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The Role of Working Memory Capacity in Spatial Learning Depends on Spatial Information Integration Difficulty in the Environment

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A substantial amount of research has been conducted to uncover factors underlying the pronounced individual differences in spatial navigation. Spatial working memory capacity (SWM) is shown to be one important factor. In other domains such as reading comprehension, the role of working memory capacity in task performance differences depends on the difficulty of other task demands. In the current study, we investigated whether, similarly, the relationship between SWM and spatial performance was dependent on the difficulty of spatial information integration in the environment. Based on our prior work, spatial information integration difficulty depends on (a) difficulty in observing spatial relationships between locations of interest in the environment and (b) the individual's ability to integrate such relationships. Leveraging virtual reality, we manipulated the difficulty in observing the spatial relationships during learning by changing the visibility of the buildings, and measured individual's self-report sense of direction (SOD) which modulates the ability to integrate such relationships under different degrees of visibility. We consistently found that in the "easy" spatial integration condition (high SOD with high visibility), high SWM did not significantly improve spatial learning. The same pattern was observed in the difficult condition (low SOD with low visibility). On the other hand, high SWM improved spatial learning for medium difficulty (high SOD with low visibility, or vice versa). Together, our results reveal that the role of SWM in spatial learning differences depends on spatial integration difficulty. Our results also have significant applied implications for using virtual reality to target and facilitate spatial learning.

Keywords: cognitive map, individual differences, spatial navigation, virtual reality, working memory

Supplemental materials: http://dx.doi.org/10.1037/xge0000972.supp

Navigating to various destinations is one of the most fundamental functions in our daily life, and there are pronounced individual differences in spatial navigation ability. On one hand, London taxi drivers can memorize relationships among the city's labyrinthine 25,000 streets. On the other hand, individuals without any acquired brain damage or neurological disorder can lose track of their current location even in extremely familiar surroundings (Iaria & Burles, 2016). A substantial amount of research has been dedicated to the underlying causes of these individual differences (for reviews, see Weisberg & Newcombe, 2018; Wolbers & Hegarty, 2010), and some research has uncovered significant correlations between spatial working memory capacity and spatial learning performance (Blacker, Weisberg, Newcombe, & Courtney, 2017; Weisberg & Newcombe, 2015). These results suggest that working memory is important in transforming incoming perceived spatial cues into a spatial representation of the environment.

In research on individual differences, there is a common assumption or desire that the correlations between psychological traits and performance are homogeneous (i.e., correlational magnitudes are similar across groups of individuals and environments or task states). However, it is well documented that the correlations between working memory and task performance can depend on the difficulty of background tasks or individual expertise with them (Conway & Engle, 1996; Daneman & Carpenter, 1980; Engle & Martin, 2018; Macleod, Hunt, & Mathews, 1978; Turner & Engle, 1989). This raises the possibility that environmental properties and spatial abilities could modulate the extent to which SWM contributes to spatial learning. In the current study, our primary aims were to replicate and build upon findings from our prior work (He, McNamara, & Brown, 2019) and to investigate whether the relationship between spatial working memory capacity (SWM) and spatial learning performance also depends on task difficulty.

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Curvilinear Relationship Between Working Memory and Task Performance

Our hypothesized curvilinear relationship between SWM and spatial learning is based on the findings from Turner and Engle (1989). In Turner and Engle's (1989) study, the authors showed that in the correlations between verbal working memory (VWM) and reading comprehension were dependent on the difficulty of a background task. When the background task was very easy or very difficult, the magnitude of the VWM–reading comprehension correlations were smaller compared with when the background task was at medium difficulty. Similar findings have been also reported in Mano et al. (2013).

In the current study, we conceptualized integrating the spatial information in the environment as a critical parallel computational task that is intertwined with SWM maintenance of incoming information for spatial knowledge acquisition (Ishikawa & Montello, 2006; Siegel & White, 1975). In turn, we hypothesized that if the principles underlying the data on verbal performance from Turner and Engle (1989) generalize to other domains, then SWM capacity's explanatory power for spatial learning differences would be lesser when spatial information integration was easy or difficult and would be larger when this difficulty was moderate.

One mechanism through which we would predict this pattern of results for spatial knowledge acquisition could be grounded in spatial information integration difficulty. Spatial integration difficulty contributes to encoding efficiency and could significantly influence the amount of SWM resources required to encode relevant spatial relationships in the environment. When exploring an environment under easy conditions, where relational encoding is highly efficient, participants would be more likely to integrate information encountered along navigational routes (and on longer time-scales: between different navigation episodes) into a coherent representation regardless of the limits of the SWM capacity (i.e., testing can rely on one representation if all spatial information was integrated; i.e., a cognitive map, Tolman, 1948). Conversely, when people learn environments under difficult integration conditions, (a) linking distal features along a route during encoding may involve active maintenance of more information and (b) retrieval of map-like information that hasn't been well-integrated may rely more on accessing and buffering memories from multiple route episodes in order to *infer* relationships. Indeed, in our present experiment up to 36 independent routes would be encoded/retrieved in the extreme if no integration occurred (see Method). As a result, easy integration may place little demand on active maintenance processes for tests of map-like knowledge, contributing to a decoupling of variability in SWM from cognitive mapping success. Likewise, difficult integration scenarios may rapidly exceed even large SWM capacities at encoding and when retrieving or inferring relationships between episodes which could constrain the relative contribution of capacity to performance. Together, this would position variability in SWM capacity to most strongly modulate spatial learning in situations where integration is moderately efficient, such that the amount of information exceeds some but not all individuals' SWM capacities.

An alternative mechanistic framework (further considered in the Discussion), which would also predict that the pattern of results observed in Turner and Engle (1989) could generalize to spatial navigation, is Yerkes–Dodson law (Yerkes & Dodson, 1908).[1] Here, arousal would be expected to increase with integration difficulty level and could result in limited engagement of effortful SWM for when integration is perceived as very easy but an adaptive utilization of SWM to buffer and sequence information for moderate difficulties. This mechanistic framework would most notably differ from a WM capacity saturation account in its explanation of cognition in the most extreme difficulties. Here, because utilizing WM is an effortful process, SWM capacity and performance may become decoupled under high arousal (difficult spatial integration conditions) owing to a disengagement from the cognitive load of an active maintenance-based encoding strategy.

Conceivably, both WM saturation and an arousal-based rainbow of WM engagement under Yerkes–Dodson law could co-occur and contribute to the mechanism behind observations such as Turner and Engle (1989; perhaps in series, as an individual becomes cognizant of the difficulty and adapts their encoding strategies to the task demands). Importantly, for the present study the explicit prediction would be the same under either an SWM engagement-saturation framework or Yerkes–Dodson law: paralleling Turner and Engle (1989), when building relational knowledge across extended experiences (here, spatial memory), individual differences in SWM capacity would more strongly track cognitive mapping performance under moderate than both easy or difficult memory integration conditions.

A Model of the Contributions of WM Capacity and Integration Difficulty to Spatial Knowledge Acquisition

We considered that spatial information integration difficulty could be dependent on at least two factors (see Figure 1): (a) The difficulty in observing spatial relationships between locations of interest, which is a structural property and could be manipulated, and (b) an individual's ability to integrate the observed spatial relationships acquired from different bearings, which is a participant trait and could be measured. Drawing on our prior work, we know that changing the translucency of the buildings in a virtual environment can manipulate the difficulty in observing spatial relationships, and the effectiveness of the translucency manipulation interacts with self-reported sense of direction (SOD; He, McNamara, & Brown, 2019). In the current study, we replicated this approach and observation, rendering intervening buildings between locations of interest either opaque (therefore important locations could not be seen directly) or translucent (enabling learners to view locations of interest directly anywhere in the environment), and combining this with SOD. This combination is effective because SOD has been shown to correlate with individual cognitive map formation abilities (He, McNamara, & Brown, 2019; He & Brown, 2020; Hegarty, Richardson, Montello, Lovelace, & Subbiah, 2002; Pazzaglia & De Beni, 2001) and path integration abilities (Hegarty et al., 2002; Kozlowski & Bryant, 1977), which involve integrating various locations in the environment into a uniform representation (Gallistel, 1990; Wang, 2016). Based on these prior data, three predictions can be made from our model:

[1] We are grateful to the anonymous reviewer for raising this possibility.

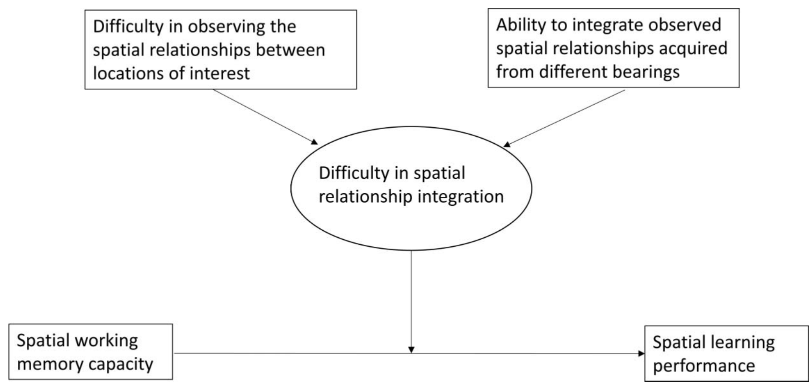

Figure 1. Conceptual model of how the relationship between spatial working memory capacity and spatial learning performance is modulated by (two aspects of) the difficulty in spatial relationship integration.

1. When it is difficult to integrate spatial information in the environment (environment visibility is low and the SOD is low), the role of SWM capacity in spatial learning differences is smaller.

2. When it is easy to integrate spatial information in the environment (environment visibility is high and SOD is high), the role of SWM capacity in spatial learning is also smaller.

3. When the difficulty integrating spatial information in the environment is moderate (environment visibility is low but SOD is high, or vice versa), the role of SWM in spatial learning is larger.

Facilitations of Spatial Learning by Manipulating the Visibility of the Environment

In addition to the theoretical importance of gaining a deeper understanding of individual differences in spatial learning, another important aim of the current project was to extend the applied implications for spatial learning and memory interventions from our previous study. In our previous study (He, McNamara, & Brown, 2019), we found that rendering the buildings translucent could improve both wayfinding efficiency and cognitive map accuracy, but the virtual environment was relatively simple and small-scale. In the current study, we created a virtual city which was structurally more naturalistic, much more complex, and 16 times larger in size. As a result, we could examine whether translucency still had similar facilitation effects on spatial learning and memory in a much more realistic environment.

