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Variations in Cognitive Maps: Understanding Individual Differences in Navigation

Steven M. Weisberg Temple University

Nora S. Newcombe and Thomas F. Shipley Temple University Russell A. Epstein University of Pennsylvania

Victor R. Schinazi

ETH Zurich

There are marked individual differences in the formation of cognitive maps both in the real world and in virtual environments (VE; e.g., Blajenkova, Motes, & Kozhevnikov, 2005; Chai & Jacobs, 2010; Ishikawa & Montello, 2006; Wen, Ishikawa, & Sato, 2011). These differences, however, are poorly understood and can be difficult to assess except by self-report methods. VEs offer an opportunity to collect objective data in environments that can be controlled and standardized. In this study, we designed a VE consisting of buildings arrayed along 2 separated routes, allowing for differentiation of between-route and within-route representation. Performance on a pointing task and a model-building task correlated with self-reported navigation ability. However, for participants with lower levels of between-route pointing, the Santa Barbara Sense of Direction scale (Hegarty, Richardson, Montello, Lovelace, & Subbiah, 2002) did not predict individual differences in accuracy when pointing to buildings within the same route. Thus, we confirm the existence of individual differences in the ability to construct a cognitive map of an environment, identify both the strengths and the potential weaknesses of self-report measures, and isolate a dimension that may help to characterize individual differences more completely. The VE designed for this study provides an objective behavioral measure of navigation ability that can be widely used as a research tool.

Keywords: virtual navigation, individual differences, spatial cognition, memory

Successful navigation requires a variety of skills and strategies (Wolbers & Hegarty, 2010). When navigational expertise is measured as a unitary construct, people vary along a continuum from expert navigational ability (e.g., Maguire, Woollett, & Spiers, 2006) to serious navigational impairments (Iaria & Barton, 2010), with many gradations in between (e.g., Hegarty, Richardson, Montello, Lovelace, & Subbiah, 2002). However, if navigation ability truly has a multidimensional structure involving the recruitment of distinct cognitive processes, measuring individual differences may not be so straightforward. Different navigation tasks require distinct subsets of cognitive processes (Wiener, Büchner, & Hölscher, 2009), each of which may exhibit individual differences. This study has three purposes.

Steven M. Weisberg, Department of Psychology, Temple University; Victor R. Schinazi, Department of Humanities, ETH Zurich, Zurich, Switzerland; Nora S. Newcombe and Thomas F. Shipley, Department of Psychology, Temple University; Russell A. Epstein, Department of Psychology, University of Pennsylvania.

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Correspondence concerning this article should be addressed to Steven M. Weisberg, Department of Psychology, Temple University, Philadelphia, PA 19122. E-mail: smweis@temple.edu First, we determine whether findings on a classic navigation task (route integration) can be replicated in a virtual environment (VE) and whether the data show individual differences on two dimensions: within-route and between-route learning. Second, we correlate psychometric and self-report data to determine whether individual differences can be predicted by extant measures. Third, we introduce an objective, virtual measure of navigation ability that can be shared.

There are several reasons to be interested in individual differences in navigation performance. On the practical side, understanding the neural and behavioral correlates of these individual differences may aid the development of procedures for improving navigation. On the theoretical side, individual differences in navigation may be relevant to the long-standing controversy concerning the existence of a *cognitive map*, proposed by many researchers (e.g., Montello, 1998; Siegel & White, 1975; Tolman, 1948) but critiqued by others (e.g., Foo, Warren, Duchon, & Tarr, 2005; Shettleworth, 2009). Supporters define cognitive maps as maplike representations of large-scale environments. A hallmark of cognitive map use is the ability to take novel shortcuts between two points that one has never directly traveled between (Bennett, 1996), in cases where direct path integration can be ruled out. Detractors of cognitive maps contend that shortcutting is possible without a maplike representation and is a product of heuristics.

While this debate usually revolves around whether cognitive maps do or do not exist, recent studies have suggested that the potential answer could be that there are individual differences in whether cognitive maps are constructed (e.g., Ishikawa & Montello, 2006; Schinazi, Nardi, Newcombe, Shipley, & Epstein, 2013). Specifically, Ishikawa and Montello (2006) found marked individual differences in the formation of accurate spatial representations in a study in which they drove participants in a car around a novel environment once a week for 10 weeks. The participants' task was to learn the locations of buildings along two separated routes. Participants varied substantially in their ability to learn the environment, as measured by their drawings of locations of buildings (sketch maps) and their accuracy in pointing to locations around the environment. Most participants performed either consistently well or consistently poorly across 10 trials, neither improving nor declining, despite also being taken on a connecting route between the two separated routes from the fourth trial on.

In that study, however, participants were passively exposed to the environment. To address whether participants could form cognitive maps given active exposure to an environment, Schinazi et al. (2013) led walking participants around a real-world environment once a week for 3 weeks. Two separated routes were learned the first week, and two paths connecting these routes were learned in the two subsequent weeks. Across the 3 weeks, Schinazi et al. found that most participants improved on spatial tasks involving buildings along both routes ultimately forming reasonably accurate spatial representations of the environment. In addition, individual differences that related to neuroanatomical variability were observed: Subjects with larger posterior hippocampi were significantly better at a pointing task (also referred to as judgments of relative direction, or JRDs) in which they were required to imagine standing next to one of the buildings while facing down the route and to point to the other buildings. This result is consistent with findings in normal adults (Hartley & Harlow, 2012) and with studies comparing London taxi drivers, who must demonstrate an accurate knowledge of the complex London street network (known as "The Knowledge") to normal controls. London taxi drivers have larger posterior hippocampi than do either control subjects (Maguire et al., 2000) or bus drivers (Maguire et al., 2006) and larger hippocampi after training compared to before (Woollett & Maguire, 2011). Thus, there is strong evidence that individuals differ in their ability to learn new environments and that these differences have specific neural correlates.

Assessing these individual differences can be challenging, however, if one must conduct lengthy and demanding spatial learning experiments in the real world. Luckily, individual differences in navigation ability can also be explored using self-report measures. Participants who self-report better sense of direction (SOD) are better at pointing to unseen targets, even when SOD is assessed by a single Likert-scale item (Kozlowski & Bryant, 1977; Sholl, 1988). More recently, two self-report measures of navigation ability have been widely used and validated: Hegarty and colleagues have developed the Santa Barbara Sense of Direction (SBSOD) scale (Hegarty et al., 2002), while Pazzaglia and De Beni (2001) have developed a different sense of direction scale, the Sense of Direction and Spatial Representation Scale (SDSR). The SBSOD (used in the current study) is a unidimensional measure of sense of direction, whereas Pazzaglia and De Beni's scale distinguishes between landmark and survey learning preferences. Both SOD scales consist of Likert-scale items that measure the participants' ability and proclivity for navigation-related tasks.

