, even when there were topologically equivalent but longer alternatives, which is indicative of a labeled graph with local metric information. Alternatively, it is possible that participants used survey knowledge for these paths; we consider this possibility in the discussion.

Map Scores

Sample sketch maps appear in Figure 6A, and the mean scores in each condition are plotted in Figure 6B. A three-way ANOVA found a main effect of decision making, $F(1, 94) = 5.097$, $p = .026$, $\eta_p^2 = 0.055$, such that participants in the free groups drew better maps than those in the guided groups, but there was no effect of information, $F(1, 94) = 2.404$, $p = .125$, $\eta_p^2 = 0.027$, and no interaction. There was also a significant Information × Sex interaction, $F(1, 92) = 4.855$, $p = .030$, $\eta_p^2 = 0.052$, although none of the post hoc Tukey's tests were significant for this interaction. The sketch maps thus confirm a decision-making advantage.

Group Differences

Due to our between-subjects design, it is possible that the effects we observed were due to inadvertent sampling bias in the assignment of participants to experimental groups rather than to the experimental manipulations. Thus, we briefly examine other possible sources of group differences.

Spatial ability. To assess whether the spatial abilities of participants differed between groups, we performed three-way ANOVAs (2 information × 2 decision × 2 sex) on four individual measures. There were no statistical differences in age between the experimental groups, and each group had an equal number of men and women. Sex, rather than group, accounted for most of the significant differences in spatial ability: Men performed better than women on the SBSOD, $F(1, 94) = 10.792$, $p = .001$, $\eta_p^2 = 0.109$, the PTSOT, $F(1, 94) = 3.974$, $p = .049$, $\eta_p^2 = 0.043$, and the Road

Table 3
Percentage of Trials (SD) in Which the Shortest Route Was Taken to the Target, for Both Direct and Barrier Trials

	Decisions			
	Direct trials		Barrier trials	
	Free	Guided	Free	Guided
Information				
Walk	64.34% (27.38)	66.80% (27.78)	72.90% (19.22)	61.43% (33.05)
Video	67.13% (22.37)	58.14% (21.23)	64.87% (20.74)	49.07% (28.34)

Table 4
Proportion of Correct Trials in Which Participants Took the Shortest Path Compared With Alternatives With an Equal Number of Nodes in the Graph

Trial Type (direct/barrier) (No. of alternatives)	Proportion Taking Shortest Path	Proportion Taking Any Topologically Equal Alternative	N	p
1 (direct) (2)	0.370	0.520	68	.073
2 (barrier) (1)	0.822	0.089	45	<.001
3 (barrier) (1)	0.690	0.080	44	<.001
4 (direct) (1)	0.620	0.170	53	<.001
7 (barrier) (1)	0.660	0.130	46	.001

Note. Some participants did not have correct trials for certain trial types and were excluded from analysis.

Map Test, $F(1, 94) = 9.402$, $p = .003$, $\eta_p^2 = 0.097$. The only other observations were opposing trends for idiothetic information: On the SBSOD, the video groups reported a marginally worse sense of direction than did the walking groups, $F(1, 94) = 3.9124$, $p = .051$, $\eta_p^2 = 0.043$, yet on the PTSOT, the video groups showed a better perspective-taking ability than did the walking groups, $F(1, 94) = 6.527$, $p = .012$, $\eta_p^2 = 0.069$. Perspective-taking ability could contribute during learning by helping to link different views of the maze together into a larger path structure. Thus the PTSOT difference could account for the lack of an effect of idiothetic information, but it seems to be countervailed by the SBSOD result.

Video gaming. The three video game measures also primarily differed by sex, including current video game use, $F(1, 94) = 8.394$, $p = .005$, $\eta_p^2 = 0.087$, as well as current, $F(1, 94) = 5.374$, $p = .023$, $\eta_p^2 = 0.058$, and past use, $F(1, 94) = 6.896$, $p = .010$, $\eta_p^2 = 0.073$, of first-person navigational video games, with men spending more time playing video games than women. Thus, sex differences on spatial ability measures and video game experience might account for the sex differences observed in our shortest route task.