Other visual manipulations of virtual environments have been shown to facilitate spatial learning by potentially reducing interference from unimportant buildings. Lokka, Çöltekin, Wiener, Fabrikant, and Röcke (2018) removed textures from buildings in noncritical locations, which in turn highlighted the buildings in the critical locations (here, we describe these as "abstract" environments to contrast with the environment conditions using naturalistic texturing across buildings). The authors compared learning performance between the realistic and abstract environments and found that spatial memory was better in the abstract environment. From the applied perspective of our work, we were interested in whether a combination of translucency and abstractness could yield an even stronger facilitation in learning. Therefore, we designed our experiment with a factorial combination of translucency and abstractness manipulations to our environment, enabling us to explore this additional virtual training manipulation and its relationship to learning outcomes for people with different levels of SWM. Importantly, regardless of which virtual environment participants were trained in, their spatial memory was probed in an opaque, naturalistic environment. In this way, we can examine whether the enhanced learning enabled by either translucency or abstractness could transfer to real life–like environment, greatly strengthening the theoretical and applied contributions of this study.

In sum, the current project aimed to examine (a) whether the relative contribution of SWM capacity to spatial learning differences could be modulated by difficulty of spatial information integration and (b) whether translucency and/or abstractness could facilitate spatial learning in a larger-scale, complex environment. To foreshadow, we found that the relationship between SWM and spatial learning was modulated by the difficulty of spatial information integration. Likewise, translucency could improve wayfinding efficiency and cognitive map accuracy, but only for participants with specific combinations of SOD and SWM.

Method

Participants

One hundred thirteen participants from Georgia Institute of Technology and the Atlanta community participated in this experiment, either for course credits or monetary compensation. Participants spent 60–90 min completing the experiment. Three participants were unable to finish the experiment in 120 min and were therefore excluded from the study. Fourteen participants felt motion stick and could not finish the experiment. As a result, 96 participants were included in the data analysis, with 24 participants in each experimental condition (see Materials and Design). Three blocks of data from two participants were not recorded properly because of technical difficulties. Our target sample size was determined using a power analysis on He, McNamara, and Brown (2019) upon which this study built. The power analysis showed that a sample size of 20 participants in each experimental condition could achieve a power >0.80 in the interaction between SOD and translucency on spatial learning performance.

Before the experiment, all participants completed the Questionnaire of Spatial Representation (QSR) to evaluate SOD (Pazzaglia & De Beni, 2001) and the advanced symmetry span task (Unsworth, Heitz, Schrock, & Engle, 2005) to measure SWM capacity. As in our previous study (He, McNamara, & Brown, 2019), we calculated participants' SOD scores as the sum of scores from items 1, 2, 3c, 8, 9 and 11 of QSR (item 11 was reverse scored). These questions were shown to be clustered into one factor (Pazzaglia & De Beni, 2001), which was associated with sense of direction (these questionnaire items are detailed in the Appendix). We utilized QSR, rather than Santa Barbara Sense of Direction scale (SBSOD; Hegarty et al., 2002), because on the one hand their aggregate scores measure a very similar psychological construct, but QSR was also used in our prior study which this work directly replicates and builds upon (He, McNamara, & Brown, 2019), ensuring the most direct comparability.

Each participant completed three blocks of the advanced symmetry span task, and we used the sum of the partial scores to reflect participants' SWM capacity, as suggested by Conway et al. (2005).

All participants (age 18–23) gave written, informed consent. The research was approved by the Institutional Review Board of Georgia Institute of Technology (IRB approval Code: H17456). All procedures were performed in accordance with the institutional guidelines.

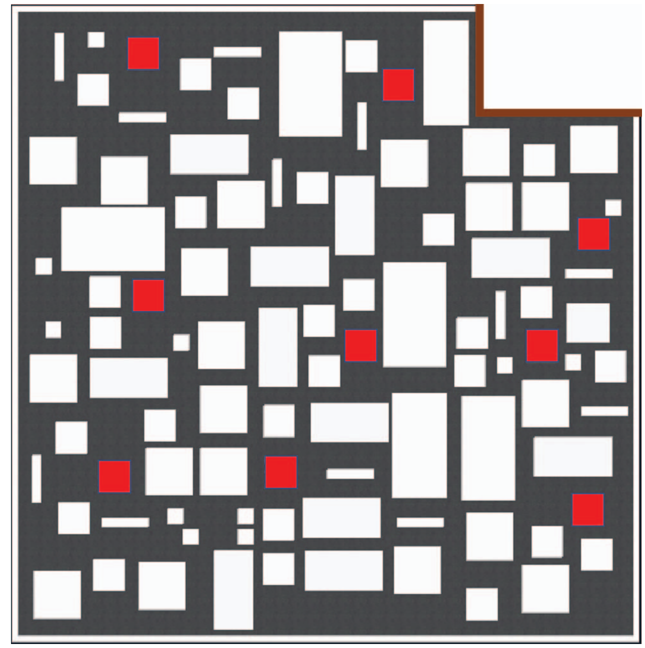

Figure 2. The layout of the virtual environment for the current study. Red (dark gray) squares indicate target buildings, which are only shown as red (dark gray) here for illustration purposes. See the online article for the color version of this figure.

Materials and Design

Independent variables. Using a between-subjects design, we manipulated the translucency of the buildings using an adaptive algorithm in which participants could either (a) control how many buildings that they could see through in the environment (video demo—translucent realistic and translucent abstract) or (b) could only perceive the environment with opaque buildings (video demo - opaque realistic and abstract). We also manipulated the abstractness (Lokka et al., 2018) of the environment, in which only the target buildings (i.e., buildings that participants were asked to find repeatedly throughout the experiment) were textured in the abstract environments (video demo—opaque abstract and translucent abstract). Additionally, SOD and SWM were key participant (quasi-independent) variables for our study, with SOD combining with visibility (translucency) to govern integration difficulty (He, McNamara, & Brown, 2019). We detail the procedures for these independent variable manipulations below. The independent variables were factorially combined (i.e., opaque-realistic, opaque-abstract, translucent-realistic and translucent-abstract) and were implemented in the following environment:

Virtual environment. The layout of the virtual environment was structured as a scattered grid-shape, Manhattan-style city setting (see Figure 2) and was rendered in Unity3D (www.unity3d.com). The virtual environment consisted of a 200 × 200 virtual meters-squared enclosure with a concave corner in the northeast, which was painted with a different texture from the rest of the enclosure (see Figure 2). The grid-shape layout and the distinct corner of the enclosure were designed to facilitate spatial updating (He, McNamara, Bodenheimer, et al., 2019; Kelly, McNamara, Bodenheimer, Carr, & Rieser, 2008; Li & Giudice, 2018), which, as we hypothesized in our previous study (He, McNamara, & Brown, 2019), could make the translucency manipulation more effective for participants with low SOD.

There were 98 buildings in this environment, 62 of which were generic buildings (e.g., apartment) with no names and 36 of which were stores with unique names. Nine of these stores were selected as target buildings, scattering around the environment (see Figure 2). Because participants could be asked to recall the spatial relationships between any of the two target buildings (see Procedure), there were $^9C_2 = 36$ spatial relationships to be encoded (i.e., up to 36 routes to remember at test in an extreme case of no integration of locations). The same set of target buildings was selected for all participants to control for visual saliency and semantic processing between conditions. During navigation, participants were only considered to have reached a target building when they collided with it. The floor of the virtual environment was textured with a repeating tile pattern and the outer rectangular boundary wall was textured with a repeating brick pattern to provide simple optic flow. The sky was textured with a sky dome.

Translucency and abstractness environmental manipulations. The translucency manipulated the opaqueness of the buildings, and the abstractness manipulated whether the nontarget buildings were textured. The translucent and abstract manipulations were factorially combined, resulting in four virtual environment presentations (see Figure 3). One important strength of our perceptual manipulation approach is that it allows us to manipulate the difficulty of the environment while preserving the geometric complexity and layout across conditions, rather than changing structural properties of the map between conditions to examine impacts on the SWM-learning relationship.

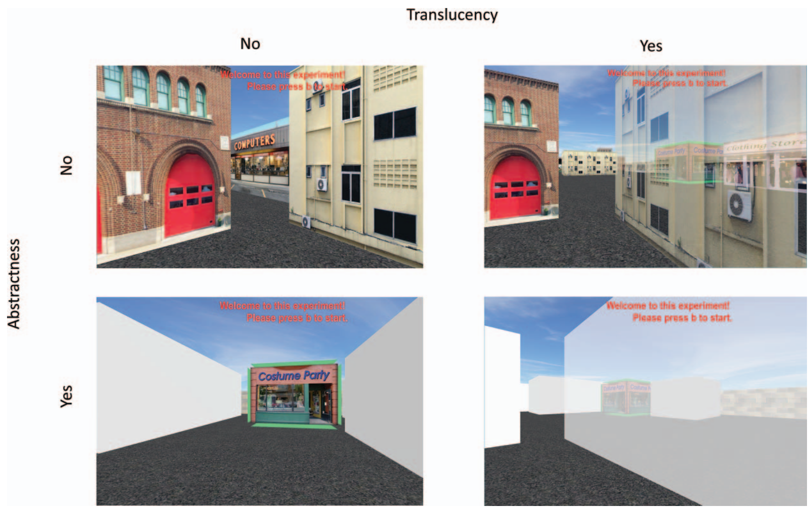

Figure 3. Illustrations of the translucent and the abstract manipulations in the training phase. Note that all participants, regardless of the condition assigned, navigated in the opaque, realistic environment in the testing phase. Upper left: opaque-realistic environment. Lower left: opaque-abstract environment. Upper right: translucent-realistic environment. Lower right: translucent-abstract environment. The target buildings were highlighted with a green (light gray) outline (costume party) in the training phase. This outline was removed in the testing phase. See the online article for the color version of this figure.

