Entropy and a sub-group of geometric measures of paths predict the navigability of an environment

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Abstract

Despite extensive research on navigation it remains unclear which features of an environment predict how difficult it will be to navigate. We analysed 478,170 trajectories from 10,626 participants who navigated 45 virtual environments in the research app-based game Sea Hero Quest. Levels were designed to vary in a range of properties such as their layout, number of goals, visibility (varying fog) and landmarks. We calculated 58 spatial measures grouped into four families: task-specific metrics, space syntax configurational metrics, space syntax geometric metrics, and general geometric metrics. We used Lasso, a variable selection method, to select the most predictive measures of navigation difficulty. Geometric features such as entropy, area of navigable space, number of circular paths and closeness centrality of path networks were amongst the most significant factors determining the navigational difficulty. By contrast a range of other measures did not predict difficulty, including measures of intelligibility. Unsurprisingly, other task specific features (e.g. number of destinations) and fog also predicted navigation difficulty. These findings have implications for study of spatial behaviour in ethological settings, as well as predicting human movements in different settings, such as complex buildings and transport networks and may aid the design of more navigable environments.

Keywords: navigation, environmental features, virtual environments, space syntax

1. Introduction

Some environments are famously hard to navigate. Patients in Homey Hospital (USA) reportedly avoided leaving their rooms for fear of getting lost (Peponis et al., 1990). The Seattle Central Library, while being widely acclaimed for its aesthetics, is renowned for being difficult to navigate (Carlson et al., 2010; Kuliga et al., 2019). In a recent incident in Australia, a man died after getting lost in a rarely-used stairwell in a shopping mall, and he was only found three weeks later (Jeffrey, 2019a). Poor building design has real-world consequences. But what factors make an environment hard to navigate? Many factors proposed. These include: entropy of path orientations (Batty et al., 2014), connectivity of paths (Li & Klippel, 2012, 2016), interconnection density (Slone et al., 2016), visibility (He et al., 2019; Li & Klippel, 2012), existence of landmarks (Golledge, 1999) and intelligibility of the paths/streets (Hillier 1996, Barton et al., 2014). Intelligibility is a metric derived in the field of space syntax that relates the local and global connections of the paths. Environment with a better local and global connectedness are deemed to be more intelligible.

Four main approaches have been used to study how the environment impacts navigation and spatial behaviour. These are: a) examining GPS trajectory data in real-world environments collected as part of daily activities such as running (e.g. Bongiorno 2021), b) GPS trajectories from participants navigating real-world environments (e.g. Coutrot et al., 2019), c) testing navigation in the physical lab setting (e.g. Hamburger & Knauff, 2011), and d) testing with virtual reality (VR) environments (e.g. Slone et al. 2015; Javadi et al., 2019a; Brown et al., 2020; Ekstrom et al., 2018).

A challenge with studying navigation in the real-world is that environmental features are hard to separate experimentally, and, as a result of their interaction, it is hard to deduce their impact on the difficulty of navigating an environment (Carlson et al., 2010; Montello 2007; Jeffery 2019b). A good example is Haq and Girotto's (2003) study, in which they examined wayfinding in two separate hospital buildings in the U.S. to understand the relationship between wayfinding and intelligibility. While they found that intelligibility was a good predictor of success in map-sketching and pointing tasks, these results did not translate into wayfinding performance. They conducted a further analysis of the layouts to understand the results, which revealed that the more intelligible environment was arranged around a very long corridor (with many decision points) along which most of the destinations were located. Small wayfinding errors would therefore result in participants having to retrace their steps, and thus incurring redundant decision point use and repeat decision points use (Haq & Girotto, 2003). In another wayfinding experiment found that analysing performance in only two environments was a significant limitation, because a host of unaccounted factors (e.g. the rectilinearity of the street network) could account for the differences in the studied measures (Long and Baran, 2012). Recent research exploring when patients with dementia become lost in real-world environments helps to extend beyond two environments (Puthusseryppady et al., 2019; Puthusseryppady et al., 2020), but lacks the capacity for systematic comparison of variables that can be achieved in lab experiments.

Previous studies in the lab and in virtual settings have compared a small number of environments while measuring a small number of environmental features. For instance, Slone et al. (2015) compared two virtual layouts systematically varying in one objective measure of plan complexity, the interconnection density (Li & Klippel, 2012; O'Neill, 1991; Slone et al., 2016). They found that more complex layouts were harder to navigate. The difficulty in assessing a given variable is that in the real-world it may interact with a plethora of other environmental features to determine the navigability of an environment. It is possible that when included with a range of other metrics across many environments the impact of a given metric becomes minimal.

To address the question of what factors are important it is ideal to measure many environmental features in a variety of environments, and then analyse wayfinding performance across many participants to account for individual differences in performance. This is a challenge because the time taken to test many environments may be longer than a standard experiment and testing many participants with such a test is difficult.

Here, we surmounted these challenges calculating 58 spatial metrics to examine the trajectories of over 10,000 participants navigating 45 virtual environments in the mobile video game Sea Hero Quest (Coutrot et al., 2018; Spiers, Coutrot and Hornberger, 2021). The richness and volume of this data set allowed us to study different combinations of environmental features and their impact on wayfinding. Analysing the data with a variable selection method, we isolated eight spatial metrics that best explained navigability.

2. Material and Methods

2.1) Participants

Between May 2016 and March 2019, 3,881,449 participants from every country downloaded and completed at least the first level of the game. 60.8% of the participants entered their demographics (age, gender, and nationality). Level progression was linear, so participants needed to complete level N in order to access level N+1. The profile of the participants who played only the first levels of the game is likely quite different from the participants who completed all 45 wayfinding levels. To avoid selection biases and to be able to compare the levels with one another, we used the subsample of participants who completed all the levels in the game and provided demographics for the further analysis. As a result of this sampling process, 10,626 participants were included in the analysis. Among them, 5,219 were male (age: M=41.89 years, SD=15.95 years) and 5,407 were female (age: 41.98 years, SD=16.32 years).

2.2) Task

In Sea Hero Quest, participants navigate a boat through a series of virtual environments (for an extensive description, see Coutrot et al., 2018; Spiers, Coutrot & Hornberger, 2021, see Fig. 1). The wayfinding task was designed with consideration of Wiener et al. 's taxonomy of human wayfinding tasks (2009) to involve wayfinding with path planning. The wayfinding performance in SHQ has been shown to be predictive of real-world navigation performance (Coutrot et al., 2019).

Participants navigated through 45 different levels. At the beginning of each level, participants were presented a map showing a series of goal locations. They had to navigate to the goal locations in the indicated order (i.e., they needed to reach goal 1 first, then goal 2, etc). Participants could study the map and, after clicking the close button, the map disappeared and participants started to navigate (Figure 1). They used four commands during the game to move the boat: they tapped right to turn to the right, tapped left to turn to the left and swiped up to speed up, and swiped down to stop the boat. This was explained in the first levels. If goals were not encountered in the required order, participants had to return from one goal to another in order to complete the task. The task was marked as complete once all goal locations had been visited in the appropriate order and the participant received between one and three stars depending on how quick they completed the level. If the participant took longer than a set time, an arrow indicated the direction to the goal along the Euclidean line to aid navigation. The results were uploaded on a server as soon as participants completed a level. If they were offline, then the data was stored on their device and sent when they were online again.

2.3) Level design

The levels were designed to vary in terms of spatial configuration, the number of goal locations, visibility conditions (i.e., fog versus clear environments), themes (e.g. arctic environment, swamps, etc), and landmark saliency. Salient landmarks were visually noticeable objects (due to their shape, size, colour, or background). In some levels there were no landmarks, and in others landmarks varied both in terms of saliency –salient and less salient landmarks– and in terms of the accessibility of their location –global and local landmarks– (for more information about landmarks see Yesiltepe et al., 2021a, 2021b; Yesiltepe et al., 2020a, 2020b, 2020c). Some levels also used partially occluded maps (see Figure 1), such that participants did not have a full preview of the environment, just the start locations and the arrangement of goals.

The levels were designed to have specific and controlled degrees of complexity that varied across levels. To this aim, we employed O'Neill's 'interconnection density' measure (ICD). As we mentioned, ICD is the average number of choices at decision points. In graph terms, ICD is the sum of the degrees of all decision points, divided by the total number of decision points in the graph. The reason we used ICD is that it has been found to be strongly correlated with the degree of perceived complexity of building layouts ($r=0.78$, $p<0.01$) (O'Neill, 1991).

We generated layouts with a specific number of decision points and connections, resulting in a specific ICD measure for each layout. We produced a series of layouts varying in ICD values, and then analysed each potential layout to measure its intelligibility. Intelligibility is defined as the correlation between how well connected a space is (linked to the metric of degree centrality) and how accessible it is, which is expressed using a variation of the graph measure closeness centrality (Hillier et al., 1987). In this process, intelligibility served as a fitness function for inclusion in the game levels. We selected the final layouts so that they formed three groups varying in intelligibility: highly intelligible (0.8-0.85), averagely intelligible (0.5), and highly unintelligible (0.15-0.2). The game was designed such that levels with lower intelligibility values were generally encountered later in the game, and we expected these levels to be harder to complete (and that they would result in higher difficulty scores). The bottom part of Figure 1 includes the difficulty of each level, which shows that the later levels are on average harder to navigate compared to the first wayfinding levels.

Once all the layouts were selected, they were transformed into the game levels by the game design company Glitchers Ltd. Another analysis was undertaken after the game design process to ensure that they retained the correct levels of intelligibility, post-transformation. At the final stage, each level was user-tested by the design team and the scientific and architectural team to ensure it was suitable. For example, if a level was too easy/hard to complete the navigation task, then the level was revised by adding/removing deadends and landmarks, and simplifying/increasing what was estimated by the design team for complexity of the layout.