Experience in VR. It is possible that the experimental conditions were associated with different personal experiences in VR. There was only a significant effect of information condition on nausea rating, $F(1, 94) = 4.604$, $p = .035$, $\eta_p^2 = 0.050$, with video groups reporting greater nausea than the walking groups, a marginal effect of sex, $F(1, 94) = 3.322$, $p = .072$, $\eta_p^2 = 0.036$, and an Information $\times$ Sex interaction, $F(1, 92) = 11.193$, $p = .001$, $\eta_p^2 = 0.113$. Post hoc Tukey's tests showed that women in the video groups gave significantly higher ratings of nausea than did women in the walking group or men in either group (all $p < .05$). Greater nausea ratings could imply that participants in the video groups, especially women, were more distracted during learning. However, there were no group differences in ratings of immersion in the virtual environment.

Exploration behavior. It is possible that different patterns of exploration during the 10-min learning phase might account for

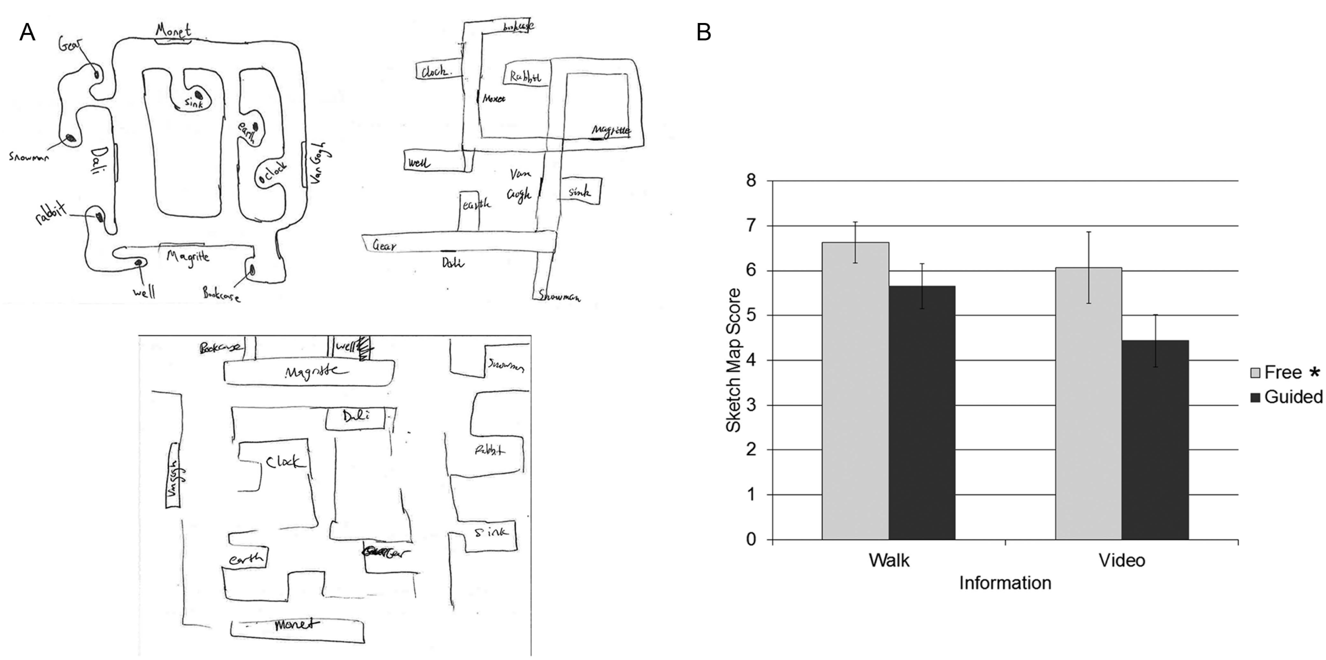

Figure 6. A: Examples of sketch maps drawn by participants. B: Sketch map scores. Error bars indicate between-subjects standard error. Significant effects are indicated by asterisks.

group differences in the test phase. The video groups (M = 360.76 m, SD = 60.47) had a greater total distance traveled than did the walking groups (M = 321.31 m, SD = 56.54; F[1, 94] = 9.870, p = .002, $\eta_p^2 = 0.101$) and had higher total angular rotation during exploration (video group: M = 46022.5°, SD = 8351.9; walking group: M = 40688.1°, SD = 9767.0; F[1, 94] = 7.600, p = .007, $\eta_p^2 = 0.079$).