The SBSOD and SDSR are highly reliable and have been shown to be well correlated with tasks that require some form of survey knowledge. Specifically, the SOD scales have been shown to correlate with performance on large-scale navigation tasks but not with performance on smaller-scale spatial tasks (Hegarty et al., 2002; Kozhevnikov & Hegarty, 2001); with the selection of fewer, but more reliable, landmarks in real-world navigation tasks (Ishikawa & Nakamura, 2012); with greater reliance on spatial than verbal working memory in an interference paradigm (Wen, Ishikawa, & Sato, 2011); with better learning in a desktop VE (Pazzaglia & Taylor, 2007); and with greater sensitivity to stimulus repetition in the parahippocampal cortex—a cortical region that supports representations of scenes, when observing views of buildings and rooms shown from different vantage points (Epstein, Higgins, & Thompson-Schill, 2005).

These studies strongly suggest that good and poor navigators may differ in important ways. However, there are several reasons to be wary about exclusive reliance on self-report measures of navigation ability. First, in self-reporting navigation ability, participants may sample from a small number of recent events. Heth, Cornell, and Flood (2002) found that self-report sense of direction was correlated with performance on a route-reversal task when the SBSOD was completed after, but not before, the navigation task. Second, self-report measures are unlikely to be reliable for measuring improvement or change in navigation ability, because people are likely to regard their sense of direction as a stable trait or be unaware of gradual or relatively small changes. Measuring how navigation ability changes after training protocols requires an objective and consistent form of assessment.

The virtual environment and paradigm used in the current study matched, as closely as possible, the environment and paradigm used in the real-world study described above (Schinazi et al., 2013). We chose to match this environment because its layout (see Figure 1) allowed us to investigate a distinction between two categories of pointing judgments-within route and between routes-that have been widely investigated in navigation studies. Previous research has shown the relative difficulty of integrating two routes into one spatial representation because within-route judgments are quicker and more accurate than between-routes judgments (Blajenkova, Motes, & Kozhevnikov, 2005; Golledge, Ruggles, Pellegrino, & Gale, 1993; Hanley & Levine, 1983; Holding & Holding, 1989; Ishikawa & Montello, 2006; Moar & Carleton, 1982; Montello & Pick, 1993; Schinazi et al., 2013). However, only two of these studies assessed the role of individual differences in performing these two types of tasks. Ishikawa and Montello (2006) showed participants had differential rates of acquisition for between-routes pointing. Schinazi and colleagues (2013) related the rates of acquisition of between-routes pointing to hippocampal volume.

We sought to extend these findings in two ways. First, we evaluated in a VE whether making within-route judgments is easier than making between-routes judgments, as has been found previously in real-world settings. Second, we designed this study to determine whether both within-route and between-routes navigation tasks exhibit individual differences and whether self-report and spatial measures predict these individual differences. We were interested in how well self-report data predicted navigation ability, regardless of navigational strategy preference, so we chose to administer the SBSOD instead of the SDSR. Previous research has shown that the SBSOD correlates with pointing judgments when buildings are not mutually visible (Hegarty et al., 2002). We hypothesized that the SBSOD would predict between-routes point-



Figure 1. Aerial view map of the layout of buildings, main routes, and connecting routes for the virtual environment. Note that the spatial arrangement of buildings was identical to that in a real-world environment (used in Schinazi et al., 2013). The letter–number combinations indicate starting and ending points along each of the routes learned. All participants began each route at 1, traveled the entire route to 2, and walked back to 1. Participants always learned the main routes (solid lines) first, but route A and route B were counterbalanced between participants. Then participants learned both connecting routes (dashed lines), and route C and route D were similarly counterbalanced.

ing judgments better than would within-route pointing judgments. We were also interested in the little-explored relationship between self-report data from cognitive processes that may be less related to navigation directly. To that end, we tested correlations between navigation ability and self-reported small-scale spatial ability and verbal ability (Hegarty, Crookes, Dara-Abrams, & Shipley, 2010).

Because our VE is based on a real-world environment (Schinazi et al., 2013), it can potentially be used to conduct future studies that directly compare virtual and real-world navigation performance. With this prospect in mind, we took care to match the spatial layout and the location of buildings and other objects in the VE to their real-world equivalents. As in the real-world experiment, participants in the current experiment learned two routes each containing four buildings, followed by two paths that connected the first two routes. Motion was self-generated in both the virtual environment (using the mouse and keyboard) and in the real world (by walking). After participants learned the names and locations of buildings around the environment, their spatial knowledge of the environment was tested with a pointing task (similar to JRDs) and a model-building task. We expected to find individual differences in overall performance on both tasks but also expected the two tests to give us different insights into the distinct navigational processes. The onsite pointing task allowed us to examine, directly, differences in within-route compared to between-routes pointing. The model-building task, on the other hand, provided a more holistic measure of the participants' representation of the environment. Administering both tasks also allowed us to examine the relationship between the two categories of pointing judgments and the model-building task.

Participants

Forty-nine undergraduate students at Temple University (23 male) participated in the experiment in return for course credit or \$10. All participants provided informed consent in compliance with the Institutional Review Board at Temple University.

Method

Materials

The experiment was administered on an Alienware computer running Windows 7 64-bit with an Intel Core i7 960 @ 3.20 GHz processor and NVidia GeForce GTX 460 graphics card. The VE was displayed on a 32-cm by 52-cm LCD monitor with a refresh rate of 59 Hz and a resolution of 1920×1200 . The viewing distance from the screen was approximately 50 cm giving a field of view of about 60°. The VE was identical to the spatial layout of the buildings in a real-world college campus (see Schinazi et al., 2013), created using Unity3D (www.unity3d.com) and populated with buildings and other objects that were modeled in Google Sketchup and freely available online (http://sketchup.google.com/). While the VE buildings differed in architectural design compared to those used in the real-world experiment, effort was made to match them on saliency and place them in the precise spatial location of the physical buildings in order to keep the relative distance and angles identical. As far as was practical, nonbuilding objects (e.g., signs, trees, trash cans) were also matched from VE to real world, particularly when those objects could be used as reference points. For specific comparisons, see Figures 1 and 2, below, and Schinazi et al. (2013).



Figure 2. Screenshots from the main route B (Panel A) and a connecting route C (Panel B) of a virtual environment. Panel B displays an arrow that marked the path participants were instructed to follow in the virtual environment; a blue diamond (symbolized with a white diamond) indicated a building participants had to remember as well as a sign with the name of the building (Snow Church).