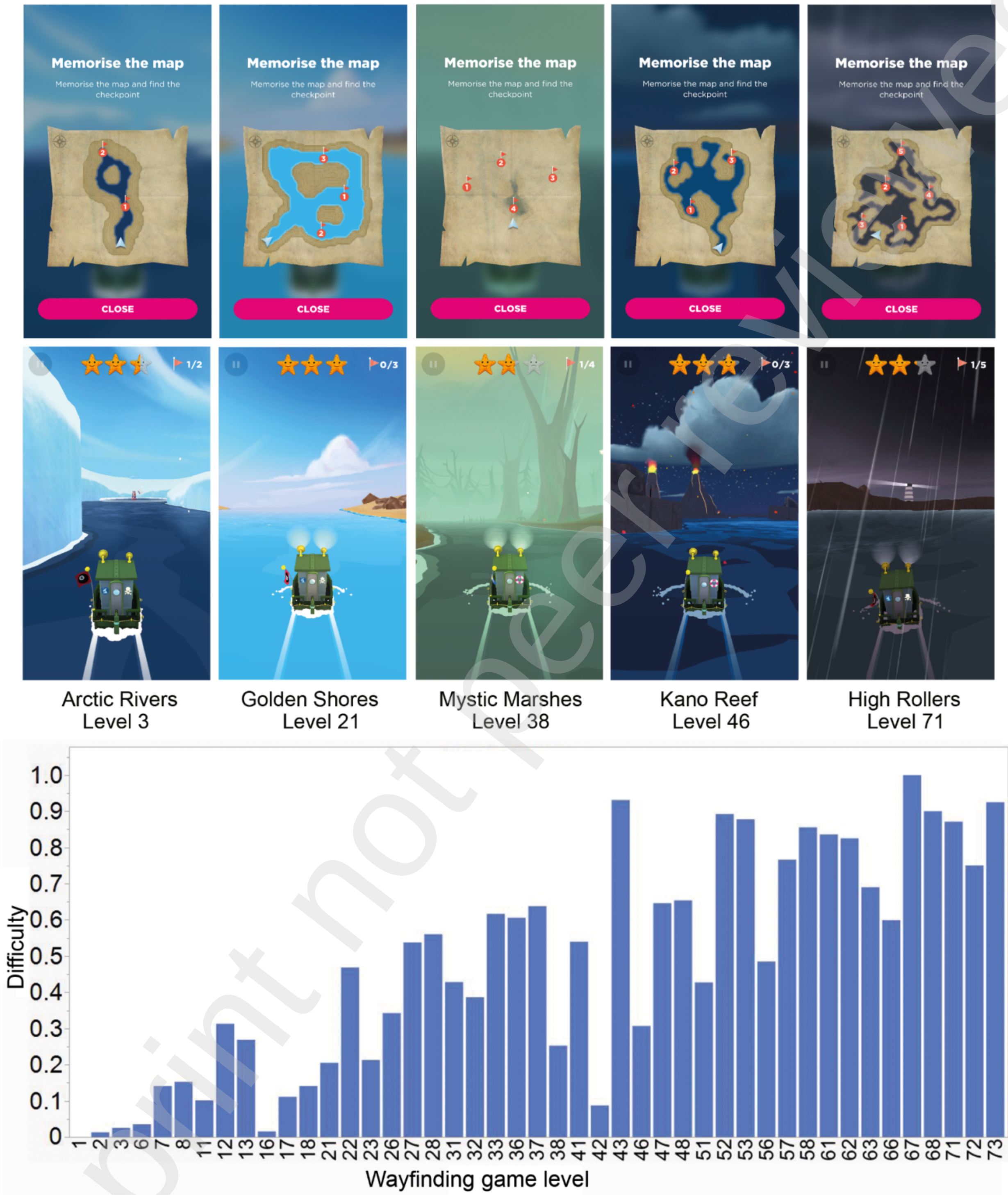

Figure 1. Navigation Task Sea Hero Quest. Top row: Example maps shown to participants at the start of 5 of the 45 wayfinding levels tested. Each map is from a different themed region in the game. Maps show starting location (blue arrow) and checkpoints (orange circles) to be navigated to in the order indicated by the numbers in the circles. Middle map (level 38) shows an example of a map where the layout is obscured in the map image. Participants touched the close icon to close the map after studying the map (self-paced). Middle row: Views from the first-person view navigation period of the task. Tapping left or right of the boat allowed for steering. Stars at the top given an indication of time remaining to obtain 3, 2 or 1 star reward. Number of check-points reached is indicated top right. Level 38

provides an example of a level with fog obscuring the depth of view. Note: Levels with an obscured map layout were not consistently linked to levels with fog in the navigation phase. Bottom: Scaled difficulty of the levels is shown across time. The 45 wayfinding levels of the game were distributed across the 75 levels of the game which included other features of the game (see Spiers, Coutrot and Hornberger, 2021).

2.4) Environment analysis

To analyse the environmental configuration of each of the 45 levels, we employed 58 separate metrics (see Appendix A Table A.1. to see the metrics we used), which, based on previous studies, were all potentially linked to wayfinding performance. The metrics fall into four families: task-specific metrics; space syntax relational metrics; space syntax geometric metrics; and general geometric metrics (for a detailed description of each of the metrics, see Appendix A Table A2).

Task-specific measures correspond to those features that are not intrinsic to the spatial layout itself but that instead depend on the task that was set for participants to complete. These include: (a) the number of destinations (i.e. the number of goals the participant must reach before the task is marked as complete), (b) the weather (i.e. the presence or absence of fog within a level), map occlusion (i.e. whether or not the map is partially occluded) and the (c) shortest route (i.e. the shortest path passing all of the goal locations in the correct order from the starting point). In principle, tasks are made easier if goals are placed in a sequence that matches their ordering, while they are made more difficult if the shortest route between subsequent goals involves a lot of backtracking and crossing of previous routes. Other task related measures included map condition (occluded map vs clear map) and landmark conditions (landmark saliency and global landmark conditions) .

Space syntax relational metrics and space syntax geometric metrics were developed using space syntax (see Appendix B.1-B.11. for the images we prepared to illustrate some of the space syntax metrics for each level), a set of techniques designed to measure the spatial configuration of built environments (Hillier & Hanson, 1984). These methods are based on the analysis of either lines of sight/movement (drawn according to inter-visibility between two points) or points/grids. This includes axial and segment analysis —which are line-based—, and visibility graph analysis (VGA) and isovist analysis —which are based on points/grids. Axial analysis is based on drawing lines of sight, which relate the visibility and movement through navigable spaces. A segment is a line that transects the space between two junctions/decision points (Al-Sayed et al., 2014; Hillier & Iida, 2005). VGA is based on the visibility of each point (or grid) from the rest of the environment (Turner et al., 2001; Jiang & Claramunt, 2002). Isovists measure the set of visible sub-spaces from a specific point.

The space syntax analysis of the levels followed several stages. First, the layouts of all 45 levels were collected as .png files, in the form of solid-void versions of the layouts: black for barriers to navigation and white for navigable space. These were then converted to .dxf files to produce editable versions of the layouts. We used Depthmap X 0.50 to run the space syntax analysis (Varoudis, 2012). Axial maps were automatically generated with the software and the fewest-line layouts were used. In order to create segment maps of the layouts, the edges of navigable spaces were first defined with points in ArcMap, and Voronoi polygons were generated using those points. These Voronoi polygons were used to define segment maps, with the edges of the polygons shaping the segment lines (Figure 2a). Once the segment maps and the axial maps had been created, we computed axial and segment analysis to generate the space syntax measures. VGA analysis was also automatically generated (Figure 2b). The resulting space syntax measures are either relational or geometric.

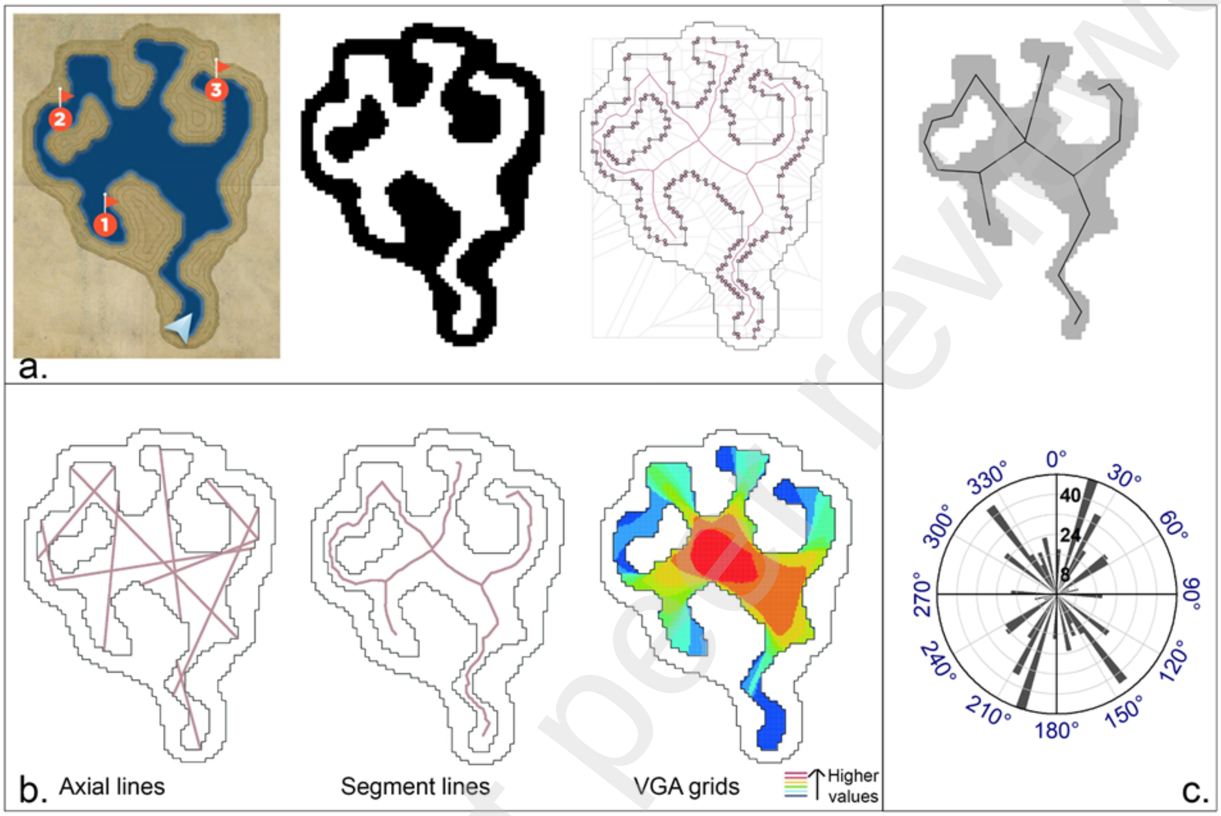

Figure 2. a: The procedure to create segment maps, b: analysis that can be done using space syntax. On left and in the middle, line-based maps; on right, point/grid based analysis), c: Simplified segment map and a rose plot of the segments' bearings. All the figures are produced from the layout of level 46.