The number of visits per object during learning indicates how thoroughly the maze was explored. There was a marginal effect of information, $F(1, 94) = 3.959$, $p = .050$, $\eta_p^2 = 0.043$, such that the video groups (M = 3.59, SD = 0.65) had more visits per object than the walking groups (M = 3.29, SD = 0.70). The within-subject standard deviation of number of visits reflects how evenly participants explored all parts of the maze, and here there was a main effect of decision making, $F(1, 94) = 7.316$, $p = .008$, $\eta_p^2 = .077$, and a significant Information × Decision Making interaction, $F(1, 92) = 6.320$, $p = .014$, $\eta_p^2 = 0.067$. Post hoc Tukey's tests revealed that these effects were due to participants in the free video group, who had a higher standard deviation than the other three groups, which had matching paths (all $p < .05$). Thus, the effects on standard deviation of visits are actually driven by the fact that the free walking group visited objects more evenly than the free video group.

The main finding of the exploration analysis is that the free walking group visited objects more evenly than the free video group, implying that idiothetic information helps participants keep track of the locations they have previously explored. On the other hand, the free video group traveled farther, had greater angular rotation, and visited each object more frequently than did the free walking group (and hence the matched guided walking and guided video groups), which is likely due to the ease of exploration with the keyboard and could have undercut an idiothetic advantage in spatial learning.

Discussion

To investigate potential components of active and passive spatial learning, we tested the contributions of idiothetic information and cognitive decision making to the acquisition of route and graph knowledge compared with visual information alone. The results support five conclusions about active spatial learning. First, we found that decision making during exploration significantly contributes to graph learning. Second, in contrast, we find no evidence that idiothetic information alone significantly contributes to graph learning. However, we note that the decision-making advantage is significant in the presence of idiothetic information, but not without it, which may help explain previous inconsistent findings in desktop VR. Third, humans acquire not merely route knowledge but graph knowledge of the connectivity of the environment early in learning. Specifically, the data support a level of spatial knowledge that incorporates local metric information, most likely a labeled graph. This leads to our main conclusion, that the findings support the exploration-specific learning hypothesis. Whereas idiothetic information during exploration is the primary contributor to survey knowledge, decision making is the primary contributor to graph knowledge. Finally, there is a reliable sex difference in graph learning, such that men perform the route-finding task more successfully than do women. We discuss these conclusions in more depth.

Contribution of Decision Making to Graph Knowledge

First, the results of this experiment demonstrate that decision making significantly contributes to graph knowledge. Overall, participants who made decisions during exploration (free groups) were more accurate in the test phase, took more successful and shorter detours, and drew better sketch maps than those who did not (guided groups). In particular, the free walking group had a significantly greater proportion of correct trials than the guided walking group. This result is consistent with the hypothesis that making decisions about one's exploration path facilitates learning the network of connections between places. It is possible, for example, that making decisions directs the navigators' attention to aspects of the environment that are relevant to graph learning. Decision making might aid route learning by promoting the formation of place–action associations during exploration. Furthermore, it could facilitate graph learning by eliciting predictions about the consequences of each turn, which were then consolidated via feedback.

It is important to point out that passive visual information alone (including optic flow, binocular disparity, and perspective) was sufficient for some graph learning, for accuracy in the guided video group was well above chance. Thus, although decision making yields a significant improvement, it is not necessary for the acquisition of some graph knowledge.

Contribution of Idiothetic Information to Graph Knowledge

Second, we found little evidence that idiothetic information alone significantly contributes to graph knowledge. Overall, participants who walked during exploration did not perform better than seated participants who viewed a video. In particular, performance in the guided walking group was virtually identical to that in the guided video group. The results are consistent with the hypothesis that idiothetic information is not necessary for the acquisition of topological graph or route knowledge. In addition, local metric distances and angles in a weighted graph can be estimated from visual information such as optic flow (Bertin, Israel, & Lappe, 2000; Frenz, Bremmer, & Lappe, 2003).