In the *opaque-realistic* environment, all buildings were presented naturalistically (Figure 3, upper left). In the *opaque-abstract* environment, only the target buildings were textured (Figure 3, lower left). In the *translucent-realistic* environment (Figure 3, upper right), all buildings were textured but participants controlled the translucency of the buildings with which their viewing directions intersected (see Figure 4): By default, our translucency algorithm made the building that participants were directly facing translucent, and all the buildings behind it fully transparent, except for any target buildings in that heading (Figures 3 and 4; see video demo—translucent-realistic). Other buildings that did not intersect with viewing direction remained opaque.

One interesting comment on our prior study (He, McNamara, & Brown, 2019) was that enforcing a particular level of translucency on all participants could, perhaps counterintuitively, introduce noise and therefore reduce the efficacy of the translucency. This could be because some individuals could see too many or too few cues at once to complement their other spatial abilities. In response to this idea, in the present study participants could scroll the mouse wheel down to make the transparent or translucent buildings return from the default maximum visibility to opaque, or they could scroll the mouse wheel up to undo these changes. In other words, participants in the translucent conditions had full control of the extent of translucency/transparency in the virtual environment (although note: we ultimately did not observe differences in the use of translucency between our conditions of interest; see Results). In the *translucent-abstract* environment (Figure 3, lower right), the visual presentation was similar to the translucent-realistic environment except that only the target buildings were textured. To examine whether our manipulations could enhance spatial learning and memory in a manner which transfers to naturalistic perceptual conditions, the manipulations of translucency and abstractness only occurred in the training phase but not in the testing phase (i.e., all participants, regardless of the experimental conditions, performed the testing phase in the opaque-realistic environment).

Dependent variables. As in our previous studies (He, McNamara, Bodenheimer, et al., 2019; He, McNamara, & Brown, 2019), navigation efficiency was quantified by excessive distance in the wayfinding task (see Procedure), which was defined as:

$$(\text{actual traversed distance} - \text{optimal distance})/\text{optimal distance}.$$

Excessive distance indicates how much further participants had traversed relative to the optimal distance. An excessive distance of 0 indicated perfect wayfinding performance (actual traversed distance equals optimal distance) and an index of 1 indicated the actual traversed distance was 100% longer than the optimal distance.

To measure cognitive map accuracy, we developed a novel placing task which allowed us to measure both direction and distance representations of participants' cognitive map from the egocentric perspective (see video demo—placing task and Procedure). We used position error, which was the distance between the correct location and participants' placing location, to quantify cognitive map accuracy.

Procedure

The procedure of the experiment is summarized in Figure 5. The procedures for training and testing were identical in all conditions.

Training phase. After completing the QSR and the symmetry span task, participants practiced searching for various destinations in a different environment from the one used in the experiment. Participants were asked to find three buildings in any order they preferred. The practice trials ensured participants knew how to navigate in the virtual environment via keyboard and mouse.

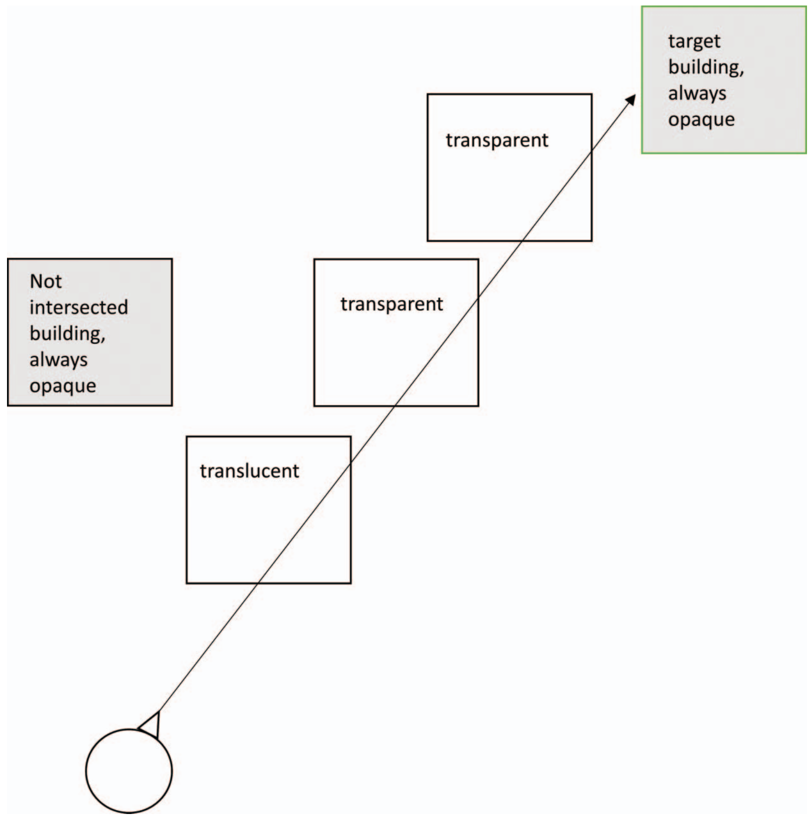

Figure 4. Schematic illustrations of the default visibility with the translucency algorithm. Black squares: nontarget buildings. Green (light gray) square: target building. Gray background indicates opaque buildings and white background indicates translucent or transparent buildings. The arrow indicates participant's viewing direction. See the online article for the color version of this figure.

After practice, participants were instructed that the experiment included a training and a testing phase, and the environments between the training and testing phases were identical. Participants were encouraged to encode the spatial relationships between the target buildings during the training phase so that they would find the testing phase easier. Participants were also informed that the target buildings were highlighted with a green (light gray) outline (Figures 3 and 6) in the training phase, and these outlines would be removed in the testing phase.

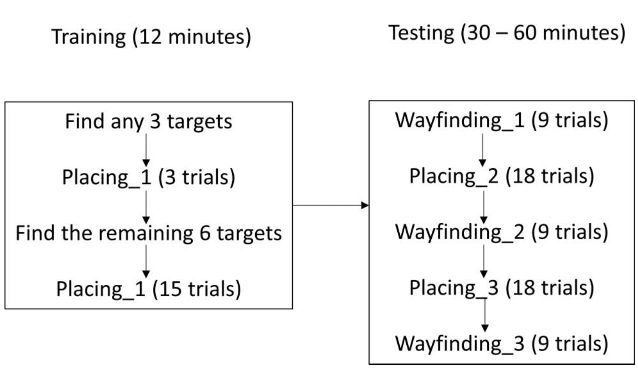

Figure 5. Procedures for the training and testing phases.

Participants were provided with a list of the nine target buildings they needed to find throughout the experiment (see Figure S1 in the online supplemental materials for how this list was presented). Participants were told that they could find the target storefronts in any order they preferred in the training phase, and they would be asked to find these target buildings again in the testing phase. After finding three target buildings, participants performed a placing task of three trials (Figure 6; see video demo—placing task). By performing the placing task early in the training, participants were more aware of the necessity to encode the spatial relationship between target buildings and they could adjust their spatial learning strategy accordingly.

In each placing trial, participants were teleported to the south side of one of the visited target buildings and were asked to place a red circle to the location of another visited storefront using a mouse. During the placing trial, participants could rotate their orientation and slide the location marker toward/away from themselves to the desired location, but their own position was fixed. In addition, all buildings except for the building at which they were located were removed. Participants could right click the mouse to make this building appear or disappear. Note that each side of the building shared the same texture and participants could use the distinct corner of the enclosure to orient themselves. This procedure was used to (a)

Figure 6. Illustrations of a placing trial. Participants' position was fixed on the south side of one of the target buildings, and participants placed a red circle to where they thought the other target building was. All buildings except for the building at which participants were located were removed during the placing task. See the online article for the color version of this figure.

ensure that participants were informed of their current location and orientation after teleportation and (b) encourage participants to rely on their cognitive map in the placing task because other building cues were not available. After responding, participants were teleported to a different, visited target building and repeated the process. The buildings from which placing judgments were made and the buildings to which participants placed were pseudorandomized to ensure that each target building served both roles. Specifically, the placing-from and placing-to locations lists, each of which contained all nine target buildings, were shuffled independently until there was no pair with the same placing-from and placing-to storefronts. This randomization process resulted in nine trials and was repeated until 18 trials were obtained for each block of the placing task. The randomization of the placing task was independent in each block and was independent of the randomization in the wayfinding task (see Testing Phase). Placing performance was measured by distance error (see Dependent Variable section) and no feedback was given.

After the three placing trials, participants were asked to find the remaining six target buildings. Participants were required to spend at least 12 min in the training phase. If participants found all of the target buildings under 12 min, they were encouraged to keep exploring and learn the environment until time was up. Participants finished with 15 placing trials at the end of the training phase.

Testing phase. The testing phase took place in the *opaque*, *naturalistic* version of the environment (Figure 3, upper left). The testing phase consisted of wayfinding tasks and placing tasks. In the wayfinding task, one of the target building names used in the training phase was presented on the screen and participants needed to find it. When participants reached this building, the name of the next target building appeared on the screen and participants started the next wayfinding trial from the previous location. Participants had to find the target buildings in a specific order in the testing phase, instead of in any order they preferred in the training phase. The order was randomized for each block and for each participant.

Each wayfinding task consisted of nine wayfinding trials, which contained all the nine target buildings used in the training. The placing task was the same as in the training phase, and each placing task in the testing phase consisted of 18 pointing trials. The placing task we developed for this study was similar to the pointing task which has been used to measure cognitive map accuracy (He, McNamara, & Brown, 2019; Ishikawa & Montello, 2006). The major difference between the placing and pointing tasks was that the placing task could measure both distance and angular errors whereas pointing task could only measure angular errors.

Results

SOD, SWM and gender distributions were similar across conditions (Supplemental Table 1). SOD and SWM were largely independent, $r(96) = 0.18$, $p = .085$. Participants were characterized based on whether their SOD and SWM scores were equal or above the median SOD and SWM scores (e.g., high SOD and high SWM individual), calculated from all 96 participants. Median split is a common statistical method in studies of individual differences in navigation (Auger & Maguire, 2013; He, McNamara, & Brown, 2019; Wegman et al., 2014; Wen, Ishikawa, & Sato, 2011), and a recent review showed that it was appropriate when the independent variables are uncorrelated (Iacobucci, Posavac, Kardes, Schneider, & Popovich, 2015), which are largely independent in our study (only 3% of SWM variance was explained by SOD). We also tested the relationship between SWM and spatial learning in a continuous manner.