Geometric space syntax measures are *axial number of lines*, *axial line length* and the *ratio of the isovist view area* (from the start point) to the total area. These measures focus on geometric characteristics of the defined spaces. Relational metrics, on the other hand, include all syntactic measures that analyse the relationship between each space and all others, and they rely on an underlying graph-representation (decision points and edges) for their calculation.

In brief, each of the space syntax relational measures are as follows: *Connectivity* measures the number of other lines that each line is connected to (Hillier & Hanson, 1984). *Integration* is a measure of centrality which calculates how accessible each segment is from the rest of the system in terms of the number of direction changes (which is strongly related to closeness centrality). *Integration* can be calculated at different radii from the centre of the environment, with the largest radius corresponding to a measure of global integration. *Intelligibility* is the correlation between global integration and connectivity, and it is generally understood to indicate how easy it is to comprehend the layout (Hillier, 1996; Hillier et al., 1987). Separate measures of integration, connectivity and intelligibility were first produced using line-based analysis (e.g. Seg_Connectivity) and then using VGA (e.g. VGA_Connectivity).

Metric choice measures the possibility for each segment to be selected as a part of the shortest route between origin and destination (Al-Sayed et al., 2014; Hillier & Hanson, 1984). Here, we used both choice and normalised choice, which adjusts choice values according to the depth of each segment in the system so that different environments can be compared (Hillier et al., 2012). Finally, *metric reach* measures the total street length that can be reached from an origin to all possible directions up to a certain distance threshold (Peponis et al., 2008), and directional reach measures the total street length captured with a specific number of direction changes (Ozbil & Peponis, 2007).

In addition to space syntax measures, we employed the following general geometric measures, which were calculated employing methods outside of space syntax techniques: *number of decision points* (# of decisionpoint), the *area of navigable spaces* (area_moveable spaces), the *number of dead ends* for both axial (# of_deadends axial map) and segment maps (# of deadends_seg-map), the *number of circles* (# of circles), *average segment length* (avrg_segmnt_length), *maximum segment length* (max_sgmnt_length), *total segment length* (total segment length), and *entropy*. Here, we included segment length as an equivalent to street length, which, as mentioned in the background section, has been hypothesised to be important for environmental layout complexity (Boeing, 2018). *Number of circles* corresponds to the number of circular paths in the environment, where circularity relates to a loop leading back to a prior location. *Entropy* is theoretically connected to many complexity metrics (Boeing, 2018, 2019), so that the higher the *entropy*, the more complex –i.e. less ordered– the network. To calculate *entropy*, we used the following formula:

$$H = -\sum_{i=1}^{36} P(o_i) log(P(o_i))$$

Equation 1. Entropy formula

In the formula, H represents entropy, i indexes the bins and P(o_i) represents the proportion of segment orientations that fall in the ith bin. This formula is based on Shannon's entropy and was originally defined to compute the Street Network Entropy (SNE) in a city street network (Boeing, 2018; Coutrot et al., 2022). To calculate the entropy, segment lines were used and the Douglas-Peucker algorithm (1973) was used to simplify the line made of the connected segments (Figure 2c). For all game levels, maximum offset tolerance was used between the original and the simplified line of three pixels.

2.5) Task Difficulty

To quantify the navigation difficulty score, we used the 10,626 trajectories we recorded for each level. The difficulty score for each level was calculated by subtracting the minimum trajectory length from the median trajectory length and then normalising it with the minimum trajectory length. The minimum trajectory corresponds to the optimal trajectory for a given level. Hence, the difference between the median and the minimum trajectories shows how far the median performance is from being optimal. We divided this difference by the minimum trajectory length to normalize the difficulty score according to the size of the level. Without this step, this difference would be proportional to the size of the level rather than to its navigation difficulty.

$$Difficulty\ Score = (median(trajectory\ length)\ -\ min(trajectory\ length))\ /\ min(trajectory\ length)$$

Equation 2. Difficulty score formula

We computed the difficulty score for each level, and for different demographics. We computed the difficulty score for Male vs Female participants, and for Younger (below the median age, 40 y.o.) vs Older (above 40 y.o.) participants.

Equipped with the spatial metrics outlined in sub-section c) and with the difficulty score, we can now rephrase our central research question as follows: Which spatial metrics (including task-specific metrics) best explain how difficult a level is?

The challenge to answer this question empirically is that we had as many as 58 metrics (some of which were strongly correlated) and 45 levels. This multicollinearity means that we could not simply apply a standard regression to predict difficulty from metrics. We applied a principal component analysis (PCA), but the interpretation of its loadings was not straightforward, as highlighted in the results sections. Rather, we used a shrinkage and variable selection method for regression models: the Least Absolute Shrinkage and Selection Operator (LASSO) regression (Tibshirani, 1996). LASSO is similar to standard regression, but it penalises the number of predictors, leading to a sparser and more interpretable model. The formula for the LASSO regression is as follows:

$$L_{lasso}(\hat{ß}) = \sum_{i=1}^{n}(y_i - x_i^T\hat{ß})^2 + \lambda\sum_{j=1}^{m}|\hat{ß}_j|$$

Equation 3. Lasso regression formula

Where ß are the coefficients (i.e., the importance) of the selected metrics x in predicting the difficulty, i is the level number, yi is the difficulty score of the ith level, and λ penalizes the number of variables (the higher λ, the sparser the model). The selected metrics x are normalized (z-score) to be on the same scale.

The penalisation variable λ is determined with 10-fold cross validations for different values of λ. We chose the λ corresponding to the minimum cross-validation error plus one standard deviation.

We bootstrapped the LASSO regression 1000 times to generate 95% confidence intervals for each coefficient. We first ran the LASSO regression for each of the four families of metrics: task-specific metrics; space syntax relational metrics; space syntax geometric metrics; and general geometric metrics. We then ran a LASSO regression for all the selected metrics from each family. We also generated a correlation matrix with all the selected metrics in the four families.

Finally, we explored whether different demographics affected the selection of metrics. To this end, we re-ran the whole analysis outlined above for Male vs Female participants, and for Younger (below the median age, 40 y.o.) vs Older (above 40 y.o.) participants.

3. Results

3.1) Principal Component Analysis

Our primary aim was to understand which spatial metrics best explain how difficult a virtual environment is to navigate. As a first approach, we ran a Principal Component Analysis (PCA) on the 58 metrics of the 45 levels. The first component of the PCA (C1) explained 40% of the variance, and the second component (C2) explained 18% of the variance. The first component was strongly and positively correlated with difficulty ($r = 0.74$, $p < 0.001$), and the second component was weakly and negatively correlated with difficulty ($r = -0.25$, $p = 0.12$). As mentioned in the methods section, the issue with the Principal Component Analysis is that with 58 metrics, interpreting the loadings is not straightforward. In contrast, a Lasso regression allows us to select a limited number of important variables, which is much more useful when addressing our central question.

3.2) Lasso regression

We computed Lasso regressions independently for the four different families of metrics and selected the metrics with non-zero coefficients.
- For task-specific features, the metrics selected were: *number of destinations* and *weather*.
- For general geometric features, the metrics selected were: *number of decision points*, *area of navigable* spaces, *number of circles*, and *Entropy.*
- For space syntax geometric features, the metrics selected were: *number of axial lines*, and isovist view area *from the start/total.*
- For space syntax relational features, the metrics selected were: *axial choice*, *axial integration, VGA connectivity, segment integration*, and *metric reach* for a threshold of 25 units[1] (MR 25).

We plotted all of the resulting metrics, together with difficulty, in a correlation matrix (Fig 3). The correlation matrix shows that the difficulty of levels is positively correlated with the number of decision points (r=0.76), number of circles (r=0.76) and number of destinations (r=0.74). There is a negative correlation between the difficulty and isovist view area from the start/total (r=-0.54), weather (r=-0.48; i.e. worse performance with fog) and segment integration (r=-0.41). The results show that several geometric (general) and task specific features correlated with difficulty.

[1] We used 25, 50, 75, 100 units based on the size of all environments. 25 units mean 0.5cm here.