Procedure

The procedure used took approximately 1 hr. Participants first completed psychometric and self-report measures, either on the computer or on paper. Next, participants familiarized themselves with the VE and learned first the two main routes, then the two connecting routes. Participants then completed the pointing task, followed by the model-building task. They were then debriefed and released.

Psychometric and Self-Report Measures

Santa Barbara Sense of Direction Scale (SBSOD; Hegarty et al., 2002). The SBSOD consists of 15 items that participants respond to on a 7-point Likert scale (Cronbach's $\alpha = .79$). The scale is designed to measure how strong a navigator participants feel they are, with lower scores indicating lower navigation ability. Sample items include "I am very good at reading maps" and "I very easily get lost in a new city."

Philadelphia Spatial Ability Scale (PSAS; Hegarty et al., 2010). The PSAS consists of 16 items that participants respond to on a 7-point Likert scale (Cronbach's $\alpha = .77$). This scale is designed to measure how well participants feel they can perform small-scale spatial tasks such as visualizing and transforming small- or medium-sized objects. Sample items include "I can easily visualize my room with a different furniture arrangement" and "I enjoy putting together puzzles."

Philadelphia Verbal Ability Scale (PVAS; Hegarty et al., 2010). The PVAS consists of 10 items that participants respond to on a 7-point Likert scale (Cronbach's $\alpha = .78$). This scale is designed to measure how strong participants feel their verbal ability is. This scale was completed via paper and pencil. Sample items include "I am very good at Scrabble" and "I often have trouble expressing what I mean in words."

Mental Rotation Test (MRT; Vandenberg & Kuse, 1978). The MRT (adapted by Peters et al., 1995) consists of items made up of one target image composed of a number of individual cubes. Participants must choose the two (out of four) objects that correspond to the target after being rigidly rotated. Scoring that corrected for guessing was applied such that participants received 2 points for each correct response but lost 2 points for an incorrect response. No points were awarded or rescinded for omissions. The MRT consists of two parts of 10 items each, with 3 min allotted for each part of the test.

Spatial Orientation Test (SOT; Kozhevnikov & Hegarty, 2001). The SOT (we used the revised version by Hegarty & Waller, 2004) requires viewing an array of objects on a piece of paper, then taking the perspective of standing next to one object and facing another, with the task of pointing to a third object. Participants are allowed 5 min to complete the 12-item measure. The angle between the correct answer and each response is recorded for each item and averaged to yield an overall error score. This test was completed via paper and pencil.

Virtual Environment Learning

After participants completed all questionnaires, the experimenter explained the navigation tasks. First, the experimenter explained the controls for moving and looking around the VE and provided participants an opportunity to move around the environment before being required to learn the buildings. Movement through the environment was controlled using the arrow keys (up for forward, down for backward, and left and right for lateral movement). In addition, participants could look around the environment by moving a standard computer mouse to rotate the camera 360 degrees horizontally and 60 degrees away from parallel to the ground both up and down. The experimenter explained and demonstrated that the mouse and arrow keys could be used in conjunction to turn (i.e., rotate the camera to the right with the mouse while pressing the up arrow to turn to the right). Practice always occurred in the first route in the virtual environment used in the study, but the experimenter instructed participants not to navigate past the first building.

Once participants indicated comfort and familiarity with the controls, the experimenter told them they would be learning four different routes through a VE. Along the first two routes, partici-

After learning all eight buildings, participants traveled on two paths that connected the first two routes to each other and were told to pay attention to how the two sets of buildings were positioned in the VE. Participants were clearly instructed that no additional buildings would need to be learned but that these two routes would provide additional spatial information. The order the connecting routes were presented was counterbalanced across participants but always occurred after the first two routes. For all routes, participants traveled from the start to the finish and back to the start but had as much time as they needed.

Virtual Environment Spatial Tasks

Pointing. In this task, participants were placed at the start of one of the two routes (determined randomly), directly adjacent to the first building of that route. By moving the mouse, participants could rotate their viewing direction in the horizontal plane to point a crosshair in the center of the screen in any direction. A prompt at the top of the screen provided the name of one of the other seven buildings. Participants were instructed to rotate the mouse until the crosshair pointed to the front door of the building in the prompt and to click once to register their answer. In some cases, the front door was visible from the pointing location, and in other cases it was not. Clicking the mouse also changed the name of the building in the prompt, and participants then pointed to that building. Once participants had pointed to all seven buildings from the first building, they were automatically and instantly repositioned at the next building along that route, and they then pointed to the other seven buildings in the same manner. After participants completed this for the buildings on the first route, they completed the same task for buildings on the second route. The order of locations from which participants pointed matched the order of learning, but the order of which buildings to point at was random. The pointing task was scored by measuring the smallest possible angle between the correct answer and each participant's estimate, yielding the error value in degrees for each trial.

Model building. In the model-building task, participants viewed a blank box on the computer screen with aerial images of each of the eight buildings beneath it. The experimenter told participants that the box represented the entire VE. The participants' task was to drag and drop each building to where it belonged in the environment using the mouse. Buildings could be moved as much or as little as necessary, and no time limit was given. The orientation of the buildings was fixed so they could not be rotated, but no instruction was provided about the orientation of the environment. Participants were instructed, however, that they could place the buildings in whatever orientation felt most comfortable. Accuracy on the model-building task was measured using a bidimensional regression analysis (Friedman & Kohler, 2003; Tobler, 1994).

Results

Pointing Task

For the pointing task, the absolute value of the angular difference between participants' answers and the correct angle was calculated for each trial and then averaged across trials to yield the overall error score. For example, if the correct angle for a given trial had the value of 295° and the participant responded 100°, then the absolute value of the difference was calculated and corrected to be below 180° by subtracting the result from 360 (e.g., 1100 – 295I = 195, then 360 – 195 = 165). Guessing with no knowledge of the environment would yield an average score of 90°. Participants were able to learn the locations of the buildings significantly better than chance, one-sample t(48) = 25.13, p < .001, d = 7.25. No individual participant's pointing error was above the 90° threshold (maximum = 62.90), but there was large variability in performance overall ($M = 42.56^\circ$, SD = 13.21, range = 51.73).

Between- and Within-Route Pointing Task Trials

We examined differences between participants based on their performance on the two types of pointing trials, Between-Route or Within-Route. We separated trials based on whether the target building was on the route that the participant was currently standing (Within-Route) or on the other main route (Between-Route). Dividing the trials in this manner resulted in 24 Within trials and 32 Between trials per participant. A paired-sample *t* test on Within versus Between trial types revealed a significant difference, t(48) = 12.28, p < .001, r = .55, such that error on Within trials (M = 24.06, SD = 12.13) was significantly lower than error on Between trials (M = 46.47, SD = 14.54). Note that participants varied widely on both Between-Route and Within-Route Trials (see Figure 3).