First, we verified that, as in our prior study (He, McNamara, & Brown, 2019), SOD and translucency combined to influence overall spatial learning difficulty. We used the performance in the first placing task, which measured participants' cognitive map accuracy, to demonstrate the difficulty difference (i.e., easy, medium and hard). This is because it probed participants' spatial memory in the training phase, during which visual presentations of the environments were different across participants (i.e., not yet naturalistic and opaque for the difficulty manipulated groups). When collapsing across additional participant subgroups (SWM) and conditions (abstractness), a linear contrast revealed a significant effect of difficulty, $F(1, 93) =$

8.04, p = .006. The critical question posed by the present study is whether individual differences in SWM modulate spatial learning differently across difficulty levels.

Our procedures to conduct ANOVAs are summarized in Figure 7. In particular, for each spatial performance measure (wayfinding and placing tasks), we first conducted a three-way ANOVA (SWM [2x; high or low] × Difficulty [2×; Extremity or Medium] × Abstractness [2×; realistic or abstract]) to test whether difficulty modulated the relationship between SWM and performance. As described in the Introduction, difficulty was defined by a combination of self-reported SOD and manipulated translucency: Extremity conditions consisted of hard (low SOD + opaque environment) and easy (high SOD + translucent environment) conditions, and medium conditions also consisted of two conditions (low SOD + translucent environment or high SOD + opaque environment). A significant two-way interaction between difficulty and SWM would suggest that the role of SWM in spatial learning differences was modulated by difficulty. If this two-way interaction was significant, we then ran a four-way ANOVA (SOD [high or low] × SWM [high or low] × Translucency [opaque or translucent] × Abstractness [realistic or abstract]) to test how difficulty modulated the relationship between SWM and spatial learning and to examine whether our three predictions stated in the Introduction bore out within more specific subgroups of the data (e.g., whether SWM effects were absent in both difficulty extremities). Although we designed the experiment with specific planned group comparisons, we only conducted pairwise comparisons on significant interactions to ensure stringent control of Type I error rate.

Difficulty level was not continuous by the nature of our environmental manipulations. However, if the above two-way interaction between difficulty and SWM was significant we also conducted correlations between the continuous range of SWM and performance within the Extremity and Medium conditions (n = 46 and 50, respectively) and verified that there were significant differences in the correlations between the difficulty-based data groupings.

Wayfinding Performance

The first wayfinding task. Excessive distance, which was the ratio of participants' actual traversed distance over the optimal distance (the smaller the better) and reflected individual's navigation efficiency, was first analyzed in a three-way ANOVA (SWM, difficulty and abstractness). The interaction between difficulty and SWM was significant ($F(1, 88) = 5.60$, $MSE = 1.97$, $p = .020$, $\eta^2 = 0.06$; Figure 8, upper panels). We then conducted a four-way ANOVA (translucency, abstractness, SOD and SWM) to study the break-down of this significant interaction. The main effect of translucency, $F(1, 80) = 4.17$, $MSE = 1.94$, $p = .044$, $\eta^2 = 0.05$ and the main effect of memory capacity, $F(1, 80) = 5.47$, $MSE = 1.94$, $p = .022$, $\eta^2 = 0.06$ were significant. Importantly, the three-way interaction between translucency, SOD and SWM was significant, $F(1, 80) = 7.67$, $MSE = 1.94$, $p = .007$, $\eta^2 = 0.09$ (Figure 8, lower panels). No other main effects or interactions were significant.

To test our model, we conducted planned comparisons on the significant three-way interaction. The results showed that high SWM participants benefitted in the opaque environments if they also reported high SOD, $F(1, 80) = 7.92$, $p = .006$ (Figure 8, medium). Performance of High SWM with low SOD also benefitted in the translucent environments, $F(1, 80) = 6.33$, $p = .014$

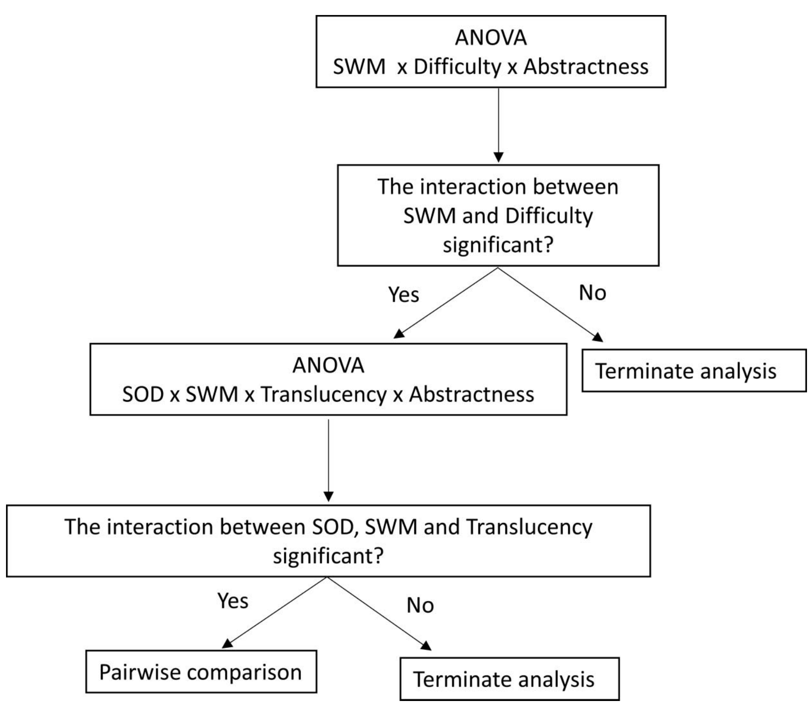

Figure 7. Procedures to conduct analyses of variance (ANOVAs) for each of the six dependent variables. SOD = sense of direction; SWM = spatial working memory.

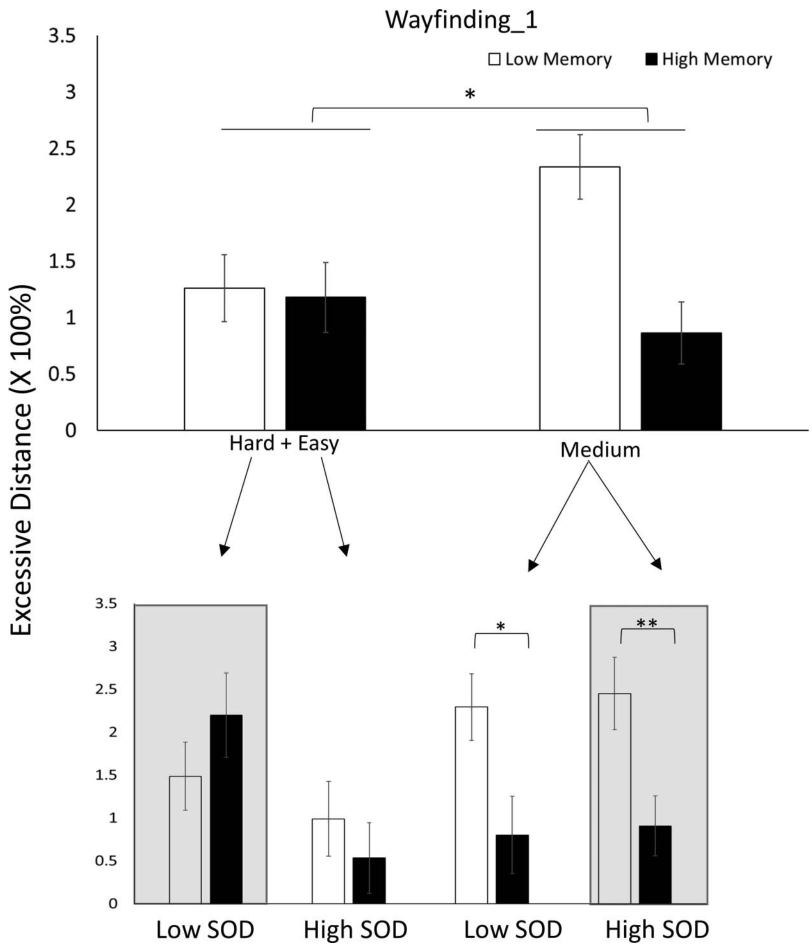

Figure 8. Significant two-way interaction between spatial working memory (SWM) and difficulty (upper panels) and the breakdown of this interaction in the first wayfinding task (lower panels). In the lower panels, gray background indicates opaque environments and white background indicates translucent environments. Error bar stands for standard error of the mean. SOD = sense of direction. * $p < .05$. ** $p < .01$.

(Figure 8, medium). In contrast, high SWM did not play a significant role for participants with low SOD who navigated in the opaque environments, $F(1, 80) = 1.27$, $p = .26$ (Figure 8, hard), or participants with high SOD who navigated in the translucent environments, $F(1, 80) = 0.58$, $p = .45$ (Figure 8, easy). In other words, we found that SWM played a significant role in performance differences when the difficulty of integrating spatial information in the environment was moderate (based on the combination of manipulated and measured factors), but not so when this difficulty was easy or hard.

Indeed, from a continuous perspective, SWM exhibited a significant linear relationship with learning performance in the medium integration difficulty cases, $r(50) = -0.625$, $p < .001$, and no significant relationship in the easy + hard data, $r(46) = -0.114$, $p = .452$. The correlation in the medium difficulty was significantly greater than that in the easy + hard data ($Z = 2.93$, $p = .003$).

As discussed previously, another research interest of the current study was to investigate whether translucency could still facilitate spatial learning in complex, large-scale environments. Because the significant three-way interaction included translucency, we conducted pairwise comparisons between corresponding participant trait groups in opaque and translucent conditions, revealing the characteristics of the participants who benefitted from translucency. We found that participants with high SOD and low SWM, $F(1, 80) = 5.81$, $p = .018$, and the participants with low SOD and high SWM, $F(1, 80) = 4.39$, $p = .039$, benefitted from our translucency intervention (i.e., outperformed their counterparts in the opaque environments). On the other hand, high SOD–high SWM individuals, along with low SOD–low SWM individuals, did not benefit from the translucency manipulation (Fs < 2.12, ps $> .15$).