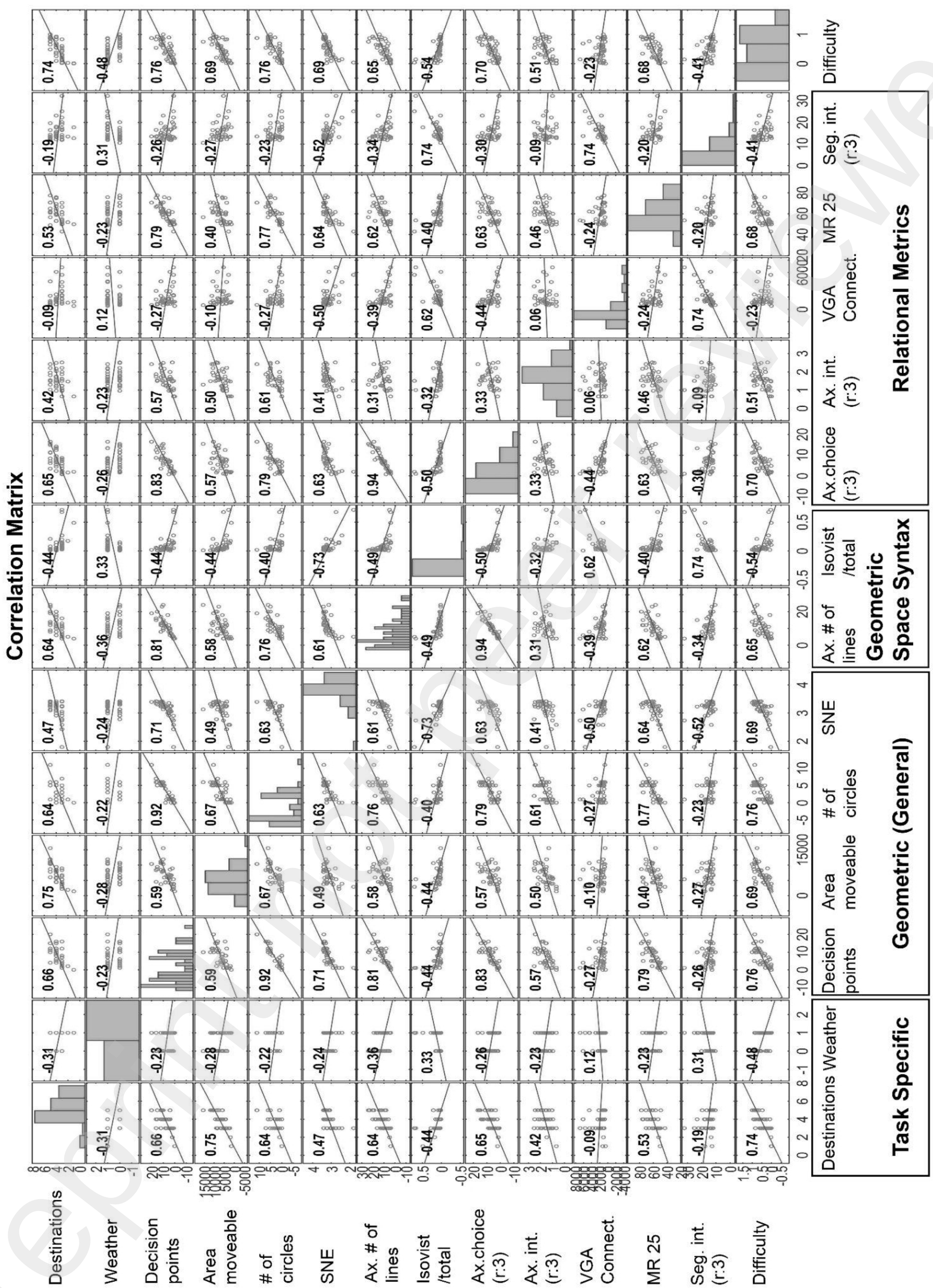

Figure 3. Correlation matrix with all the metrics that met threshold for significant correlation with difficulty using our Lasso approach. Each data point represents a wayfinding level. The red line represents the least square regression line and the number next to it the regression coefficient.

We then ran another LASSO regression including all the selected metrics from each family (Fig 4a). *Weather* and *segment integration* were selected with negative coefficients, and *number of destinations, number of decision points*, *area of navigable* spaces, *number of circles, entropy* and *metric reach* were selected with positive coefficients.

3.3) Effects of demographics

We re-ran the Lasso regression to separately predict the level difficulty computed for Male and Female participants, then for Younger (below 40 y.o.) and Older (above 40 y.o.) participants. Younger and older participants were defined considering median age as a cut-off point. This resulted in different sets of coefficients for each demographic (see Figure 4b and Figure 4c, respectively). For several metrics, there was a difference in the resulting coefficients but not in whether these were positive or negative (e.g. *area of navigable space* has a higher coefficient for Older than for Younger participants). Notably, there were some metrics that were selected only for one demographic profile but not for the others. *Number of decision points* and *axial integration* were selected for Female but not for Male participants. Finally, *axial integration* was selected for Older but not for Younger participants.

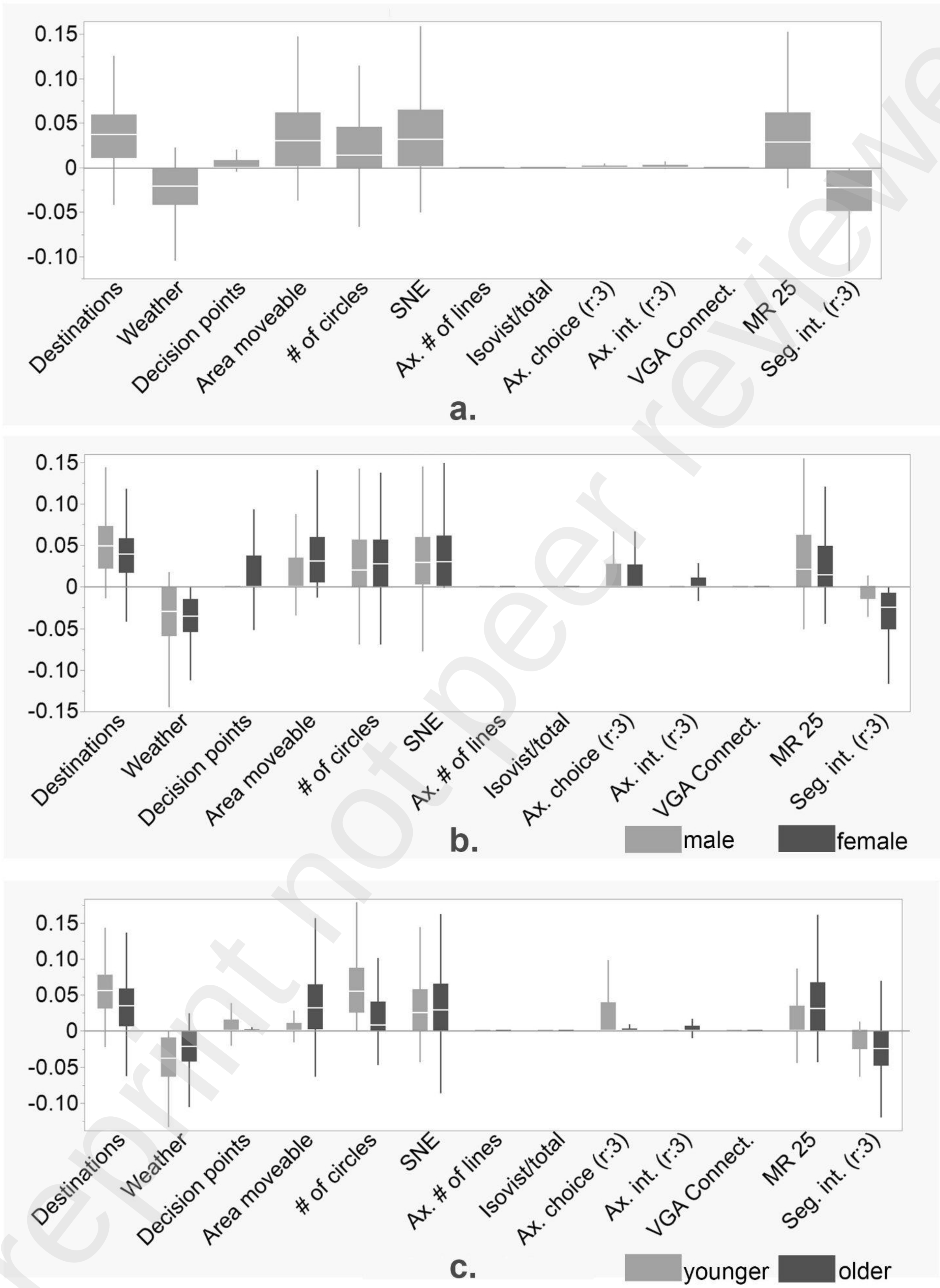

Figure 4. Lasso coefficients for the selected metrics from each family (a), coefficients for Males and Females (b), and coefficients for different Younger and Older participants (c). The Lasso computation was bootstrapped

1000 times, and the boxplots represent the distribution of the coefficients across these iterations. In the boxplots, the horizontal bar represents the sample median, the hinges represent the first and third quartiles, and the whiskers extend from the hinges to the largest/lowest value no further than ±1.5 * IQR from the hinge (where IQR is the interquartile range).

4. Discussion

In this study, we use an online app-based navigation test with a variety of virtual environments and a large sample of participants to determine which environmental features best explain how difficult an environment is to navigate. We measured 58 spatial metrics —divided into four families— and, using a Lasso regression, we found the set of metrics from each family that were best at explaining navigation difficulty. Re-applying the Lasso regression for the selected metrics returned a final selection of eight metrics. Several of these are consistent with past predictions of factors that make environments difficult to navigate (e.g. *number of decision points*, *the presence of fog*, *area of navigable* spaces, and *metric reach)*, other factors were more nuanced and relate to the complexity of the path structure of an environment (e.g. *entropy, number of circles* and *segment integration*). Critically, we also find several other predicted metrics did not predict navigability, such as intelligibility. Thus, our results indicate that perceived 'complexity' of an environment is insufficient to predict how hard it will be to navigate, but rather it is important to measure specific geometric features. These findings help explain why some environments are harder to navigate than others and provide principles for the design of navigable environments.

It is hardly disputable that the more complex an environment is, the harder it is to navigate. The challenge is how to measure that complexity (Boeing, 2019). Street network entropy had been previously hypothesised to be a good measure of the complexity of spatial configuration (Batty, 2005; Batty et al., 2014). This is exactly what we find using SHQ: the higher the path network entropy of an environment, the harder it is to navigate that environment. Entropy is an informational measure of unpredictability, and our study shows that it is not only a reliable indicator of complexity but also predicts wayfinding difficulty. This is consistent with a recent study that showed that people who grew up in more entropic environments (e.g. rural environments or organic cities) are better at navigating more entropic game levels in SHQ than people who grew up in less entropic environments (e.g. griddy cities like Chicago) (Coutrot et al., 2022). Here we provide evidence that growing up in more entropic environments would provide greater challenge for navigation ability compared to growing up in environments with more organised grid-like layout.