This result departs from two previous experiments that examined route (but not graph) knowledge that reported an idiothetic advantage when participants walked on a prescribed path during learning without making decisions (Grant & Magee, 1998; Ruddle et al., 2011b), which corresponds to the guided walking and guided video groups in our experiment (see Figure 3). It is possible that the performance of our video group was inflated because they had better PTSOT scores (lower errors) than the walking group. Yet SBSOD scores showed the opposite effect, and there were no group differences in video game experience. The present results thus provide no evidence that idiothetic information by itself improves graph learning.

We note, however, that we observed a significant decision-making effect in the walking condition when idiothetic information was available, but not in the video condition when idiothetic information was absent. This is best illustrated by Figure 4, which shows a systematic decision-making advantage with idiothetic information (left panel) but no reliable advantage without it (right panel). The pattern suggests that graph learning may be enhanced by the combination of decision making and idiothetic information, perhaps by augmenting local metric information in a weighted graph. However, because the interaction between decision making and information was not statistically significant, we cannot draw a firm conclusion. It is possible that the lack of a significant decision-making effect in the video condition was due to insufficient statistical power, given that the video groups ($n = 16$) were smaller than the walking groups ($n = 32$). However, the stable effect size in the video condition was half that of the walking condition. We thus believe the pattern of results is well-represented by Figure 4, implying that any influence of decision making in the video condition is quite weak.

This observation might help explain why we find a reliable decision-making advantage when prior research was inconclusive (Farrell et al., 2003; Péruch et al., 1995; Tan et al., 2006; Wilson, 1999; Wilson et al., 1997; Wilson & Péruch, 2002). These studies were conducted in desktop VR, under conditions similar to our video condition. A weak influence of decision making without idiothetic information would account for these equivocal results. Conversely, a decision-making advantage with idiothetic information would explain Hazen's (1982) finding that walking children learned routes better when they freely explored than when they were led about by their parents. It is also consistent with Ruddle et al.'s (2011a) report that the combination of decision making and idiothetic information contributed to graph learning, although they did not dissociate the two. We thus suggest that previous mixed results for decision making may be attributable to the absence of idiothetic information in desktop VR.

Route, Graph, and Survey Knowledge

The results support a third more general conclusion, that humans acquire not merely route knowledge but graph knowledge of the environment early in learning. This graph also includes some local metric information, consistent with a labeled graph. Together with our previous findings on survey knowledge (Chrastil & Warren, 2013), this finding implies that primary spatial knowledge is best characterized as a labeled graph.

In contrast to the route knowledge prediction, participants did not just reproduce routes that they had traveled during exploration, but took novel routes to the target on three-quarters of the correct trials. This finding indicates that participants had learned path segments during exploration and could recombine them to generate novel routes during the test phase, consistent with graph knowledge of the network of connections between places.

Furthermore, participants took the metrically shortest route on two-thirds of correct trials, suggesting that they had also encoded some metric information about these path segments. Participants took the metrically shorter route rather than a topologically equivalent but longer route in four out of five cases (see Table 4), indicating that they did not just select a path with the fewest number of segments or intersections. This result supports the hypothesis that the primary structure of spatial knowledge is not purely topological but can be characterized as a labeled graph that incorporates local metric information. Moreover, as noted above (see Table 3), participants who made decisions during exploration took the shortest detours more often during test (significantly), as did those who walked during exploration (marginally). This finding reinforces the conclusion that decision making facilitates graph learning and idiothetic information contributes local metric knowledge.