Because a disproportionate number of buildings were mutually visible for Within-Route trials, while none were mutually visible in the Between-Route trials, we further analyzed the data by dividing trials based on intervisibility of the pointing to and from buildings into three groups: Seen-Within, Unseen-Within, or Between. This resulted in 14 Seen-Within trials, 10 Unseen-Within trials, and 32 Between trials. Performance was significantly better for Seen-Within trials (M = 19.81, SD = 14.32) than Unseen-Within trials (M = 30.64, SD = 13.77), t(48) = 5.05, p < .001, r = .43, and Between trials, t(48) = 11.94, p < .001, r = .41. Unseen-Within trials were also significantly easier than Between trials, t(48) = 7.88, p < .001 r = .51.¹ For brevity and because the results were similar regardless of the divisions used, the following analyses use

¹ To disentangle the effects of Within and Between Routes from the possible confound of spatial distance, we ran a multiple stepwise regression for only Unseen building pairs with distance of the building pair and whether the buildings were Within or Between Route as predictor variables in that order. Distance alone did not correlate with pointing error. When Between or Within Route was added to the model, it explained a significant portion of the variance and the effect of distance became significant but was negatively correlated with pointing error (the farther the building, the pointing error). Thus, the effect of pointing for Between or Within Route is not a product of buildings within one route being closer together than buildings on two separate routes.



Figure 3. Scatterplot of individuals' accuracy on Within and Between pointing trials. Participants' error was calculated for each trial type and plotted. Each dot represents one participant's error rates on Within-Route (*y*-axis) and Between-Route (*x*-axis) trials. The shape of the dot indicates the group that the participant was assigned to by the cluster analysis. The shading patterns denote approximate divisions to match the bars on Figure 5. Note that just one participant appears in the upper left quadrant, barely below the threshold for good Between-Route performance but performing poorly on Within-Route trials. The lack of any other data points in that quadrant suggests that accurate representation of local spatial position is important for forming an accurate global spatial configuration.

divisions based on Between/Within scores, not divisions based on Seen/Unseen scores. 2

Figure 3 plots each participant's average error for Within-Route trials (on the *y*-axis) by the average error for Between-Route trials (on the *x*-axis). Although the linear correlation between the two trial types was high and significant (r = .55, p < .001), the pattern of results was different for the Within versus the Between pointing trials. Nearly all participants with good performance on the Between trials had good performance on the Within trials. But participants with poor performance on the Between trials exhibited a range of values on the Within trials. Only two participants exhibited average accuracy on the Between trials and low accuracy on the Within trials (observe that the upper left quadrant of the scatter plot in Figure 3 is nearly vacant).

Cluster Analysis on Pointing Judgments

In order to analyze whether performance on the psychometric and self-report measures was related to performance on the two types of pointing trials, we used Within and Between pointing error in a cluster analysis to assemble the participants into groups. Using SPSS 18 statistical software's two-step cluster analysis algorithm with log-likelihood as the distance measure, we clustered participants based on their scores on Between and Within trials. The two-step algorithm first assigns individual values into preclusters, which in turn are clustered together to maximize the log-likelihood of a case belonging to that cluster. Nearly identical results were obtained after clustering in several different ways. The same analyses were performed (a) using the SPSS k-means algorithm instead of two-step, (b) using Seen and Unseen trial scores, and (c) using Unseen-Within and Between trials scores, all of which resulted in differences of only one or two cases (and no differences for the subsequent analyses). In the interest of space, only the two-step results are reported here.

First, participants were clustered on each of the variables (Between and Within pointing trial average) separately. The analysis clustered participants into two groups—nominally good and bad performance—for each variable. Based on their group for each variable, participants were then assigned into one of four possible combinations: Good Between/Good Within, Good Between/Bad Within, Bad Between/Good Within, and Bad Between/Bad Within. The Good Between/Bad Within group only had one participant, while the other three groups had 12, 17, and 19 participants, respectively.³

Based on this analysis and the distribution of participants along these two dimensions, a second two-step cluster analysis was conducted with both variables entered at the same time and the number of clusters constrained to three. Conducting the cluster analysis in this manner resulted in clusters that were similar to those when the variables were entered separately (14 Bad/Bad, 22 Bad/Good, and 13 Good/Good). This grouping is displayed by the three different textures in Figure 3 and used in all subsequent analyses. Using the alternative groupings did not substantially alter the results for the subsequent analyses.⁴ Performance on Seen-

² Removing Seen trials from the Within pointing trial type did not substantially change the following pattern of results.

³ The four-group cluster analysis was somewhat exploratory, allowing participants to vary along both types of pointing judgments. Given that the fourth group Good Between/Bad Within is unlikely to exist on the basis that Within-Route pointing should be easier, we take the finding that only one participant was clustered in that group to be good evidence that the data contain three clusters and consider the fourth cluster not easily interpretable.

⁴ Cluster groups did not differ substantially when the number of groups was constrained to four or five, regardless of the clustering algorithm used. *K*-means clustering was also used with no difference in the makeup of the groups. In the interest of space, only the results from the two-step cluster analysis constrained to three groups are reported.

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Within trials compared to Unseen-Within trials did vary between the three groups. Bad/Bad participants performed equally poorly on Seen-Within (M = 37.68, SD = 10.32) and Unseen-Within (M = 41.75, SD = 8.35) trials, paired-sample t(13) = 0.96, p =.36. The Bad/Good participants performed significantly better on Seen-Within trials (M = 15.57, SD = 8.81) compared to Unseen-Within trials (M = 31.75, SD = 9.50), paired-sample t(21) = 5.57, p < .001. Last, the Good/Good participants performed well on both types of Within trials but significantly better on Seen-Within (M = 7.75, SD = 2.43) compared to Unseen-Within (M = 16.78, SD = 13.06) trials, paired-sample t(12) = 2.34, p = .037.

Individual Differences Based on Pointing Performance

We wanted to know how the three different pointing groups, classified based on their performance (Good or Bad) on the two different trial types (Within or Between), differed on the psychometric and self-report tests we administered. First, the psychometric and self-report measures were z-scored to normalize the scales and allow easier comparison between measures. Results from one-way analyses of variance (ANOVAs) with pointing group as a between-subjects variable and z scores of each of the other measures as dependent variables are displayed in Figure 4. We observed significant differences between groups for the mental rotation test, F(2, 46) = 3.35, p = .04, $\eta^2 = .13$, and the Santa Barbara Sense of Direction scale, F(2, 46) = 5.64, p = .006, $\eta^2 = .20$. The groups were not significantly different on the Spatial Orientation Test, F(2, 46) = 2.78, p = .07, $\eta^2 = .12$, Philadelphia Spatial Abilities Scale, F(2, 46) = 1.47, p = .24, $\eta^2 = .06$, or Philadelphia Verbal Abilities Scale, F(2, 46) = 0.21, p = .81, $\eta^2 = .01$.