The second wayfinding task. Excessive distance was first analyzed in a three-way ANOVA (SWM, difficulty and abstractness). The interaction between difficulty and SWM was only marginally significant, $F(1, 88) = 4.25$, $MSE = 2.75$, $p = .086$, $\eta^2 = 0.02$. Although the two-way interaction was only marginally significant, its patterns were similar to the ones in the first wayfinding task (see Figure 9).

The third wayfinding task. The interaction between difficulty and SWM was not significant, $F(1, 86) = 2.32$, $MSE = 1.02$, $p = .139$, $\eta^2 = 0.025$. To compare the significant or marginally significant

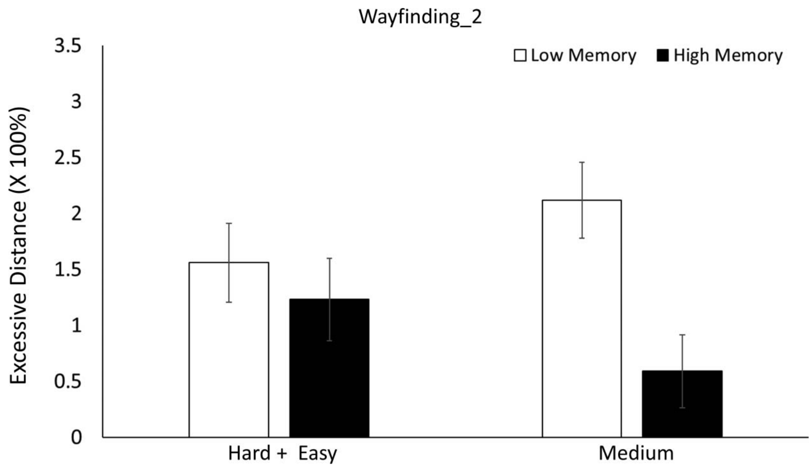

Figure 9. Performance in the second wayfinding task, grouped by spatial working memory (SWM) and difficulty. Error bar stands for standard error of the mean.

two-way interactions (SWM × Difficulty) observed in the previous wayfinding tasks, we plotted the performance similarly in Figure 10.

Placing Task Performance

The first placing task. Position error, which was the Euclidean distance difference between the responded and the actual position and reflected individual's cognitive map accuracy, was first analyzed in a three-way ANOVA (SWM, difficulty and abstractness). The interaction between difficulty and SWM was significant, $F(1, 88) = 4.44$, $MSE = 444.88$, $p = .038$, $\eta^2 = 0.05$ (Figure 11, upper panels). We then conducted a four-way ANOVA (translucency, abstractness, SOD and SWM) to study the break-down this significant interaction. The main effect of memory capacity, $F(1, 80) = 11.54$, $MSE = 447.83$, $p = .001$, $\eta^2 = 0.13$, and the main effect of abstractness, $F(1, 80) = 8.24$, $MSE = 447.83$, $p = .005$, $\eta^2 = 0.09$, were significant. Importantly, the three-way interaction between translucency, SOD and SWM was significant, $F(1, 80) = 5.40$, $MSE = 447.83$, $p = .023$, $\eta^2 = 0.06$ (Figure 11, lower panels). In addition, the three-way interaction between translucency, abstractness and SOD was also significant, $F(1, 80) = 7.18$, $MSE = 447.83$, $p = .009$, $\eta^2 = 0.08$. No other main effects or interactions were significant.

As in the wayfinding performance analysis, we investigated the role of SWM in spatial learning differences by conducting planned comparisons on the significant three-way ANOVA. Results showed that high memory capacity benefitted participants with high SOD who navigated in the opaque environments, $F(1, 80) = 9.41$, $p = .003$ (Figure 11, medium). High memory capacity also benefitted participants with low SOD who navigated in the translucent environments, $F(1, 80) = 8.38$, $p = .0049$ (Figure 11). In contrast, high memory capacity did not play a significant role in performance differences for participants with low SOD who navigated in the opaque environments, $F(1, 80) = 0.48$, $p = .49$ (Figure 11, hard), or participants with high SOD who navigated in the translucent environments, $F(1, 80) = 0.11$, $p = .74$ (Figure 11, easy). In

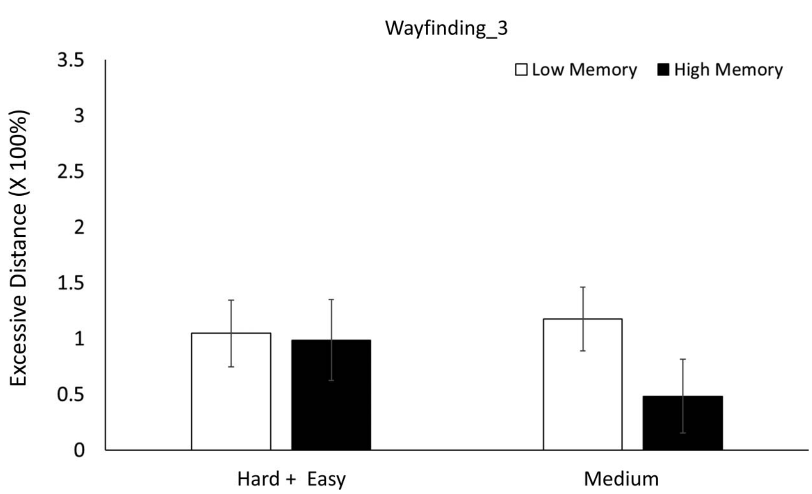

Figure 10. Performance in the third wayfinding task, grouped by spatial working memory (SWM) and difficulty. Error bar stands for standard error of the mean.

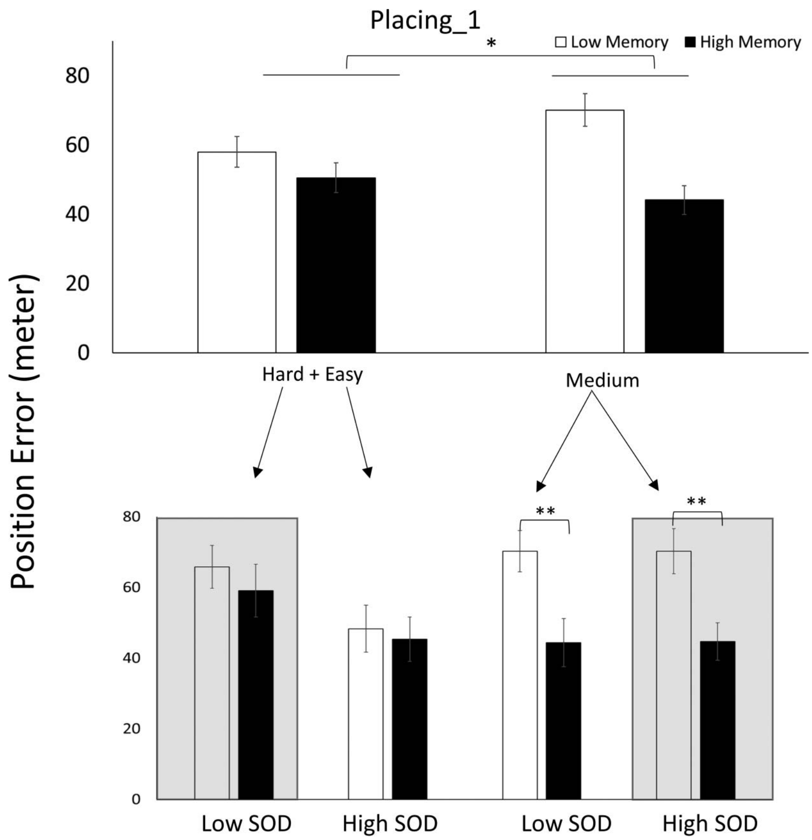

Figure 11. Significant two-way interaction between spatial working memory (SWM) and difficulty (upper panels), and the breakdown of this interaction in the first placing task (lower panels). In the lower panels, gray background indicates opaque environments and white background indicates translucent environments. Error bar stands for standard error of the mean. SOD = sense of direction. * $p < .05$. ** $p < .01$.

sum, the patterns of results were very similar to the first wayfinding task, which showed that the difficulty of spatial information integration modulated the relationship between SWM and spatial learning.

Indeed, from a continuous perspective, SWM exhibited a significant linear relationship with learning performance in the medium integration difficulty cases, $r(50) = -0.633$, $p < .001$, and no significant relationship in the easy + hard data, $r(46) = -0.206$, $p = .170$. The correlation in the medium difficulty was significantly greater than that in the easy + hard data ($Z = 2.55$, $p = .011$).

The three-way interaction among translucency, SOD and SWM also revealed that translucency benefitted participants with high SOD and low SWM, $F(1, 80) = 5.66$, $p = .02$. The significant three-way interaction between translucency, abstractness and SOD revealed that the translucent and abstract environment uniquely benefitted participants with high SOD, making them outperform participants who were trained in other types of environments (translucent and realistic, opaque and realistic, opaque and abstract), regardless of their SOD (Fs > 5.48, ps $< .02$).

The second placing task. The interaction between difficulty and SWM was significant, $F(1, 88) = 6.05$, $MSE = 532.07$, $p = .016$, $\eta^2 = 0.06$ (Figure 12, upper panels). We then conducted a four-way ANOVA (translucency, abstractness, SOD and SWM) to study the break-down significant interaction. The main effect of memory was significant, $F(1, 80) = 8.42$, $MSE = 548.22$, $p = .005$, $\eta^2 = .09$. Importantly, the three-way interaction between translucency, SOD, and SWM was significant, $F(1, 80) = 6.13$, $MSE = 548.22$, $p = .015$, $\eta^2 = 0.07$ (Figure 12, lower panels). No other main effects or interactions were significant.

Planned comparisons showed that, again, high memory capacity benefitted participants with high SOD who navigated in the opaque environments, $F(1, 80) = 13.31$, $p < .001$ (Figure 12, medium). High memory capacity also benefitted participants with low SOD who navigated in the translucent environments, $F(1, 80) = 4.06$, $p = .047$ (Figure 12, medium). In contrast, high memory capacity did not play a significant role in performance differences for participants with low SOD who navigated in the opaque environments, $F(1, 80) = 0.14$, $p = .71$ (Figure 12, hard), or participants with high SOD who navigated in the translucent environments, $F(1, 80) = 0.001$, $p = .98$ (Figure 12, easy). Again, the patterns of results were very similar to ones in the first wayfinding and placing tasks.