Using a similar experimental design, we previously tested active contributions to survey knowledge of the same hedge-maze environment (Chrastil & Warren, 2013). We probed survey knowledge with a direct shortcut task, in which participants were instructed to walk from the start object to the target object on a straight-line path, rather than staying in the corridors of the maze. Accurate performance required survey knowledge of the metric distances and directions between learned locations. Although participants in the free walking condition were above chance overall, absolute shortcut errors averaged around 70°, and half of the participants were near chance (90°). Although a few participants may have learned accurate survey knowledge (12% had absolute errors around 20°), there is little indication that this is the primary form of spatial knowledge acquired. In contrast, in the present study only 10% of participants in the free walking condition performed at the chance level, whereas half were successful in route finding on about 60% or more trials. This pattern of results implies that the majority of participants acquired graph knowledge but not survey knowledge, when freely exploring the same environment.

Together, these findings suggest that the primary form of human spatial knowledge may be best described as a labeled graph that incorporates local metric information (Chrastil & Warren, 2014b). Such a knowledge structure would be sufficient for tasks including route finding, taking novel detours, choosing the shortest route, and even taking approximate shortcuts, without requiring a globally consistent metric cognitive map (Byrne, 1979; Chown et al., 1995; Kuipers et al., 2003; Meilinger, 2008; Trullier et al., 1997; Werner et al., 2000). Behavior that appears to implicate a global metric map could actually be supported by a labeled graph, despite rough and inconsistent metric information.

The pattern of errors offers some additional clues about the information that may be encoded in a graph structure. The analysis of target difficulty revealed that the best predictor of errors was the number of turns in the maze between the start location and the target. For example, referring to Figure 1, the easiest object pair (bookcase–well) was separated by only two turns, whereas the hardest pair (snowman–rabbit) was separated by four. Thus, difficulty in learning the graph structure is related to the number of the turns in the trajectory, not just the number of intersections, suggesting that turns (with angle labels) may be entered as nodes in graph knowledge. In addition, the rabbit was located in a branch hallway whose shape was almost identical to that of three other objects. Indeed, on rabbit trials participants tended to go to the gear location more frequently, for it had the same branch hallway shape and was closer to the start location (snowman). Such errors imply that participants may have occasionally relied on a view-based strategy, which suggests that view information may also be incorporated into graph knowledge.

The Exploration-Specific Learning Hypothesis

Together with our previous results, the present findings support the exploration-specific learning hypothesis that the components of active learning differentially contribute to particular forms of spatial knowledge. Specifically, decision making is the primary component of active learning for the acquisition of topological graph knowledge, whereas idiothetic information is the primary component for metric survey knowledge. Idiothetic information may also contribute local metric information to a labeled graph.

Chrastil and Warren's (2013) shortcut test demonstrated that idiothetic information (specifically podokinetic information during walking) made a significant contribution to survey knowledge, reflected in lower absolute errors in the direction of shortcuts. In contrast, decision making during exploration made no significant contribution to survey knowledge. Those findings stand in contrast to the present results for graph knowledge, in which decision making makes a significant contribution but idiothetic information by itself does not. We note that the decision-making effect was significant in combination with idiothetic information, consistent with a contribution of local metric information to labeled graph knowledge.

The contrasting results in these two experiments imply that the components of active learning differentially affect particular types of spatial knowledge. Decision making helped participants in the present experiment learn the graph structure of the maze, presumably by facilitating acquisition of the topological connections between locations. But it did not contribute to survey knowledge (Chrastil & Warren, 2013), which depends on metric information about the distances and angles between those locations. A navigator with graph knowledge may be able find a route through the maze to the target location without knowing its metric location, whereas an accurate shortcut requires knowing the target's direction and distance with respect to the starting position.

On the other hand, idiothetic information from walking specifies the metric distances and angles needed to acquire survey knowledge. Indeed, Chrastil and Warren (2013) found that walking during exploration led to more accurate shortcuts in the test phase. Such metric relations may be derived from path integration (McNaughton et al., 2006), and idiothetic information has been shown to contribute to path integration over and above visual information alone (Kearns, 2003; Tcheang et al., 2011). It is possible that idiothetic information also plays a subtle role in graph learning. We find that navigators learn not just the connectivity of their environment, but a labeled graph that incorporates some local metric information (Chrastil & Warren, 2014b). This knowledge could aid route finding by constraining the direction of initial segments that lead to a successful path and the selection of the shortest path. If a labeled graph is the primary form of spatial knowledge, it would explain why we observed a decision-making advantage in the presence of idiothetic information. Thus, graph and survey knowledge rely on different types and amounts of information during learning and possibly different learning mechanisms.