Follow-up post hoc pairwise contrasts using a critical value of α = .016 (because standard deviations were similar between groups the standard deviation of the entire sample), revealed that the Good Between/Good Within group outperformed the Bad Between/Bad Within group on the MRT, t(46) = 2.56, p < .05, d = 0.75, and SBSOD, t(46) = 3.09, p < .05, d = 0.91. Additionally, the Good Between/Good Within group outperformed the Bad Between/Good Within group outperformed the Bad Between/Good Within group outperformed the Bad Between/Good Within group on SBSOD, t(46) = 2.85, p < .05, d = 0.84. The Bad Between/Good Within and Bad Between/Bad Within groups were not significantly different for any post hoc contrasts. SBSOD and MRT were able to distinguish between groups of participants based on performance for Between-Route trials but not based on performance for Within-Route trials.

Model-Building Task

The model-building task was analyzed using bidimensional regression (Friedman & Kohler, 2003; Tobler, 1994). Bidimensional regression is the correlation between a set of independent X–Y points (in this case, the correct locations of all eight buildings) and a set of dependent A–B points (the participant's placement of the eight buildings). The set of eight dependent points are optimally rotated, scaled, and translated to match the fixed independent points on these dimensions. Although the participants could not rotate the building images, they were informed that they could orient the map any way they preferred with no change in error. The adjusted points are then correlated with the correct response, which yields a correlation coefficient. Squared, the correlation coefficient describes the proportion of variance explained in the actual layout of buildings by the participant's arrangement of buildings. As in



Figure 4. Mean *z* scores for participants grouped by performance on both types of pointing trial. Participants were divided into three groups by means of a cluster analysis based on their average scores on Between pointing trials and Within pointing trials. The graph presents the average *z* score for participants within each pointing group on each of the psychometric and self-report measures, as well as the model-building task. Omnibus ANOVAs demonstrate significant differences between the groups on the MRT test, the SBSOD, and the model-building task (the Perspective Taking Test [PTT] is reverse *z*-scored). MRT = Mental Rotation Test; SBSOD = Santa Barbara Sense of Direction; PSAS = Philadelphia Spatial Abilities Scale; PVAS = Philadelphia Verbal Abilities Scale. Error bars = ± 1 SEM. * *p* < .05. ** *p* < .001.

the pointing task, participants exhibited a range of performance on the model-building task (M = .48, SD = .27, range = .93). A one-factor ANOVA using the three cluster groups discussed above revealed significant differences in performance on the modelbuilding task, F(2, 46) = 7.99, p < .001, $\eta^2 = .33$. Post hoc follow-up contrasts on the model-building task, corrected in the same way as above, indicated the Good Between/Good Within group outperformed the Bad Between/Good Within, t(46) = 4.18, p < .05, d = 1.23, and the Bad Between/Bad Within, t(46) = 4.31, p < .05, d = 1.27, which did not differ from each other.

To assess whether average virtual environment (VE) performance was above chance, a Monte Carlo simulation was conducted. Random X and Y coordinates were independently generated for each of the buildings and entered into the bidimensional regression formula as the dependent variables. This process was repeated 1,000 times, with each set of eight points representing a randomly chosen set of positions for the eight buildings. Participants' performance on the model-building task was significantly better than the Monte Carlo simulation average (M = .35, SD =.17), one-sample t(48) = 3.58, p = .001, d = 1.03.

To determine whether participants who performed poorly or well on the Within-Route pointing task also created poor configurations of buildings within one route on the model-building task, we performed the bidimensional regression separately for the four buildings along one route, then the other. The two routes had similar average performance (Route A, M = .59, SD = .30; Route B, M = .65, SD = .29), t(48) = 1.19, p = .24, but the cluster groups performed significantly differently on the model-building task for Route A, F(2, 46) = 9.21, p < .001, and for Route B, F(2, 46) = 8.88, p = .001. Post hoc follow-up contrasts (Bonferroni-corrected for family-wise error rate at $\alpha = .05/6 = .008$) revealed that participants in the Good Between/Good Within group outperformed the Bad Between/ Bad Within group on both Route A, t(25) = 4.10, p < .001, d =1.64, and Route B, t(25) = 3.88, p = .001, d = 1.55 (see Figure 5). The Good Between/Good Within group outperformed the Bad Between/Good Within group on Route A, t(33) = 3.64, p = .001, d = 1.27, but not Route B, t(33) = 0.86, p = .39, d =0.30. Finally, the Bad Between/Good Within group outperformed the Bad Between/Bad Within group on Route B, t(34) =3.25, p = .003, d = 1.11, but not Route A, t(34) = 1.18, p = 1.18.25, d = 0.40. Routes A and B differed on the number of pairs of buildings that were intervisible, a factor that allows for similar interpretation between group differences on the pointing task and the model-building task, discussed further below.

Correlations and Regression Analyses

The correlations displayed in Table 1 show that the SBSOD, MRT, and SOT (error) correlate significantly with both Within and Between pointing error (see Figure 6 for scatterplots), as well as the model-building task. To assess the amount of variability the psychometric and self-report measures were able to account for in the dependent variables, multiple two-step regressions were conducted with the navigation tasks as dependent variables (see Table 2). In the first step, the MRT, SOT, PSAS, and PVAS were first included in the model. These measures did not explain a significant proportion of the variance for any of the dependent variables. In the second step, the SBSOD was added to the model. The SBSOD was a significant predictor of the Between-Route trials and the model-building task. The models from the second step explained a significant proportion of the variance for both Between-Route trials and the model-building task but not Within-Route trials. Adding the SBSOD also explained a significantly higher proportion of variance over the variables from the first step.⁵

Sex Differences

We were not specifically interested in sex differences, but they have been widely reported in navigation studies, particularly when navigation strategy is manipulated (e.g., Chai & Jacobs, 2010) or during survey but not route-based tasks (Ishikawa & Montello, 2006; Montello, Lovelace, Golledge, & Self, 1999). We ran independent samples *t* tests on all navigation tasks, psychometric measures, and self-report measures. On the SOT, men (M = 32.77, SD = 19.09) outperformed women (M = 51.24, SD = 33.85), t(47) = 2.31, p = .03, d = 0.67. On Within-Route pointing, men (M = 20.41, SD = 10.07) outperformed women (M = 27.29, SD = 13.04). All other spatial measures were not significantly different (although the MRT and the PSAS trended toward significant; ps < .10). There were no significant sex differences on the pointing task overall, t(47) = 1.66, p = .10, d = 0.48, or on the model-building task, t(47) = 1.05, p = .30, d = 0.31.