Indeed, from a continuous perspective, SWM exhibited a significant linear relationship with learning performance in the medium integration difficulty cases, $r(50) = -0.632$, $p < .001$, and no significant relationship in the easy + hard data, $r(46) = -0.120$, $p = .426$. The correlation in the medium difficulty was significantly greater than that in the easy + hard data ($Z = 2.96$, $p = .003$). This

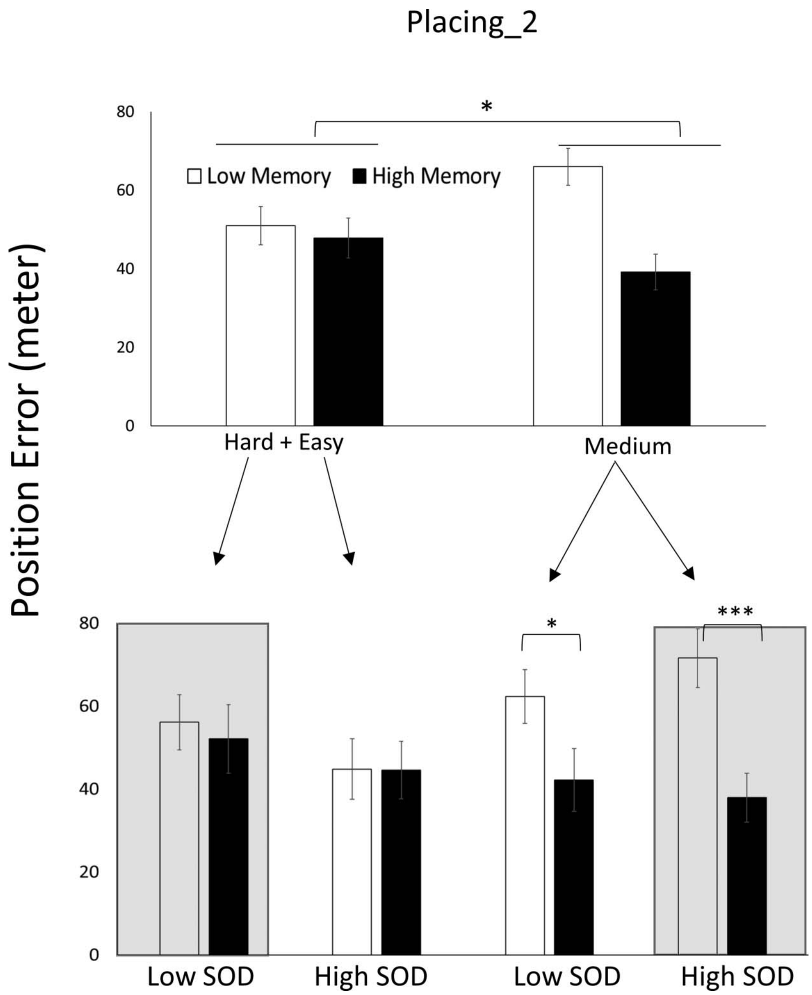

Figure 12. Significant two-way interaction between spatial working memory (SWM) and difficulty (upper panels), and the breakdown of this interaction in the second placing task (lower panels). In the lower panels, gray background indicates opaque environments and white background indicates translucent environments. Error bar stands for standard error of the mean. SOD = sense of direction. * $p < .05$. *** $p < .001$.

interaction also revealed that translucency benefitted participants with high SOD and low SWM, $F(1, 80) = 6.89$, $p = .01$.

The third placing task. The interaction between difficulty and SWM was only marginally significant, $F(1, 88) = 3.41$, $MSE = 545.12$, $p = .068$, $\eta^2 = 0.04$. Although the two-way interaction was only marginally significant, its patterns were similar to the ones in the previous placing tasks (see Figure 13).

To summarize the results, in both wayfinding and placing tasks, we consistently found that the difficulty of spatial information integration in the environment modulated the relationship between SWM and spatial learning: higher SWM only improved spatial learning at medium difficulty. The modulation seemed to become weaker at the end of the experiment as low SWM groups gradually approached the performance of their high SWM counterparts. Interestingly, we note that performance of participant groups in the easy and hard integration conditions was not at a statistical floor or ceiling. Therefore, high SWM participants could have performed substantially better than their low SWM counterparts in such conditions—but did not, particularly in the earlier testing repetitions. Rather, the results showed that high SWM only facilitated spatial learning in the medium integration difficulty. Another important finding was that translucency could still improve navigation efficiency and cognitive map formation even in complex, large-scale environment, but only for participants with some specific combinations of SOD and SWM. The facilitation effect from translucency also became nonsignificant at the end of the experiment. Finally, when translucency and abstractness were combined, we found that this combination could further enhance spatial learning compared to translucency or abstractness alone, but this facilitation was only observed in high SOD individuals and only in the very early stage of learning.

Control Analyses

Did participants behave differently in the training phase across conditions and can these differences explain the observed pattern of results? All the patterns of results and significance determinations reported above remained the same when gender was controlled for. To examine whether the training

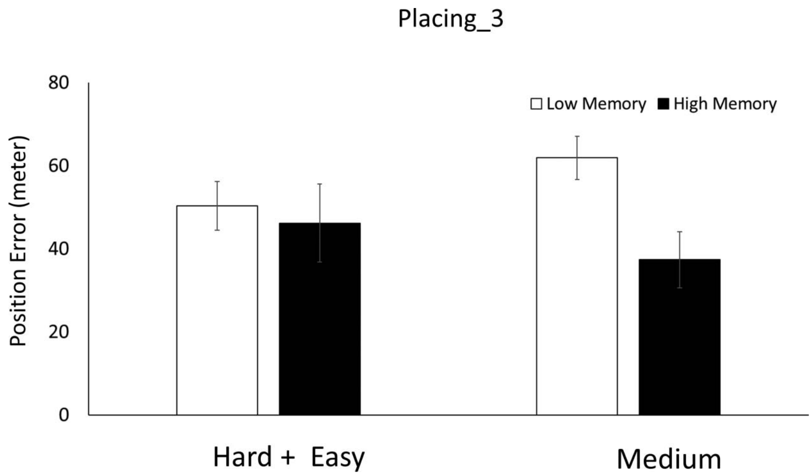

Figure 13. Performance in the third placing task, grouped by spatial working memory (SWM) and difficulty. Error bar stands for standard error of the mean.

behaviors differed across groups, we ran a similar three-way ANOVAs (SWM × Difficulty × Abstractness) on each behavioral measure (total traversed distance, total training time, amount of orientation changes [i.e., "searching" behavior]) in the training phase. For total traversed distance, the only significant main effect or interaction was the interaction between difficulty and abstractness (p = .010). Pairwise comparisons examining this revealed that abstract environments, but not realistic environments, significantly reduced traversed distance in the extreme conditions than in the medium conditions. For total traversed time or orientation change, no significant main effect or interaction was observed, as almost all participants found all target buildings in 12 min. For orientation changes, only the main effect of SWM was significant (p = .019), which showed that high SWM changed their viewing orientation more often than low SWM individuals, regardless of translucency or SOD.

Because participants in the translucent environments could manipulate the number of translucent/transparent buildings by scrolling the mouse wheel, the number of scrolls might indicate how actively participants used the translucency algorithm. We ran a three-way ANOVA (Abstractness × SOD × SWM) on number of scrolls but did not find any significant main effect or interaction. The only marginally significant effect was abstractness, in which participants in the translucent-realistic environment tended to scroll more than those in the translucent-abstract environment (p = .059).

Taken together, there was no clear evidence that behavioral differences across conditions and groups of participants explained the modulation effect.

Did angular and distance errors contribute differently to the patterns observed in the placing tasks? Our placing task builds on and extends the indicators of spatial knowledge from a first-person perspective that have previously been assessed with angular error in pointing tasks (He, McNamara, Bodenheimer, et al., 2019; He, McNamara, & Brown, 2019) and in turn related with SWM (Weisberg & Newcombe, 2015). In our primary placing task performance analysis, we used position error, a composite of angular (i.e., the absolute angular difference between the correct and response angles) and distance errors (i.e., the absolute difference between correct and the response distances), to indicate cognitive map accuracy. Here, we examined whether the significant interactions observed in the placing task, especially in the first and second placing tasks, were mainly due to angular or distance error. To address this, we ran two separate three-way ANOVAs (SWM, difficulty and abstractness) with angular and distance errors as dependent variables in the first and second placing tasks. We found that the relationship between SWM and angular error was either marginally or significantly modulated by difficulty (p = .089 and p = .039) in the first and second placing task, respectively (Figure S2 in the online supplemental materials). Similarly, the relationship between SWM and distance error was marginally modulated by difficulty (p = .051 and p = .075; Figure S2 in the online supplemental materials). Taken together, it seems that angular and distance errors contributed similarly to the patterns we observed in the position error, indicating that both aspects of the judgment are useful assessments for CMF evaluation and relating it to other cognitive metrics.

Was the modulation effect explained by less variability in the easy and hard conditions than in the medium conditions (heteroscedasticity)? We conducted Levene's test to assess the equality of variance of our dependent variables. First, we confirmed that the variance of SWM was not heterogeneous across easy, medium and hard conditions (p = .24; Table S1 in the online supplemental materials). We then applied the same analysis to the dependent variables in the first wayfinding task, the first and the second placing tasks. In the first wayfinding task, the variance of excessive distance was heterogeneous across conditions (p = .002). Pairwise comparisons showed that the variance between the medium and hard conditions did not differ (p = .48), but variance was significantly smaller in the easy condition than in the medium and hard conditions (ps < 0.02). We note, however, that even in this case, performance in the easy condition was not at ceiling (around 100% longer than the optimal path length) and variance was sizable (std = 0.75). In the first placing task, position error variance was not heterogeneous across conditions (p = .74) or in the second (p = .61). Taken together, we did not observe any strong evidence that the reported modulation of medium versus extreme effect could be solely explained by heteroscedasticity.