Segment integration – which is linked to the closeness centrality of paths – measures how accessible each segment of a path is from the rest of the system. Our novel finding that segment integration is a key determinant of what makes an environment difficult to navigate may help explain some prior brain dynamics during navigation. Using neuroimaging, we have previously found the right anterior hippocampus tracked the changes segment integration of streets entered during navigation of Soho in London UK (Javadi et al. 2017). Given the central importance of the hippocampus in navigation guidance (Nyberg et al., 2022) our new results may explain why segment integration is tracked by the hippocampus during navigation. Previous behavioural studies have also shown a link between wayfinding and segment integration. Peponis et al. (1990) and

Willham (1992) found high correlations between wayfinding behaviour and local integration values. More recently, Haq et al. (2009) found local integration to be an effective predictor of both exploration and wayfinding. As for global integration values, such as the one we employed, Emo et al. (2012) tasked participants with a search task and found global integration to be the most effective measure of spatial configuration when explaining their path choices. Our results go beyond past studies showing integration is not only a good predictor of trajectories (Hillier et al., 1993; Penn, 2003), but also help predict how difficult an environment is to navigate.

The findings here also speak to the use of line-based vs grid-based analyses. In isovist and visibility graph analyses, navigable space is represented with grids and the relationship between grids are investigated. Previous studies comparing the two approaches discovered that grid-based analysis produces a better correlation with movement (Desyllas & Duxbury, 2001). While that might remain the case for predicting pedestrian movement, our findings show that line-based analysis (in our case *segment integration*) is better at predicting navigation difficulty.

Richter (2009) had previously hypothesised that the more branches there are at a given decision point, the more difficult it is to navigate that intersection. Here, we find evidence supportive of the impact of decision points on navigability, in that we found the *number of decision points* is a key metric to explain navigational difficulty. In addition, the inclusion of the *number of circles* in the set of significant factors is interesting because it has been the subject of debate. Some architects considered that paths with a circular shape might aid navigation, as it makes it easier for people to remediate their wrong turns (see also Natapov et al., 2020). This idea, which was not substantiated by empirical findings, resulted in many newly built nursing homes being constructed in the shape of a continuous path around an inside courtyard, but when Marquardt and Schmieg (2009) put the hypothesis to an empirical test, they found an effect in the opposite direction: circular floor plans hindered orientation. This can be explained with architectural differentiations: a circular path ensures that many locations look similar to other locations, in which case, confusion can arise. Hence, the relationship between simplicity of plan configurations and orientation needs to be considered (Weisman, 1981). Our study further supports the finding that circular paths make an environment harder to navigate. Circular paths in Sea Here Quest provided alternative routes for the participants (e.g., they could take one route to a location and another one to go back). Therefore, the more circles an environment has, the more navigational choices participants have. This could cause confusion and make it harder for people to complete the wayfinding task. Furthermore, environments with many circles will require more circumnavigation of a region. Such circumnavigation has been found to distort representation of travel time and Euclidean distance between locations (Brunec et al., 2017). Such distortions may play a role in leading to more errors in navigation.

In the context of this experiment, the metric *weather* indicates the presence/absence of fog, and by extension, the degree of visibility within a level. Unsurprisingly fog leads to worse navigation. The importance of *weather* makes sense when we consider the importance of vision for human navigation (Ekstrom, 2015). The inclusion of the *number of destinations* in the final list is also not altogether surprising either, given that goals were not generally encountered in the order of passage. This results in a higher demand to keep multiple goals in mind and more back-tracking, both features of navigation found to drive increased activity in the prefrontal cortex (Javadi et al., 2019b; Patai and Spiers, 2021). An increase in the *number of destinations* corresponds to an increase in the ‘intrinsic cognitive load’ (Sweller, 2010) of the task itself, which in turn is argued to increase wayfinding difficulty (Armougum et al., 2019; Giannopoulos et al., 2014).

We also found that the larger the *area of navigable* spaces, the more difficult that level was to navigate. This finding is consistent with evidence that participants who travel longer distances tend to make larger directional errors (Ishikawa et al., 2008). We note that by including minimum trajectory length in the calculation, we normalised the difficulty score according to the area of each level, to avoid larger environments resulting automatically in higher difficulty scores due the very fact of being larger.

The two other measures of complexity that made the final Lasso selection were *metric reach* and *segment integration*, which originate in Space Syntax methods. *Metric reach* captures the density of paths and path connections accessible from each individual path segment (Peponis et al., 2008). The higher the *metric reach* of an environment, the more complex it is. *Metric reach* has previously been found to be a good predictor of pedestrian movement (Ozbil et al., 2015). Here, we find that it is also a good predictor of wayfinding difficulty.

Prior studies have suggested intelligibility would be an important factor for predicting navigability (Conroy 2001; Hillier 2012; Kim 1999). Yet, we found no relationship between it and difficulty. This may be because other variables manipulated here, such as the number of decision points, may have a more dramatic effect on navigability and these can be high in environments which score high on intelligibility. Similarly, we surprisingly found little evidence that landmark salience or the presence of global landmarks had significant correlations with performance across levels. This may be due to more subtle manipulations of these stimuli relative to some other factors. The complete absence of landmarks from the presence of fog had a significant impact on navigation difficulty. Our past research specifically exploring the impact of landmarks across a sub-set of levels has shown that relatively trivial features (e.g. some reeds or small stones) can become important features for wayfinding (Yesiltepe et al., 2021b) and sometimes more useful than global landmarks (Yesiltepe et al., 2019). Here we find that the geometric features of the layout/paths dominate in determining navigability.

Finally, our analysis stratified participants by gender and age. Notably, we found a roughly equal proportion of men and women in the pool of participants who completed the 45 levels, similar to the proportion who initially downloaded the game. This is interesting because on average men perform better at navigating in SHQ (Coutrot et al, 2018). Thus, this suggests that persisting in completing the game was not simply a function of navigation skill. There were a few differences between groups in our lasso analysis. *Axial integration* was selected for Female and Older participants but not for Male or Younger participants. Axial lines are determined in terms of visibility, following the “line of sight” concept (Hillier & Hanson, 1984). This implies that female participants and older participants are more sensitive to length of the view in an environment. Additionally, we found female, but not male, participants were impacted by the *number of decision points*. It is unclear why this is. Female participants tend to be more likely to re-use prior learned routes or follow route strategies (Fields & Shelton, 2006; Marchette, Bakker, & Shelton, 2011; Boone et al., 2019). It may be that increasing the *number of decision points* makes determining a route (e.g. left, then right, etc) more difficult, but more research would be useful to replicate this finding and explore it further.

Our study contains a number of limitations that are useful to consider. Firstly, although we have shown navigation in Sea Hero Quest predicts real-world navigation (Coutrot et al. 2019) and that flat-screen VR is a good approximation to the real-world for spatial memory (Zisch et al., 2022) there are many differences in our experiment to real-world navigation. Navigation in physical environments typically provides a wide field of view, idiothetic information is available and the control of movement is different. Thus, it will be useful to use the findings from this study to make predictions about the navigability of real-world environments. Due to constraints in creating a coherent video game we were limited in the extent to which we could make environments that were extreme for particular properties. For example, it would be useful to contrast an extremely griddy to maximally entropic environment to show the extent of the impact of street network entropy on navigation. A similar approach could be taken for the other variables, such as the impact of regional boundaries on navigation (Greisbauer et al., 2022), and extended to other animals and artificial agents (de Cothi et al., 2020). Finally, the participants who entered our analysis were those that completed all the levels. Further research may be useful to explore different sampled groups of participants.

5. Conclusion

In conclusion, we find the key elements that determine the navigability of an environment are: *entropy, segment integration* (closeness centrality of paths), *number of decision points*, *number of circles, weather*, *number of destinations, area of navigable* spaces, and *metric reach*. Further empirical work could look at environments that vary along our proposed key environmental features. Researchers could also study the way in which the proposed set of key environmental features interact with other important elements for navigation, such as landmarks. Finally, further analysis could be carried out to understand in detail why particular metrics did not pass the selection process, such as intelligibility, which had previously been hypothesised to predict navigability (Kim 1999; Conroy 2001; Hillier 2012). Overall, our findings are relevant for psychology and neuroscience, and they can also inform future urban planning and architectural design. Built environments can be designed considering these factors in order to help people find their way.

Ethics

Participant consent was provided by UCL Ethics project ID: CPB/2013/015. The procedure followed to conduct environmental analyses was approved by Northumbria University Ethics Committee (Submission ID: 7939).

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Declaration of interests:

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A.Data

Data from this study are available at https://osf.io/acmkb/?view_only=6c90e16f89d846109f207def12d92a80 .

Appendix Table A. 1. Fifty-eight metrics used in this study and the results of each level. Note that task-related conditions are converted to numeric data. More specifically, landmark saliency is shown as 0-1 or 2 where 2 represents "salient landmarks" and 0 represents "no landmark" conditions. Global landmark condition is represented with 0 or 1 where 0 represents "no global landmarks" condition and 1 represents "existence of global landmark" condition. Weather and map conditions were shown as 0 or 1. In both conditions, "1" represents clear weather/ map conditions and "0" represents occluded map/ low visibility conditions.