Discussion

Navigation ability is multifaceted. Navigators must encode different types of visual, spatial, and verbal information (e.g., names, images, sequences, and spatial positions of buildings) using different cognitive mechanisms and synthesize that information into a useful representation. We have shown that individual differences occur across two of these facets. Participants walked separate routes in a virtual environment (VE) and then made pointing judgments for buildings within the same route and between routes. Self-reported sense of direction accounted for unique variance in between-route pointing after controlling for other self-report and spatial measures. On the other hand, self-reported sense of direction did not account for unique variance in within-route pointing (see Table 2). The present study also demonstrates the advantages of objectively studying individual differences in VEs. VEs afford easy replication attempts, inexpensive collection of large samples across populations, and control of variables of interest (e.g., length and shape of routes, presence of landmarks). We first discuss our findings on individual differences and then describe the implications of our findings on theories of cognitive map development. Finally, we consider future applications and benefits to the field of using the virtual environment presented here.

⁵ Changing the order of loadings in the regression analyses did not change the pattern of results. The data were analyzed with hierarchical instead of standard regression so that the unique variance attributable to the SBSOD could be examined, controlling for the other measured variables. This shows the predictive power of the SBSOD for the model-building task and for Between- but not Within-Route pointing. Entering the variables all at once would not allow us to examine the change in R^2 (improved fit of the model).



Figure 5. Bidimensional regression scores for buildings along each route separately. The Good Between/Good Within group outperformed both of the other groups for Route A and the overall configuration of the buildings (see Figure 4). Participants who were accurate for within-route pointing outperformed participants who were poor on both types of pointing trials for Route B. Error bars $= \pm 1$ SEM.

Individual Differences

Individual differences in navigation ability go beyond what self-report measures are able to predict. The SBSOD was highly predictive of performance on Between-Route pointing trials and on the model-building task, and it explained a significant proportion of the variance on these tasks, beyond the other self-report and spatial measures included (see Table 2). The SBSOD was also significantly correlated with Within-Route pointing, but it did not predict a significant proportion of variance beyond the other measures (see Table 2). Additionally, despite correlating with error rates for both Between and Within trials, the SBSOD could not distinguish between participants performing poorly on both types of trials and participants performing poorly on just Between-Route pointing judgments. Visual analysis of the correlations between the SBSOD and both types of pointing tasks reveals they are driven primarily by high-SBSOD participants who scored well on both trial types and poor-SBSOD participants who scored poorly on both trial types (see Table 1 and Figure 6). The correlation coefficient obscures the fact that participants who scored poorly on only Between trials rated themselves no higher on the SBSOD than did participants who scored poorly on both trial types. This suggests that the linear relationship between self-reported sense of direction and performance on objective navigation tasks is nuanced and depends on the particular type of navigation task.

Others have shown that self-reported SOD correlates with some navigation-related tasks but not others (e.g., Hegarty et al., 2002; Ishikawa & Montello, 2006; Muehl & Sholl, 2004). Muehl and Sholl (2004) showed that SOD predicted participants' ability to path-integrate over longer routes with more turns in a virtual environment but not shorter routes, for which path integration occurs in all participants. A limitation of that work is that participants viewed the virtual environment passively via a movie and did not actively explore the environment. Nevertheless, results from the present study are largely consistent with these findings. In the present work, the high-SBSOD-scoring Good Between/Good Within group performed better than did the low-SBSOD-scoring Bad Between/Good Within group on only the longer path, A, for which more buildings were not mutually visible, but not the shorter route, B. However, the Bad Between/Good Within group outperformed the Bad Between/Bad Within group on the shorter route but not the longer route. For the lower scoring SBSOD groups, they performed equally poorly on the longer route, suggesting, like

| Table | 1 |
|-------|---|
| - | |

Intercorrelations, Means, and Standard Deviations for Psychometric and Navigation Tasks

| Measure | 1 | 2 | 3 | 4 | 5 | 6 | 7 | М | SD |
|-----------------------------|-----------|-------|-------|------|-----|------|-------|-------|-------|
| 1. MRT | | | | | | | | 27.51 | 20.22 |
| 2. SOT (Error) | 48^{**} | | | | | | | 42.57 | 29.17 |
| 3. SBSOD | .06 | 14 | _ | | | | | 4.46 | 0.84 |
| 4. PSAS | .28 | 38** | .58** | | | | | 4.69 | 0.92 |
| 5. PVAS | .001 | .09 | .31* | .33* | _ | | | 4.32 | 0.97 |
| 6. Model building (R^2) | .28 | 36* | .33* | .14 | 05 | _ | | 0.48 | 0.27 |
| 7. Pointing Within (Error) | 38** | .31* | 34* | 28 | 003 | 56** | _ | 19.81 | 14.32 |
| 8. Pointing Between (Error) | 35^{*} | .49** | 42** | 19 | 09 | 61** | .55** | 42.56 | 13.21 |

Note. Bivariate correlations, means, and standard deviations for all participants (N = 49) are presented above. Rows labeled (Error) should be interpreted as higher values indicate worse performance. Rows not labeled (Error) should be interpreted as accuracy, where higher values indicate better performance. MRT = Mental Rotation Test; SOT = Spatial Orientation Test; SBSOD = Santa Barbara Sense of Direction; PSAS = Philadelphia Spatial Ability Scale; PVAS = Philadelphia Verbal Ability Scale. * p < .05. ** p < .01.



Figure 6. Scatterplots of the Santa Barbara Sense of Direction (SBSOD) scale with virtual environment navigation measures divided by pointing group. The scatterplots show variation in SBSOD score and the various navigation tasks between the three groups identified with cluster analysis. Note the relative spread along the SBSOD for participants in the Bad Between/Bad Within and Bad Between/Good Within groups, despite differences in pointing performance.

Muehl and Sholl (2004), a lack of good path integration in virtual environments over long routes. The Bad Between/Good Within group performed better than did the Bad Between/Bad Within group on Seen-Within pointing trials but not Unseen-Within trials, and it had more accurate maps of the shorter route, which had more Seen-Within trials than did the longer route. These data suggest a difference between the two Bad Between groups in cognitive processing that is not related to learning spatial relationships across unseen locations, which is supported by path integration.