Is the curvilinear relationship between spatial learning and SWM still present when other cognitive dimensions are accounted for?[2] Because SWM is moderately correlated with Gf and verbal working memory capacity (VWM; Engle, 2018; Redick et al., 2016), it is possible that the curvilinear relationship with symmetry span measured here could reflect Gf, VWM or a combination of SWM-related capacities. We did not measure participants' Gf or VWM capacity in the current study and so we do not emphasize spatial domain specificity. However, established empirical relationships with Gf and VWM using our SWM task enabled us to simulate distributions of statistically probable SWM-spatial learning relationships once Gf and VWM are accounted for (see Data Simulation Procedure in the online supplemental materials for details). In brief, expected ranges of Gf and VWM for our observed SWM values in our dataset were repeatedly drawn (1,000 permutations) from two independent normal distributions. These simulated data were then transformed to have correlation matrix congruent with the empirical findings from the literature (Đokić, Koso-Drljević, & Đapo, 2018; Kanazawa, 2004; Redick et al., 2016; Silverman et al., 2000; Weisberg & Newcombe, 2015). We then divided participants based on their condition (Extreme or Medium) and ran multiple regressions with our observed SWM and simulated Gf and VWM as predictors. In this way, we could estimate over 1,000 permutations a probable range of unique contributions of SWM to spatial learning while controlling for expected Gf and VWM variance. Although such a simulation is not a substitute for direct measurement, this computational approach based on past observations with our task enables us to make a statement about whether the relationships between SWM and spatial learning are likely to be explained by these other cognitive dimensions. The simulation results showed that in the first wayfinding, first placing and second placing tasks, the correlations between SWM and spatial learning differed significantly between medium and extreme conditions, $ts(998) > 100$, $ps < 2.2 \times 10^{-10}$, suggesting that it was extremely unlikely that our modulation could be explained solely by related Gf and VWM constructs.

Discussion

The current study aimed to investigate (a) from a theoretical perspective, whether the relative contribution of SWM capacity to spatial learning differences was modulated by spatial information integration difficulty, similar to observations in reading comprehension by Turner and Engle (1989), and (b) from an applied perspective, whether translucency or the combination of translucency and abstractness could facilitate spatial learning in complex, large-scale environments. We found that SWM capacity differences played a significant role in spatial learning when the spatial integration difficulty was moderate (through the combination of manipulations and participant's sense of direction) but less so when the difficulty was easy or hard. These patterns were most robust at the early stages of testing, with continued practice allowing low SWM individuals to approach the performance of their peers. From our applied angle, we found that translucency during encoding could facilitate subsequent navigation efficiency, but only for participants with low SOD and high SWM or participants with high SOD and low SWM. Translucency could also facilitate placing performance, but only significantly for participants with high SOD and low SWM. The combination of translucency and abstractness specifically benefitted high SOD individuals at the very early stage of the experiment.

The findings that correlations between traits/ability and task performance can be modulated by other factors have been reported in social psychology (e.g., personality—job performance modulated by autonomy; Barrick & Mount, 1993), cognitive psychology (e.g., cognition—reading achievement modulated by socioeconomic background; Noble, Farah, & McCandliss, 2006), industrial/organizational psychology (exhaustion—performance modulated by coworker reciprocity; Halbesleben & Wheeler, 2011) and neuroscience (brain size—cognitive ability modulated by age; Rushton & Ankney, 1996). Given the prevalence of modulations on predictors of individual performance in other domains, it is surprising that very limited research has applied this model to examine individual differences in spatial navigation. Considering that spatial navigation occurs in environments where the visual features can vary considerably, it is also surprising that very limited research has manipulated the environmental visual cues to investigate how they affect the relationship between psychological traits/ability and spatial learning. The current project addressed this gap in the literature, and we show that the relationship between SWM and spatial learning is modulated by spatial information integration difficulty in the environment. This difficulty can be influenced by structural and perceptual features, the first we held constant and the second we manipulated, and by participant traits which can be measured, including SOD. The difficulty-based modulation was observed in both wayfinding and placing tasks, which are assumed to reflect a coarser and a more precise form of cognitive map, respectively (He, McNamara, Bodenheimer, et al., 2019; He, McNamara, & Brown, 2019). Our results also reveal that the modulation effect manifests through accelerated learning, and decreases as people become more familiar with the environment.

Mechanisms of the Curvilinear Relationship Between SWM and Spatial Learning

In terms of the mechanisms underlying the modulation effect, we reasoned that spatial information integration difficulty contributed to encoding efficiency, which could significantly modulate the required SWM for the task (Miller, 1956) when the number of locations to be encoded was identical across conditions. In particular, easy integration may place limited burden on even low SWM capacities to encode and retrieve relationships, whereas both encoding and relational inference in our difficult integration condition may frequently exceed even robust SWM capacities. Another possibility of the lesser contribution of SWM capacity to performance differences in the difficult condition was that SWM still played an important role but its importance plateaued after reaching a certain capacity. For example, there might be a positive correlation between SWM and performance up to an SWM score of 45 in the difficult condition, but this correlation became flat afterward. If this were the case, it would be interesting to conduct a targeted large-sample follow-up study of these high-difficulty

[2] We are grateful to the anonymous reviewer for raising this question.

situations to determine this threshold. Besides this possibility, one potential confound that we tested for is whether behavioral ceiling or floor effects in the extreme conditions, rather than moderation from differential demands on SWM capacity demands, constrained variance necessary to detect differential correlation coefficients. However, performance of the extreme conditions was not at a statistical floor or ceiling, and the control analyses showed that variance were not heterogeneous in most situations.

Although not confounds, as variance would be, it is interesting to consider how other factors could interact with SWM demands in the extreme versus medium integration difficulty conditions. These factors could be the individual differences in staying oriented when body-based cues are absent (Chrastil & Warren, 2013; He & McNamara, 2018; He, McNamara, & Kelly, 2016), in utilizing feature and geometric cues for spatial knowledge acquisition (Kelly, McNamara, Bodenheimer, Carr, & Rieser, 2009) or other cognitive factors (Wolbers & Hegarty, 2010). Such factors could give rise to the sizable performance variability in the extreme conditions which are less explained by SWM (in contrast to the medium difficulty). We hope this study prompts future research to investigate what other factors could account for such variance when SWM's role is reduced or otherwise accounted for.

We also consider the possibility that the level of arousal may be different across conditions, which could influence levels of WM recruitment for the task. For example, if utilizing SWM is generally beneficial but also effortful, when participants think the task is too hard or too easy in the extreme conditions, they may be less inclined to utilize their WM to encode the environment or support relational inferences at retrieval. In this sense, Yerkes–Dodson law shares features with the WM capacity saturation mechanism laid out above: Here again in the easiest condition effortful WM processes may be minimally engaged, and at a moderate level of arousal (modulated by task encoding difficulty) WM might be strategically relied upon—resulting in a relationship between capacity differences and performance. The most notable difference between an arousal-based rainbow of engagement under Yerkes–Dodson law and a WM capacity saturation mechanism would be expected in their account of the difficult extreme, where instead of WM capacity and performance decoupling due to a critical saturation of WM resources, this decoupling could occur due to a strategic shift back away from an encoding strategy dependent on active maintenance of route information. Both a capacity saturation mechanism and Yerkes–Dodson law would predict the curvilinear relationship observed, and can be juxtaposed with a linear model of WM engagement as arousal increases. In such a linear model, if arousal scales with utilization of effortful WM processes and there is no saturation of WM capacity, one might predict the strongest relationship with capacity in the difficult condition. This linear relationship in the influence of SWM capacity according to difficulty was not observed.

We also speculate that demands on SWM capacity for encoding (our principal argument) and Yerkes–Dodson law can jointly modulate the relationship between SWM and spatial learning—for example, a participant may adapt their reliance on effortful SWM in difficult environments or learning conditions in response to their own observation that they are struggling to maintain adequate details to build spatial knowledge. Our study prompts further research geared at teasing apart a SWM saturation versus Yerkes–Dodson law of how WM capacity predicts performance at different difficulty levels of a task.

Theoretical Implications for Studies of Individual Differences

Our proposed mechanisms build on the idea that task difficulty determines the amount of required cognitive resources, which in turn influences the relationship between the available cognitive resources and task performance. WM saturation and/or Yerkes–Dodson law could provide a shared explanation of our data and the curvilinear relationships observed in other working memory domains (e.g., verbal memory, Turner & Engle, 1989). Because most of human's cognitive resources are limited, one important implication from our study is that such curvilinear relationships may also exist for other cognitive capacities, such as relationships between attention control and multitasking (Redick et al., 2016).

Our findings using perceived sense of direction also highlight the potential importance of task expertise for studying individual differences in cognitive performance. Incorporating task expertise into analyses of memory task performance (spatial, verbal, or otherwise) may explain some inconsistent findings in the literature. For example, we recently reanalyzed a public dataset from a study investigating the correlation between hippocampal volume and spatial learning performance (Weisberg, Newcombe, & Chatterjee, 2019). We found that SOD modulates this correlation, such that the volume-performance correlation was negative among the low SOD individuals, but positive among the high SOD individuals (He & Brown, 2020). Our previous study (He, McNamara, & Brown, 2019) also demonstrated that SOD modulates the benefits of translucency for improving individual spatial learning performance. Although SOD need not reflect spatial expertise, per se, such data taken together suggest task expertise and metacognition about abilities relevant for a task could substantially modulate the way cognitive resources are utilized or the way information is processed. Future research could consider identifying meaningful participant subgroups based on individual's task expertise, and combine correlational and experimental approaches (Cronbach, 1957), as we have done here, to further our understanding of the individual differences in the domains besides spatial cognition.

Although our study focused on understanding the relationship between SWM and individual differences in spatial navigation ability in healthy young adults, our results also have clear implications for scholars studying cognitive aging and cognitive development. The brain's WM architecture undergoes changes in both periods of life span development (Sander, Lindenberger, & Werkle-Bergner, 2012), and models have examined age-related heterogeneity in the recruitment of WM architecture dependent on memory load (e.g., Cappell, Gmeindl, & Reuter-Lorenz, 2010). Given age-related changes in spatial cognition (Lester, Moffat, Wiener, Barnes, & Wolbers, 2017), we consider that future research could ask how the difficulty of spatial integration is perceived differently across the life span and how the relationship between SWM and spatial learning outcomes for a given environment changes accordingly.