Levels	Theme	Type	Difficulty	Landmarks	Landmark if	Global	Globalif	Weather	Weather if	Map	Mapif	axintelligibility	axnumberoflines	axconnectivity	axchoicen	axchoicer2	axchoicer3	axchoicer5	axchoicenormn	axchoicenormr2	axchoicenormr3	axchoicenormr5	lnhh	lnhhr2	lnr3	lnr5	axlinelength	axMeanDepth	alllinesconnectivity	alllineschn	alllinesnormchn	alllinesln	VGAConnectivity	VisualIntegrationHH
Level1	Arctic Rivers	Simple	Super Eas	<undefined	NaN	<undefine	0	<undefine	1	Normal	1	1	4	1.5	2	1	2	2	0.66	0.33	0.66	0.66	0.66	0.6	0.66	0.66	31.29	1.66	112.03	476.56	0.006	5.62	552.31	9.03
Level2	Arctic Rivers	Simple	Super Eas	Easy	2	Yes	1	Clear	1	Normal	1	1	4	1.5	2	1	2	2	0.66	0.33	0.66	0.66	0.66	0.6	0.66	0.66	51.19	1.66	160.83	583.51	0.003	7.23	1238.55	12.17
Level3	Arctic Rivers	Simple	Super Eas	Easy	2	Yes	1	Clear	1	Normal	1	1	5	2.4	1.6	1.6	1.6	1.6	0.26	0.26	0.26	0.26	1.47	1.47	1.47	1.47	51.72	1.4	152.69	523.02	0.003	7.6	1084.22	13.25
Level6	Arctic Rivers	Checkpoint	Easy	Easy	2	Yes	1	Clear	1	Normal	1	0.89	5	7	2	1.2	2	2	0.33	0.2	0.33	0.33	1.51	1.56	1.51	1.51	156.47	1.5	354.13	351.68	0.001	14.98	5621.23	18.34
Level7	Arctic Rivers	Checkpoint	Easy	Easy	2	Yes	1	Clear	1	Normal	1	1	4	3	1	1	1	1	0.33	0.33	0.33	0.33	1	1	1	1	235.2	1.33	662.12	1063.6	0.0007	13.74	6839.33	37.85
Level8	Arctic Rivers	Checkpoint	Easy	Easy	2	Yes	1	Clear	1	Obscured	0	0.83	5	2	2.4	1.6	2.4	2.4	0.4	0.3	0.4	0.4	1.09	1.14	1.09	1.09	125	1.6	423.14	1297.7	0.001	10.05	4447.21	27.43
Level11	Arctic Rivers	Checkpoint	Easy	Easy	2	Yes	1	Clear	1	Normal	1	1	4	1.5	2	1	2	2	0.66	0.33	0.66	0.66	0.66	0.6	0.66	0.66	58.64	1.66	134.03	818.54	0.003	5.97	1181.64	8.68
Level12	Arctic Rivers	Checkpoint	Easy	Easy	2	No	0	Fog	0	Normal	1	0.89	5	2.4	2	1.2	2	2	0.33	0.2	0.33	0.33	1.51	1.56	1.51	1.51	60.36	1.5	167.21	1232.8	0.003	5.45	2215.61	12.85
Level13	Arctic Rivers	Checkpoint	Easy	Easy	2	No	0	Clear	1	Normal	1	0.99	7	2.85	3.71	2.57	3.71	3.71	0.24	0.17	0.24	0.24	1.62	1.69	1.62	1.62	56.81	1.61	194.66	1942.7	0.002	5.57	1202.05	7.98
Level16	Golden Shores	Checkpoint	Easy	Easy	2	No	0	Clear	1	Normal	1	0.89	7	2	6.57	2	4.85	6.57	0.43	0.2	0.32	0.43	0.95	1.06	0.95	0.95	78.85	2.09	193.92	2106	0.002	4.95	1662.07	6.82
Level17	Golden Shores	Checkpoint	Easy	Hard	1	Yes	1	Clear	1	Normal	1	1	4	1.5	2	1	2	2	0.66	0.33	0.66	0.66	0.66	0.6	0.66	0.66	60.74	1.66	332.69	1051	0.001	9.33	2330.21	14.83
Level18	Golden Shores	Checkpoint	Easy	Easy	2	No	0	Clear	1	Obscured	0	0.29	11	6.18	15.63	2.54	5.81	15.63	0.34	0.19	0.19	0.34	0.92	1.81	1.23	0.92	65.38	2.56	284.09	4152	0.002	3.75	2955.52	5.34
Level21	Golden Shores	Checkpoint	Easy	Hard	1	No	0	Fog	0	Normal	1	0.93	6	3.33	1.66	1.66	1.66	1.66	0.16	0.16	0.16	0.16	2.52	2.52	2.52	2.52	86.01	1.33	384.1	1309.1	0.001	9.71	3727.27	15.88
Level22	Golden Shores	Checkpoint	Easy	Easy	2	No	0	Clear	1	Obscured	0	0.99	7	2.85	3.71	2.57	3.71	3.71	0.24	0.17	0.24	0.24	1.62	1.69	1.62	1.62	56.81	1.61	194.66	1942.7	0.002	5.57	1202.05	7.98
Level23	Golden Shores	Checkpoint	Medium	Hard	1	Yes	1	Clear	1	Obscured	0	0.89	8	2	0.8	0.2	0.8	0.8	0.03	0.03	0.03	0.03	1.6	1.6	1.6	1.6	27.13	0.51	296.39	933.6	0.001	9.66	1779.9	13.89
Level26	Golden Shores	Checkpoint	Medium	None	0	Yes	1	Clear	1	Normal	1	0.92	12	4.16	8.5	5.16	8.5	8.5	0.15	0.1	0.15	0.15	2.17	2.37	2.17	2.17	54.57	1.77	232.84	1604.9	0.001	7.07	1436.87	9.59
Level27	Golden Shores	Checkpoint	Medium	Hard	1	No	0	Fog	0	Normal	1	0.87	10	4.2	5.4	4.2	5.4	5.4	0.15	0.12	0.15	0.15	2.49	2.6	2.49	2.49	65.03	1.6	317.42	2709.9	0.001	7.15	1830.82	9.8
Level28	Golden Shores	Checkpoint	Medium	None	0	Yes	1	Clear	1	Obscured	0	0.94	10	3.2	8.4	3.6	7.2	8.4	0.23	0.13	0.2	0.23	1.56	1.85	1.58	1.56	54.68	1.93	142.7	1568.2	0.003	5	1211.39	6.49
Level31	Mystic Marshes	Checkpoint	Medium	Easy	2	Yes	1	Clear	1	Normal	1	0.37	13	3.23	19.53	2.46	8	19.53	0.29	0.11	0.14	0.29	1.03	2.23	1.25	1.03	59.06	2.62	197.96	3523.3	0.002	4.28	922.41	5.5
Level32	Mystic Marshes	Checkpoint	Medium	Hard	1	Yes	1	Clear	1	Normal	1	0.79	11	3.09	13.09	3.09	6.72	13.09	0.29	0.15	0.17	0.29	1.2	1.96	1.4	1.2	55.14	2.3	246.07	3233.5	0.001	5.21	1484.24	7.04
Level33	Mystic Marshes	Checkpoint	Medium	Hard	1	No	0	Fog	0	Obscured	0	0.9	13	4.3	10.46	5.23	9.53	10.46	0.15	0.1	0.14	0.15	2.02	2.36	2.04	2.02	62.49	1.87	259.7	2986.7	0.001	6.04	1672.64	8.76
Level36	Mystic Marshes	Checkpoint	Easy	Easy	2	No	0	Fog	0	Obscured	0	0.99	7	2.85	3.71	2.57	3.71	3.71	0.24	0.17	0.24	0.24	1.62	1.69	1.62	1.62	56.81	1.61	194.66	1942.7	0.002	5.57	1202.05	7.98
Level37	Mystic Marshes	Checkpoint	Medium	Hard	1	Yes	1	Clear	1	Obscured	0	0.94	15	3.73	15.33	5.86	13.33	15.33	0.16	0.09	0.14	0.16	1.73	2.11	1.75	1.73	55.17	2.09	319.67	3720.6	0.001	6.17	1592.54	7.99
Level38	Mystic Marshes	Checkpoint	Medium	Easy	2	No	0	Fog	0	Obscured	0	0.7	8	2.25	9.5	2	4.5	9.5	0.45	0.25	0.27	0.45	0.82	1.2	0.96	0.82	59.3	2.35	258.67	2866.3	0.002	5	1648.45	6.64
Level41	Mystic Marshes	Checkpoint	Easy	None	0	No	0	Clear	1	Obscured	0	0.67	16	5.12	23.75	4.25	8.75	21.25	0.22	0.11	0.13	0.2	1.27	2.52	1.87	1.3	80	2.58	433.32	4742	0.001	6.22	2995.79	9.57
Level42	Mystic Marshes	Checkpoint	Medium	Hard	1	No	0	Fog	0	Normal	1	0.34	18	2.47	47.52	3.29	7.76	19.88	0.39	0.21	0.24	0.27	0.66	1.5	1.16	0.87	50.5	3.97	145.73	6808.2	0.003	2.47	867.64	2.94
Level43	Mystic Marshes	Checkpoint	Medium	None	0	No	0	Fog	0	Normal	1	0.52	20	3.61	29.8	5.04	14.19	29.76	0.12	0.06	0.08	0.12	1.23	2.07	1.5	1.23	48.46	2.47	190.66	5053.5	0.001	4.16	768.89	5.01
Level46	Kano Reef	Checkpoint	Easy	Easy	2	Yes	1	Clear	1	Normal	1	0.98	10	3.4	7	4.2	7	7	0.19	0.12	0.19	0.19	2	2.08	2	2	63.84	1.77	454.41	2145.7	0.001	8.53	2938.01	13.24
Level47	Kano Reef	Checkpoint	Medium	Easy	2	No	0	Clear	1	Obscured	0	0.79	17	4.23	20.94	5.41	13.41	20.94	0.17	0.09	0.12	0.17	1.54	2.29	1.71	1.54	53.06	2.3	241.16	4230.7	0.001	5.06	1271.08	6.84
Level48	Kano Reef	Checkpoint	Hard	Easy	2	No	0	Clear	1	Normal	1	0.92	13	4.92	8.92	5.38	8.46	8.92	0.13	0.09	0.12	0.13	2.42	2.69	2.43	2.42	71.36	1.74	270.3	3196.5	0.001	6.1	2186.82	8.45
Level51	Kano Reef	Checkpoint	Easy	Hard	1	No	0	Clear	1	Obscured	0	0.99	7	2.85	3.71	2.57	3.71	3.71	0.24	0.17	0.24	0.24	1.62	1.69	1.62	1.62	56.81	1.61	194.66	1942.7	0.002	5.57	1202.05	7.98
Level52	Kano Reef	Checkpoint	Hard	Easy	2	No	0	Fog	0	Obscured	0	0.95	12	3.83	8.5	5.83	8.5	8.5	0.15	0.12	0.15	0.15	1.96	2.14	1.96	1.96	74.25	1.77	250.43	3999	0.001	5.64	1372.48	7.52
Level53	Kano Reef	Checkpoint	Hard	None	0	Yes	1	Clear	1	Normal	1	0.97	19	5.26	16.84	8.73	16.52	16.84	0.11	0.06	0.1	0.11	2.43	2.71	2.43	2.43	51.59	1.93	247.7	3803.5	0.001	6.17	732.79	7.04
Level56	Kano Reef	Checkpoint	Hard	Easy	2	No	0	Clear	1	Normal	1	0.89	9	2.22	10	2.66	7.11	10	0.35	0.21	0.29	0.35	0.99	1.23	1.03	0.99	49.33	2.25	172.96	2190.4	0.002	4.92	884.15	5.89
Level57	Kano Reef	Checkpoint	Hard	Hard	1	Yes	1	Clear	1	Normal	1	0.96	8	3.75	3.5	3	3.5	3.5	0.16	0.14	0.16	0.16	2.21	2.29	2.21	2.21	95.74	1.5	685.7	2933.7	0.0005	10.39	4564.93	15.3
Level58	Kano Reef	Checkpoint	Hard	Easy	2	No	0	Clear	1	Obscured	0	0.8	9	3.11	6.22	3.55	6.22	6.22	0.22	0.17	0.22	0.22	1.49	1.8	1.49	1.49	70.89	1.77	150.17	1439.1	0.002	5.78	1128.02	7.8
Level61	High Rollers	Checkpoint	Easy	Easy	2	Yes	1	Waves	0	Normal	1	0.92	12	4.33	7.66	5.66	7.66	7.66	0.13	0.11	0.13	0.13	2.22	2.38	2.22	2.22	47.28	1.69	216.17	1526.4	0.001	6.7	941.4	8.51
Level62	High Rollers	Checkpoint	Medium	Hard	1	Yes	1	Waves	0	Normal	1	0.75	15	4.13	15.73	5.06	12.53	15.73	0.17	0.09	0.14	0.17	1.67	2.34	1.75	1.67	45.3	2.12	244.37	2150.4	0.001	6.02	1615.68	8.89
Level63	High Rollers	Checkpoint	Medium	Hard	1	No	0	Waves	0	Obscured	0	0.9	6	2.66	2.33	2.33	2.33	2.33	0.23	0.23	0.23	0.23	1.74	1.74	1.74	1.74	82.67	1.46	337.98	1487.5	0.001	8.16	6094.49	24.92
Level66	High Rollers	Checkpoint	Easy	None	0	No	0	Waves	0	Obscured	0	0.99	7	2.85	3.71	2.57	3.71	3.71	0.24	0.17	0.24	0.24	1.62	1.69	1.62	1.62	56.81	1.61	194.66	1942.7	0.002	5.57	1202.05	7.98
Level67	High Rollers	Checkpoint	Hard	None	0	Yes	1	Waves	0	Normal	1	0.95	14	4	13.28	5.42	11.14	13.28	0.17	0.13	0.15	0.17	1.75	2.21	1.81	1.75	60.51	2.02	216.74	3615.5	0.001	5.29	1081.73	6.57
Level68	High Rollers	Checkpoint	Medium	Easy	2	No	0	Fog	0	Obscured	0	0.58	12	2.83	19	2.83	6.5	17.33	0.34	0.19	0.21	0.31	0.91	1.74	1.24	0.92	48.95	2.72	300.22	2636.8	0.002	5.59	2421.75	7.99
Level71	High Rollers	Checkpoint	Hard	Easy	2	No	0	Waves	0	Normal	1	0.58	23	3.73	45.04	4.95	14.86	38.95	0.19	0.11	0.14	0.17	1.15	2.1	1.55	1.18	41.24	3.04	211.28	5357.7	0.002	3.97	1175.55	5.13
Level72	High Rollers	Checkpoint	Hard	Easy	2	No	0	Fog	0	Normal	1	0.68	24	2.91	54.33	4.5	15.5	41.91	0.21	0.18	0.17	0.18	1.02	1.67	1.3	1.07	56.41	3.36	102.27	3687.9	0.003	3.11	685.55	3.98
Level73	High Rollers	Checkpoint	Hard	Hard	1	Yes	1	Waves	0	Obscured	0	0.14	20	3.6	40.2	4.2	11.4	31.2	0.23	0.14	0.17	0.19	0.99	2.11	1.54	1.07	49.71	3.11	202.11	4421.6	0.002	3.95	920.47	4.28