Ishikawa and Montello (2006) found that the SBSOD correlated with pointing and sketch-mapping tasks, whereas it did not correlate with landmark sequence tasks. As Hegarty et al. (2002) observed, the SBSOD is best at predicting performance in locating buildings that are not mutually visible. In the present study, both Within and Between pointing trials required knowledge of the routes independently (as failure to learn an individual route would yield poor performance on Within-Route as well as Between-Route trials), but only Between-Route trials required an integration of the routes. Among participants who performed poorly on Between-Route pointing, the SBSOD did not distinguish between participants who performed well on Within-Route pointing and those who performed poorly on Within-Route pointing, even when excluding the trials in which buildings were mutually visible. By showing that the SBSOD, while predictive of Between- and Within-Route pointing, does not discriminate among participants performing poorly on Between-Route trials, we have revealed that self-report methods of sense of direction taps into some, but not all, properties of navigation ability. Specifically, self-reported

| Table 2 | | | | | | | |
|------------|--------|-----|-----------|-------|-----|----------|-------|
| Regression | Models | for | Model-Bui | lding | and | Pointing | Tasks |

| Measure or variable | Model-building task | | Pointing (total) | | Pointing (within route) | | Pointing (between route) | |
|---------------------|---------------------|------------|------------------|-------------|-------------------------|------------|--------------------------|--------------|
| | Model 1 | Model 2 | Model 1 | Model 2 | Model 1 | Model 2 | Model 1 | Model 2 |
| Sex | 0.03 | -0.001 | -0.08 | -0.05 | -0.16 | -0.14 | 0.01 | 0.04 |
| SOT | -0.30 | -0.31 | 0.23 | 0.25 | 0.07 | 0.08 | 0.31 | 0.33* |
| MRT | 0.13 | 0.18 | -0.27 | -0.32^{*} | -0.26 | -0.29 | -0.22 | 027 |
| PSAS | -0.01 | -0.28 | -0.06 | 0.22 | -0.16 | 0.03 | 0.02 | 0.32 |
| PVAS | -0.02 | -0.08 | -0.04 | 0.02 | 0.05 | 0.09 | -0.13 | -0.07 |
| SBSOD | | 0.46^{*} | | -0.49^{*} | | -0.33 | | -0.53^{**} |
| R^2 | .15 | .28 | .24 | .39 | .21 | .28 | .20 | .38 |
| F | 1.50 | 2.74^{*} | 2.70^{*} | 4.44** | 2.26 | 2.68^{*} | 2.16 | 4.24* |
| ΔR^2 | | .13 | | .15 | | .07 | | .18 |
| ΔF | | 7.81^{*} | | 10.27^{*} | | 2.51 | | 11.89** |

Note. Regression analyses with data expressed as standardized betas. Controlling for sex, psychometric tests, and other self-report measures, SBSOD explains a significant portion of the variance, and improves the fit of the model for the model building task, and Between pointing trials, but is not a significant predictor and does not significantly improve the model for Within pointing trials. SOT = Spatial Orientation Test; MRT = Mental Rotation Test; PSAS = Philadelphia Spatial Ability Scale; PVAS = Philadelphia Verbal Ability Scale; SBSOD = Santa Barbara Sense of Direction. * p < .05. ** p < .01.

SOD predicts an individual's ability to make spatial inferences about locations that are in separate areas of an environment and not directly traveled between. Self-reported SOD does not predict an individual's ability to represent locations along a single path. An alternative interpretation of this finding is that both Between- and Within-Route tasks involve some integration across spatial locations that are not mutually visible but that Between-Route tasks are more difficult versions of such a task. Thus the SBSOD can distinguish between performance on relatively difficult survey tasks but not easier survey tasks.

The lack of discrimination by the SBSOD suggests that there is a factor of navigation not being measured that explains a significant portion of behavioral results. That factor may relate to general resources (e.g., attention, working memory) or to a more specific navigation-related process (i.e., binding the visual appearance of the building to the identity or name of that location). One distinction between the two groups who performed poorly on Between-Route judgments emerges when considering individual differences in performance on Seen-Within trials. The majority of participants' errors fell under 30°, but there were a few outlying participants. Given that the target building was visible during these trials, one possible explanation for why some participants struggled with this task may be that they forgot what certain buildings looked like and pointed to an incorrect location.⁶ Differences on the Seen-Within trials provide evidence that participants in the Bad Between/Good Within group committed purely spatial errors by forgetting or mistaking where a building was located (i.e., participants who could point to buildings within route, but performed poorly on between-route judgments). Participants in the Bad Between/Bad Within group, however, committed either nominal errors by forgetting the building name and the spatial position of that building by coincidence (i.e., participants who performed poorly on both types of pointing tasks) or associational errors by forgetting the association between the name and appearance and/or spatial location of the building. As has been described by others (Hegarty et al., 2002; Ishikawa & Montello, 2006), the SBSOD is not sensitive to differences in associating the name of a building with its visual appearance.

We also investigated the relationship between large-scale navigation, psychometric measures, and nonnavigation self-report measures. The MRT and the SOT, psychometric measures of figural spatial ability, while significantly correlated with both Within and Between pointing trials, were also not significantly different for the two different Bad Between groups. In the current study, the MRT, but not the SOT, was significantly correlated with pointing judgments on Within trials alone. These results suggest that the individual differences in representing the spatial properties of separate routes of an environment have distinct self-report and psychometric correlates from individual differences in representing the spatial properties within one route.

The other self-report measures administered as part of this study did not correlate with either navigation task, nor did they differentiate pointing groups identified by the cluster analysis. In the case of the PVAS, this provides divergent evidence that participants performing well on both navigation tasks do not merely have higher intelligence overall. However, given the significant correlation with the MRT and the pointing task, the relationship between navigation and small-scale spatial abilities like those assessed by the PSAS deserve more attention. These data support a multicomponent model of navigation ability (Wolbers & Hegarty, 2010), for which many types of spatial abilities can contribute to strong performance.

Although it was not the primary aim of the study, we did find sex differences on the Within-Route pointing test and the SOT, with men outperforming women on both. The Within-Route difference between men and women does not fit well with the current conceptualization of sex differences in navigation. Specifically, sex differences are thought to occur because men rely on a global reference frame and directional cues, while women focus on landmarks and positional cues (Chai & Jacobs, 2010). While there are

⁶ Note that idiosyncratic differences in precision may account for 10°–15° of error, as certain participants may have localized the front door of buildings more successfully than others, but these differences are small and relatively minor and should not differ across groups.

several possible strategies that participants could have used in the current task, it is unclear why any particular strategy would have supported better performance. Sex differences are more likely to occur in survey tasks than route-based tasks (Ishikawa & Montello, 2006; Montello et al., 1999). However, we obtained sex differences for Within-Route but not Between-Route pointing or the model-building task.