Applied Implications for Improving Spatial Learning and Memory in Real Life

Besides the important theoretical contributions, the current study also replicates and extends our previous findings that translucency can improve navigation efficiency and cognitive map accuracy (He, McNamara, & Brown, 2019). Our previous study was conducted in a relatively small-scale environment with nine buildings, and there were just one or two buildings separating each destination. The virtual environment of the current study is about 16 times larger in size and it has 96 buildings. We modified our translucency algorithm to allow participants to see through multiple buildings, so that they could relate distal locations of interest more easily.

Compared with our previous study, there are two major differences in terms of the effect of the translucency. First, our previous study showed that low SOD participants could not benefit from the translucency treatment. In that study, we hypothesized that this could be attributable to the misaligned structure and the square-shape of environment, which made it very hard for low SOD participants to stay oriented. The virtual environment used in the current study is a more regular, aligned structure and includes a distinct corner, both of which are designed to keep participants better oriented to the global structure. Indeed, here we found that low SOD participants can benefit from the translucency to improve their wayfinding efficiency if they have high SWM. It may not be surprising that low SOD and low SWM participants cannot benefit from translucency as they may not have the working memory capacity to store the spatial relationships continuously being encoded, which might otherwise have helped them better learn the layout from the route. High SOD participants, on the other hand, can still benefit from the translucency treatment if they have low SWM. Our data indicate that high SOD and high SWM participants find the task (relatively) easy even in the opaque environment, and therefore—in keeping with our theoretical model—no facilitation effect of translucency is found for this group of participants. Interestingly, the facilitation effect of translucency for cognitive map formation (measured by pointing task) emerged late in our previous study, but it emerged early (measured by placing task) in the current study. We consider that this may relate to the environmental changes we made in the current study, which could enable participants to relate the learned spatial relationships with the distinct corner in the environment, which could be especially useful for global orienting during the placing task. This distinct corner could facilitate participants taking advantage of the translucency, because participants could see through the obstacles and use this corner as a global reference point relative to which they could integrate and infer other spatial locations. In a large-scale environment like ours, each building has a uniform texture on each side and placing task trials may occur at buildings relatively far from the boundary. This is a design intended to strongly challenge spatial memory, such that a global orientation cue may be necessary to allow participants to orient and reveal their memory (if any) for the relative location. One unexamined aspect of this rationale, which will be interesting to examine in future work, is how the characteristics of environmental boundaries or global orientation cues which can increase or decrease the effectiveness of translucency.

From an applied perspective, we were also interested in investigating whether a combination of translucency and abstractness can further enhance spatial learning compared with translucency alone. We found that adding abstraction does improve cognitive map accuracy in the first placing task, but not significantly in other placing task repetitions or in the wayfinding tasks. Note that the first placing task was the only task performed in the training phase, in which participants in the abstract conditions had not seen the realistic environment yet. It is possible that in later tests the much richer visual features observed in wayfinding trials in the realistic environment may interfere with or overwrite participants' abstract representation of the environment acquired in the training phase. This could mitigate the abstract effect in later tasks. Indeed, our design contrasts with Lokka et al.'s (2018) study, in which environments were abstract in both training and testing - and there the authors showed a persistent abstract effect.

Because the translucency algorithm used in the current study allows users to see through any number of buildings they prefer, we consider that translucency could improve spatial learning in even more complex, larger-scale environments than the one used here. In terms of the characteristics of the participants who can benefit from translucency, we show that high SOD individuals are particularly suited for this treatment. Low SOD individuals with high SWM can also use translucency to improve their wayfinding efficiency. Taking these results together, our translucency algorithm provides a powerful tool for spatial training in the virtual environment, targeting specific individuals. Unlike GPS, which has been shown to harm the representation of the space (Gardony, Brunyé, & Taylor, 2015; Hejtmánek, Oravcová, Motýl, Horáček, & Fajnerová, 2018; Ishikawa, Fujiwara, Imai, & Okabe, 2008) or even impair the ability to learn new environments (Ruginski, Creem-Regehr, Stefanucci, & Cashdan, 2019), translucency can enhance both wayfinding efficiency and cognitive map formation, and does so in a manner that transfers to opaque/naturalistic wayfinding as well as low cue (placing trial) scenarios. Because previous studies have shown that the transfer of training in virtual reality can be an effective substitute for training in real world (Rose et al., 2000; Waller, Hunt, & Knapp, 1998), translucency could be of great benefit in applied settings where personnel are required to get to destinations in as quickly and as flexibly as possible in complex environments (e.g., ambulance drivers or soldiers deploying in unfamiliar settings).

Limitations and Future Directions

One limitation of examining effects within fine-grained participant subgroups (e.g., high SOD + opaque realistic) is that there are only approximately 12 participants in each group for pairwise SWM comparisons. Importantly, however, these follow-up comparisons were only run following a significant two-way interaction between SWM and difficulty, which had 24 participants per group, and following the significant three-way interaction at the finer-grained grouping level between SOD $\times$ SWM $\times$ Translucency, and are complemented by continuous correlations between SWM and performance in different difficulty classes ($ns >= 46$). Additionally, we consider the results from the follow-up pairwise comparisons reliable, because (a) significant outcomes manifest as significant in both wayfinding and placing task measures of spatial memory and (b) the patterns of results in all four pairwise comparison types clearly replicate and extend the previous studies on which the current study is based (He, McNamara, & Brown, 2019; Turner & Engle, 1989). Another limitation of the current study is that participants navigated in the virtual environment with keyboard and mouse, so body-based cues were very limited. Body-based cues are known to facilitate spatial updating (He et al., 2016; Klatzky, Loomis, Beall, Chance, & Golledge, 1998), and therefore these cues could be another factor that modulates the SWM-spatial learning relationship, or the effectiveness of translucency. With the growing prevalence of omnidirectional treadmill hardware for virtual reality, the impact of body-based cues can be studied more systematically in future research, potentially revealing more discoveries about how individual differences and spatial training paradigms can be affected by physical cues.

Our targeted measures focused on SWM and the prediction that its contribution to spatial learning performance differences is moderated by integration difficulty. It was interesting to consider the domain specificity of the relationships that we report in light of other cognitive constructs. In particular, we took a computational approach, leveraging reported cognitive factor relationships using our tasks in prior data, to simulate the likely curvilinear relationship between SWM and spatial learning that may be expected even after Gf and VWM are controlled for. However, simulated data cannot replace observed data. Future studies are needed to include measures of Gf and other type of WM capacities, so that researchers can examine the influence of other cognitive factors and validate our data simulation method. Our simulations directly lay the groundwork for this and formalize the predictions to be tested.

Conclusion

In the current study, we combined experimental and correlational approaches to test whether the role of SWM capacity in spatial learning differences could depend on spatial information integration difficulty, and our results consistently support this hypothesis. We suggest that it would be fruitful to extend the application of this combinatorial approach to psychological methods (as advocated in Cronbach, 1957) to studies in targeting the moderations of other trait-performance correlations in navigation and other areas. The resulting insights into individual differences and how they interact with environmental characteristics and task expertise may provide rich understanding of how humans utilize various cognitive resources, with varying efficacy, as we navigate our daily lives.

Context

The current study was heavily inspired by the seminal work from Turner and Engle (1989) showing that the role of working memory capacity in reading comprehension was task difficulty dependent. Our lab recently found that manipulating the translucency of obstacles in an environment could facilitate spatial learning in virtual reality, but this benefit was only observed in individuals with high self-report sense of direction. These findings suggested that visibility and sense of direction could jointly affect the difficulty of spatial learning. To investigate whether Turner and Engle's findings could be generalized to understanding individual differences in spatial learning, we adapted our translucency algorithm to a larger and more complex environment while measuring participants' sense of direction and working memory capacity. We found that similar to reading comprehension, the role of working memory capacity was also task difficulty dependent in spatial navigation. The current study not only demonstrated a curvilinear relationship between working memory and spatial learning as a function of task difficulty but also established an effective, targeted training intervention that leverages virtual reality to improve spatial learning in large, complex environments.

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Appendix

Questionnaire of Spatial Representation

1. Do you think you have a good sense of direction?

   1 (not at all) 2 3 4 5 (very good)

2. Are you considered by your family or friends to have a good sense of direction?

   1 (not at all) 2 3 4 5 (very much)

3. Think about the way you orient yourself in different environments around you. Would you describe yourself as a person:

   a. who orients him/herself by remembering routes connecting one place to another?

      1 (not at all) 2 3 4 5 (very much)

   b. who orients him/herself by looking for well-known landmarks?

      1 (not at all) 2 3 4 5 (very much)

   c. who tries to create a mental map of the environment?

      1 (not at all) 2 3 4 5 (very much)

4. Think of an unfamiliar city. Write the name.

   Now try to classify your representation of the city:

   a. survey representation, that is a map-like representation

      1 (not at all) 2 3 4 5 (very much)

   b. route representation, based on memorizing routes

      1 (not at all) 2 3 4 5 (very much)

   c. landmark-centered representation, based on memorizing single salient landmarks (such as monuments, buildings, crossroads, etc.)

      1 (not at all) 2 3 4 5 (very much)

5. When you are in a natural, open environment (mountains, seaside, country), do you naturally individuate cardinal points, that is where north, south, east, and west are?

   1 (not at all) 2 3 4 5 (very much)

6. When you are in your city do you naturally individuate cardinal points, that is do you find easily where north, south, east, and west are?

   1 (not at all) 2 3 4 5 (very much)

(*Appendix continues*)

7. Someone is describing for you the route to reach an unfamiliar place. Do you prefer:

   a. to make an image of the route?

      1 (not at all) 2 3 4 5 (very much)

   b. to remember the description verbally?

      1 (not at all) 2 3 4 5 (very much)

8. In a complex building (store, museum) do you think spontaneously and easily about your direction in relation to the general structure of the building and the external environment?

   1 (not at all) 2 3 4 5 (very much)

9. When you are inside a building can you easily visualize what there is outside the building in the direction you are looking?

   1 (not at all) 2 3 4 5 (very much)

10. When you are in an open space and you are required to indicate a compass direction (north-south-east-west), do you:

    a. point immediately?

    b. need to think before pointing?

    c. have difficulty?

11. You are in a complex building (many doors, stairs, corridors) and you have to indicate where the entrance is, do you:

    a. point immediately?

    b. need to think before pointing?

    c. have difficulty?

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