Appendix Table A.1. (Continued)

Levels	SegConnectivity	SegChoicen	SegChoice2	SegChoice3	SegChoice5	SegInn	SegIn2	SegIn3	SegIn5	avrgsegmntlength	maxsgmntlength
Level1	1.95	494	33	64.25	141.8	9.38	13.37	12.74	11.67	60	60
Level2	1.97	2106.67	66.02	154.56	400.69	14.46	18.49	17.79	17.03	138	138
Level3	2.06	552.09	30.45	74.09	231.03	13.11	13.89	13.44	13.49	38.5	58
Level6	1.87	70	65.18	70	70	25.25	25.32	25.25	25.25	32.3	47
Level7	2.03	167.96	227.72	507.76	167.96	32.44	32.03	32.32	32.44	85.5	158
Level8	2	584.49	98.2	241.75	558.28	22.62	24.19	22.33	22.56	47.3	58
Level11	2	2060.93	32.57	77.75	232.933	12.57	13.64	13.21	13	68	76
Level12	1.97	2730	68.84	151.43	404.34	13.86	18.03	17.55	16.85	115	129
Level13	2.01	3378.33	24.03	59.73	184.43	12.36	12.06	11.87	11.83	54	103
Level16	2.02	5813.61	54.1	128.49	373.81	15.18	16.81	16.71	16.66	48.1	165
Level17	2	1589	81.57	179.57	498.45	18.52	19.69	19.31	18.69	71.3	87
Level18	2.07	4727.48	50.75	125.72	367.47	12.67	16.41	16.46	16.54	28.8	97
Level21	2.07	531.93	76.05	202.56	686.4	24.3	19.35	20.23	22.49	69.6	171
Level22	2.01	3378.33	24.03	59.73	184.43	12.36	12.06	11.87	11.83	54	103
Level23	2.1	577.56	33	95.14	364.79	19.58	13.54	14.24	16.42	41.2	84
Level26	2.15	576.32	57.43	145.68	525.48	26.21	16.87	17.57	20.03	30.7	90
Level27	2.06	7179.98	40.91	97.51	296.86	16.26	14.8	14.8	15.04	29.9	131
Level28	2.06	1167.7	25.4	66.01	213.73	14.89	12.15	12.2	12.67	55.2	201
Level31	2.06	5966.37	32.43	80.56	252.46	15.96	13.26	13.42	13.81	33.5	75
Level32	2.09	4879.12	67.1	160.5	432.17	17.26	17.56	18.1	18.56	21.9	56
Level33	2.07	7751.9	34.02	85.5	279.95	15.8	14.06	14.16	14.68	29.9	81
Level36	2.01	3378.33	24.03	59.73	184.43	12.36	12.06	11.87	11.83	54	103
Level37	2.07	5334.54	135.74	301.73	819.23	27.24	22.61	23.19	24.05	33.1	93
Level38	2.05	4770.28	50.02	111.28	291.31	14.38	15.39	15.69	15.56	26.6	71
Level41	2.13	3396.43	48	129.59	478.7	24.46	15.66	16.51	18.91	24.2	49
Level42	2.03	15745.7	35.45	80.98	256.64	12.76	13.84	13.66	13.78	29.4	83
Level43	2.08	7967.31	31.87	83.24	283.44	21.98	13.4	13.71	14.7	25.8	98
Level46	2.02	5454.03	58.83	153.14	443.4	15.09	16.86	16.83	17.13	32.7	77
Level47	2.09	7021.11	40.37	108.1	360.12	20.87	14.73	15.21	16.48	29.4	58
Level48	2.13	3332.64	32.63	89.48	309.86	22.49	13.85	14.27	15.68	30.1	96
Level51	2.01	3378.33	24.03	59.73	184.43	12.36	12.06	11.87	11.83	54	103
Level52	2.11	1368.47	48.19	121.56	415.11	27.66	16.06	16.49	17.82	40.9	72
Level53	2.1	10910.6	31.95	83.02	285.89	23.64	13.22	13.59	14.6	24.1	58
Level56	2.02	6436.72	32.08	76.37	223.92	12.01	13.52	13.2	13.07	42.2	130
Level57	2.08	5024.07	72.12	180.15	557.68	24.29	18.96	19.68	20.91	28.4	82
Level58	2.06	8271.16	26.4	66.6	210.03	14.3	12.14	12.27	12.65	39.8	144
Level61	2.14	3107.25	23	60.07	169.17	12.55	11.87	12.23	12.61	18.8	67
Level62	2.21	1663.73	27.8	78.34	252.81	17.86	12.62	13.46	15.3	16.2	38
Level63	2.03	3468.11	36.32	84.2	204.6	8.77	14	13.69	13.02	45.3	171
Level66	2.01	3378.33	24.03	59.73	184.43	12.36	12.06	11.87	11.83	54	103
Level67	2.07	6280.79	26.43	63.98	204.26	17.65	12.25	12.27	12.57	38	127
Level68	2.04	7910.74	34.75	89.03	221.56	11.67	12.86	13.17	13.8	62	157
Level71	2.09	8428.59	28.27	73.04	230.95	16.9	12.79	12.69	13.12	33.2	83