Cognitive Maps

Do the current data suggest that participants formed accurate cognitive maps? Cognitive maps are typically defined as allocentric mental representations that afford calculations of distances and directions between locations and flexible planning of routes through the use of novel shortcuts (O'Keefe & Nadel, 1978; Schinazi et al., 2013). One way to characterize individual differences in the construction of cognitive maps is to compare the predictive value of Between-Route pointing judgments to Within-Route pointing judgments for the model-building task. We found that accuracy on Between-Route trials was correlated with accurate models, while accuracy on Within-Route trials (though a necessary condition for Between-Route trial accuracy) was not sufficient to yield accurate models (see Figure 4).

Siegel and White (1975) postulated that acquisition of spatial knowledge proceeds through stages, such that navigators first learn landmarks and then routes (sequential knowledge) and then acquire metric information (survey knowledge). There have been challenges to this theory. Montello (1998) argued that acquisition of spatial knowledge is continuous, regardless of the knowledge type, while Chrastil (2013) has identified a possible intermediate form of spatial knowledge called graph knowledge. We can characterize the Within- and Between-Route pointing judgments by the different types of knowledge defined by Siegel and White's (1975) framework. Landmark and sequential knowledge are certainly necessary for Within-Route pointing, while survey knowledge is necessary for Between-Route pointing. Survey knowledge is also sufficient to solve Within-Route pointing and may be necessary, depending on whether route knowledge encompasses the spatial information (e.g., the angle between two segments of a path) required to solve Within-Route pointing. The present data provide evidence that some participants acquire all stages of knowledge quickly (success on Within- and Between-Route trials). Thus, metric knowledge is clearly present in some participants even after short periods of learning. Other participants, however, never proceed past the sequential stage of knowledge and demonstrate little, if any, survey knowledge. While it is possible that participants proceed through Siegel and White's stages at vastly different rates, data from real-world studies using similar paradigms reveal that some participants have accurate between-route knowledge prior to learning the connecting routes (Ishikawa & Montello, 2006; Schinazi et al., 2013). This suggests that metric knowledge can be acquired simultaneously with route knowledge, providing support for Montello's framework. Although this finding may be a limitation of the design (i.e., participants should not be able to integrate the locations of the two routes prior to learning the connecting route), individuals nevertheless acquire survey knowledge at very different rates and with different levels of information.

Recent work in neuroimaging may offer further explanations for individual differences in Within- and Between-Route pointing.

Burgess (2006) described research that detailed how egocentric and allocentric spatial processing were supported by distinct brain regions but were combined and processed in parallel. Indeed, structural neuroimaging data from a real-world study (Schinazi et al., 2013) demonstrated that distinct neural correlates support these different navigational processes. Participants with larger hippocampi performed better on a pointing task that required taking an imagined orientation and pointing to buildings around the environment. Participants with larger caudates, on the other hand, performed worse on this task, especially when the pointing judgments were within-route and thus more likely to elicit route-based representations that compete with survey knowledge. Functional neuroimaging data suggest that this dissociation of the caudate and the hippocampus may be attributed to the application of different strategies by different participants (Hartley, Maguire, Spiers, & Burgess, 2003; Iaria, Petrides, Dagher, Pike, & Bohbot, 2003; Marchette, Bakker, & Shelton, 2011). In one virtual environment study, for instance, caudate activation was shown to be a strong predictor of response-based strategies for navigation, while hippocampal activation predicted a place-based strategy (Marchette et al., 2011).

Our findings from the pointing task suggest testable hypotheses for future neuroimaging work. Participants performing well on both pointing trial types may use a place-based strategy, supported by the hippocampus, which provides the metric information necessary to succeed on both Within- and Between-Route pointing. Neuroanatomical findings from a real-world study (Schinazi et al., 2013) support the hypothesis that accurate Within-Route pointing may be supported by the hippocampus, with response-based learning leading to inaccurate pointing judgments on both types of pointing judgments. On the other hand, participants performing well on the Within pointing trials but poorly on Between pointing trials may use a response-based strategy, supported by the caudate, which provides little metric information if any but may be sufficient to support accurate Within-Route knowledge.

A separate possible property of the spatial representation that participants used during navigation merits some consideration. Good navigators may have used a hierarchically structured representation of the two main routes that contains both coarse information (the route a particular building is on) and more fine-grained information (the general spatial position of buildings in that area). This property of integrating qualitative (or categorical) information with quantitative (or fine-grained) information has been called the category adjustment model (Huttenlocher, Hedges, & Duncan, 1991). At least one study provides evidence that when a familiar environment contains natural categories, navigators bias their estimates of locations toward the center of that category (Uttal, Friedman, Hand, & Warren, 2010). Interestingly, the bias observed by Uttal and colleagues (2010) increased with familiarity, but self-reported navigation ability was not collected in that study. In the current study, the centroids (i.e., the geometric center) of the buildings within one route were too close to the individual buildings to investigate whether this strategy was employed.

Implications

While self-report measures have important uses, there are compelling reasons to consider moving beyond them. Mounting evidence has suggested that self-report measures are unable to predict quantifiable patterns of navigational behavior observed in more nuanced investigations of individual differences (Shelton, Marchette, & Furman, 2013). As a rough measure of individual differences, self-reports are an excellent starting point, but to understand the nuanced differences in navigation ability that characterize individuals, additional, ecologically valid measures are required. The VE described in the current study presents an opportunity to investigate navigation training strategies and measure navigation ability with a variety of applications including research groups for whom moving around the world is difficult or impractical, such as the aged (Bohbot et al., 2012) and individuals with Alzheimer's or Parkinson's disease (Gazova et al., 2012).

Perhaps the largest gap in the current literature is how little is known about the relationship between navigation ability and other cognitive abilities. There is a large amount of evidence that spatial ability is a significant and unique predictor of entrance into science, technology, engineering, and mathematics disciplines (Wai, Lubinski, & Benbow, 2009), but spatial ability has been exclusively measured in these studies with paper-and-pencil tests. Despite factor analyses demonstrating that large-scale navigation may rely upon, but is certainly distinct from, figural, or small-scale, spatial abilities (Hegarty, Montello, Richardson, Ishikawa, & Lovelace, 2006), no studies have shown a link between navigation ability and educational outcomes. Understanding this relationship has implications for the increasing reliance on global positioning systems to supplement or replace place-based (i.e., hippocampal) navigation. Intriguingly, evidence from self-report measures indicates that there are substantial differences in navigational skills across academic disciplines (Hegarty et al., 2010). SBSOD scores indicate that geoscientists and geographers have reported significantly higher navigation ability than, for example, psychologists and biologists. An objective measure of navigation ability could determine whether strong navigators are more likely to enter disciplines that draw upon these skills or whether entry into these disciplines provides those individuals more navigation practice. The VE used for this study is an excellent tool to begin to address these possibilities by testing the relationship between behavioral or neural differences in various cognitive abilities along with navigation skill.

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