If different components of active learning influence graph and survey knowledge, it may indicate that these forms of spatial knowledge can be learned independently. Siegel and White (1975) proposed that landmark information is learned first, followed by route knowledge, and finally metric survey knowledge. However, recent evidence suggests that this ordering may not always hold. Ishikawa and Montello (2006) reported that some people acquire survey knowledge and route knowledge simultaneously, whereas others never acquire survey knowledge despite repeated exposure to the environment. Our results indicate that graph knowledge is acquired early in learning, after only 10 min of exploration, and is exhibited early in the test phase. Neural evidence indicates that brain areas supporting habitual route learning are active at a later stage of learning (e.g., Hartley, Maguire, Spiers, & Burgess, 2003; Packard & McGaugh, 1996). These findings imply that the primary form of spatial knowledge has a labeled graph structure and is easier to learn than route or survey knowledge, consistent with the idea that navigators acquire different types of spatial knowledge at different stages of learning (Tversky, 1993).

Sex Differences

We also observed a consistent sex difference in graph learning, such that women tended to perform worse than did men, overall. This result is particularly noticeable in the free decision-making groups, where the difference in proportion correct was 0.205. However, female participants reported less experience with video games and higher ratings of nausea, especially in the video conditions. Although nausea was not correlated with performance, it is possible that women were more distracted in these conditions than were men. Our results are consistent with previous research that has found large sex differences in spatial navigation (Moffat, Hampson, & Hatzipantelis, 1998; Waller, 2000; Wolbers & Hegarty, 2010), although other researchers have found few differences, particularly in route learning (Castelli, Corazzini, & Geminiani, 2008; Coluccia & Louse, 2004). The present results show that women performed lower on tests of spatial ability and graph learning than did men, but they do not illuminate the source of this difference. For example, spatial abilities may be susceptible to stereotype threat (Spencer, Steele, & Quinn, 1999), where membership in a group that has stereotypically poor skills in a particular area may adversely affect performance in that area. Women are typically associated with lower spatial skills, and their performance in spatial tasks has been shown to suffer depending on the level of stereotype threat or anxiety about spatial skills (Lawton & Kallai, 2002; Martens, Johns, Greenberg, & Schimel, 2006; McGlone & Aronson, 2006). It is possible that this was a factor in the observed differences.

Finally, there were also large individual differences in route finding performance. Even in the free walking group, the percent correct ranged from nearly 0% to 100% (see Figure 4A). One quarter of participants in the free walking group successfully located virtually all targets, whereas 15% of participants were near chance. This distribution of performance is similar to that reported by Ishikawa and Montello (2006) in a more difficult survey-learning task conducted over multiple sessions. Further analysis of individual differences and their relationship to route and graph performance is planned for a future article.

Conclusion

Overall, we found that decision making during exploration plays an important role in learning the graph structure of an environment. This result is consistent with the exploration-specific learning hypothesis that making decisions helps to link paths and places together in graph knowledge but does not contribute to survey knowledge. It is also possible that the role of decision making is enhanced by the presence of idiothetic information, which could contribute local metric information to labeled graph knowledge.

We began by posing several questions about active and passive spatial learning in a typical scenario: Driving back from a party after riding as a passenger on the way there. To improve your chances of getting home, our results suggest that driving to the party while receiving directions would not have been helpful. Similarly, walking to the party would not have helped either. But making decisions about the route to the party, particularly while walking there, may be optimal. In contrast, if you want to take a direct shortcut home as the crow flies, walking there is your best bet.

In sum, there are systematic differences between active and passive spatial learning. Idiothetic information and decision making are both important components of active spatial learning, over and above passive visual exposure. However, they make differential contributions to spatial knowledge: Decision making contributes to topological graph knowledge, whereas idiothetic information contributes to survey knowledge and may also contribute to local metric knowledge in a labeled graph.

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Received July 29, 2014
Revision received September 18, 2014
Accepted September 19, 2014 ■