Levels	DR100	DR102	DR200	DR202	MR10	MR25	MR50	MR75	MR100	decision points	destinations	dead ends	ofdeadendssegmap	circles
Level1	2.7	12.54	2.7	12.54	20	50	60.27	60.27	60.27	0	1	1	1	0
Level2	3.83	8.61	3.88	14.08	20	50	100	138	137.99	0	1	1	1	0
Level3	3.82	12.73	4.03	17.09	20	52.01	109.6	140.9	152.42	2	2	2	2	1
Level6	11.05	26.7	19.89	39.89	19.84	42.81	49.05	49.05	49.05	1	3	1	3	0
Level7	5.92	36.91	15.21	61.4	23.49	53.65	103.7	153.7	170.95	1	3	0	1	1
Level8	7.46	19.36	16.02	42.94	20	49.77	100.4	138.6	141.38	1	3	3	3	0
Level11	3.5	15.41	6.83	19.28	21.47	52.14	104.4	154.4	197.53	1	3	3	3	0
Level12	5.95	22.28	6.01	33.98	20	50	99.53	128.4	153.35	1	3	1	1	1
Level13	3.41	16.23	5.34	22.37	20.25	50.84	107.7	168.4	221.72	3	3	3	3	1
Level16	4.3	13.81	6.46	22.8	20.87	51.97	105.9	155.9	200.39	3	3	4	5	0
Level17	1.95	11.99	10.35	37.66	20	50	100.2	150.2	197.02	1	3	3	3	0
Level18	6.52	25.22	7.62	35.85	21.63	54.83	108.3	160.8	207.93	7	3	4	7	1
Level21	3.66	23.66	5.66	41.56	24.48	61.69	141.2	228.5	292.96	2	3	1	1	2
Level22	3.41	16.23	5.34	22.37	20.25	50.84	107.7	168.4	221.72	4	3	3	3	1
Level23	5.1	19.57	6.17	28.19	19.59	59.09	146	241.8	285.54	5	3	1	1	3
Level26	4.07	16.85	5.85	25.38	24.08	75.82	201.6	333.8	408.33	9	4	1	1	5
Level27	4.6	14.84	6.26	22.39	20.84	58.82	133.8	208.4	273.27	10	4	1	2	5
Level28	5.49	21.09	6.09	25.98	21.08	62.83	148.6	236.5	310	5	4	1	1	3
Level31	2.82	11.86	3.56	13.6	22.26	61.27	126.4	183.4	246.69	8	3	2	2	4
Level32	4.1	17.11	5.42	26.09	21.39	60.16	129.9	190.1	247.51	8	4	10	10	0
Level33	5.05	19	7.72	28.62	21.28	59.43	135.8	224.1	292.95	11	4	2	3	5
Level36	3.41	16.23	5.34	22.37	20.25	50.84	107.7	168.4	221.72	3	3	3	3	1
Level37	3.9	14.64	5.47	25.88	22.67	64.65	147.6	234.4	322.78	10	4	2	2	5
Level38	4.44	22.11	4.88	30.59	23.54	60.06	123.9	188.7	254.72	5	4	2	5	1
Level41	4.9	21.91	7.49	33.19	22.45	66.51	164.4	276.3	388.69	16	3	4	5	7
Level42	4.35	18.48	5.42	23.55	20.6	53.19	111	159.2	201.03	6	4	5	5	2
Level43	4.2	14.05	5.21	19.6	22.86	67.29	158.9	264.8	369.14	15	4	6	5	6
Level46	4.91	20.11	8.91	34.43	20	52.26	106.7	161.7	214.48	4	3	4	4	1
Level47	3.56	14.2	4.52	20.56	23.24	69.39	168.9	278.5	393.08	12	4	2	2	6
Level48	5.69	19.44	7.3	28.26	21.55	64.99	167.3	293.3	416.1	12	5	4	4	5
Level51	3.41	16.23	5.34	22.37	20.25	50.84	107.7	168.4	221.72	3	3	3	3	1
Level52	3.24	14.25	4.71	23.22	20.69	60.93	161	301.6	430.19	11	5	1	1	6
Level53	3.24	11.36	3.49	13.24	22.2	70.72	186.9	312.8	447.82	20	5	0	0	11
Level56	2.29	13.53	2.96	16.08	19.87	49.15	97.04	149.6	196.88	4	5	5	4	1
Level57	5.32	21.81	11.33	45.58	22.31	62.2	147.7	231.3	313.38	12	5	3	4	5
Level58	2.69	13.66	3.22	17.92	24.3	70.81	178.4	314	431.54	10	5	0	0	6
Level61	3.45	15.38	4.23	19.06	22.87	70.49	169.7	251.5	299.85	12	3	4	4	5
Level62	3.68	18.36	4.33	24.66	24.46	75.28	156.8	248.8	351.3	16	4	6	6	6
Level63	9.46	31.94	12.74	46.78	19.68	53.01	103.3	137.2	172.12	4	4	1	4	1
Level66	3.41	16.23	5.34	22.37	20.25	50.84	107.7	168.4	221.72	3	3	3	3	1
Level67	4.06	16.35	4.45	19.03	21.48	61.58	151.3	263.4	386.71	10	5	2	2	5
Level68	3.75	30.49	5.79	46.36	25.76	74.85	171.2	264.8	325.4	5	4	1	1	3
Level71	4.47	15.15	5.21	19.73	22.19	61.85	136.7	216	308.21	11	5	5	3	5

Levels	EntropySNE	VGAintelligibility	segmentlength	shortestroute	isovisttotal	segchoice50m	segchoice100m	segchoicenorm50m	segchoicenorm100m	areamoveablespaces	normdifficulty	normdifficulty_f	norm culty_
Level1	NaN	0.5477	60	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0	0.00647	
Level2	NaN	0.6435	138	138	0.489	NaN	NaN	NaN	NaN	1452.183	0.01311	0	0.018
Level3	NaN	0.9296	154	107	0.175	304.9	560.65	2.35	2.59	1912.475	0.025299	0.019847	0.036
Level6	1.791759	0.0705	97	106	0.712	70	70	1.68	1.68	2831.622	0.035398	0.034645	0.05
Level7	2.736339	0.8892	171	171	0.676	279.83	167.97	2.4	2.12	5360.381	0.141445	0.115209	0.288
Level8	2.426015	0.7491	142	180	0.27	226.29	584.49	2.18	2.57	3877.162	0.152368	0.138113	0.204
Level11	2.579844	0.6965	204	279	0.136	527.67	1695.64	2.56	3.05	2245.52	0.101582	0.098432	0.134
Level12	2.904216	0.847	230	193	0.049	312.61	977.57	2.42	2.89	3678.166	0.313119	0.312122	0.312
Level13	3.053883	0.7224	324	328	0.04	379.24	1418.69	2.43	2.96	6686.367	0.268694	0.283324	0.303
Level16	3.246829	0.652	337	282	0.107	512	1789.63	2.56	3.06	3908.986	0.015724	0.013551	0.041
Level17	2.582306	0.9247	214	311	0.152	389.6	1296.03	2.42	2.92	2919.505	0.111447	0.107068	0.118
Level18	3.222047	0.0379	404	326	0.085	309.3	1258.14	2.31	2.86	6356.159	0.140963	0.140038	0.146
Level21	2.776913	0.9245	348	278	0.121	347.74	1322.92	2.48	3.05	8926.24	0.205262	0.251475	0.182
Level22	3.053883	0.7224	289	328	0.04	379.24	1418.69	2.43	2.96	6686.367	0.468429	0.422239	0.468
Level23	2.986266	0.965	324	205	0.194	409.98	678.49	2.46	2.59	4315.198	0.212735	0.285545	0.18
Level26	3.200073	0.8199	431	338	0.052	774.62	1479.47	2.78	3.01	5959.818	0.342416	0.380918	0.318
Level27	3.29483	0.7652	361	354	0.057	544.3	1991.67	2.58	3.11	8252.5	0.53758	0.546499	0.508
Level28	3.0781	0.3661	261	391	0.036	424.3	1754.56	2.53	3.11	6892.525	0.560321	0.537332	0.56
Level31	3.223974	0.506	436	309	0.074	574.74	2414.94	2.63	3.09	4288.172	0.428459	0.391663	0.444
Level32	3.253179	0.6595	373	435	0.104	525.17	1902.41	2.49	2.95	4397.66	0.386449	0.402507	0.345
Level33	3.409856	0.799	539	387	0.035	613.77	2334.32	2.64	3.14	7774.218	0.616748	0.566883	0.642
Level36	3.053883	0.7224	324	328	0.04	379.24	1418.69	2.43	2.96	6686.367	0.605981	0.607674	0.568
Level37	3.225633	0.7552	531	348	0.022	931.91	3874.72	2.79	3.27	7929.059	0.637728	0.553159	0.723
Level38	2.909249	0.6351	266	433	0.149	721.9	2316.18	2.75	3.17	5655.775	0.252715	0.290925	0.209
Level41	3.414239	0.8865	655	344	0.053	418.55	1769.07	2.43	2.93	8365.439	0.539919	0.532415	0.442
Level42	2.998016	0.2001	441	539	0.02	645.34	2120.87	2.7	3.18	5969.54	0.087422	0.128833	0.061
Level43	3.408262	0.4365	647	404	0.013	966.08	4106.32	2.83	3.4	9404.3	0.931365	0.929322	0.810
Level46	3.245232	0.9649	262	370	0.027	397.61	1629.26	2.47	3.02	5256.529	0.306714	0.331157	0.307
Level47	3.363655	0.6541	559	327	0.009	738.68	3226.43	2.72	3.29	8489.448	0.645999	0.677287	0.605
Level48	3.229161	0.371	603	509	0.079	396.03	1809.91	2.46	3.05	11157.58	0.653963	0.599403	0.637
Level51	3.053883	0.7224	324	328	0.04	379.24	1418.69	2.43	2.96	6686.367	0.427375	0.419153	0.429
Level52	3.292949	0.5848	614	451	0.019	885.71	4098.85	2.89	3.53	10752.46	0.892544	0.776335	
Level53	3.393257	0.7825	724	383	0.02	1342.48	5391.07	3.02	3.54	10356.84	0.877734	0.90218	0.806
Level56	3.092351	0.4817	221	511	0.038	568.94	2292.25	2.63	3.17	5989.278	0.48497	0.468351	0.490
Level57	3.276325	0.9622	568	516	0.211	407.54	1839	2.45	3.06	10614.53	0.766321	0.739926	0.732
Level58	3.316638	0.7033	468	580	0.015	695.15	2497.15	2.73	3.17	11913.08	0.855751	0.798989	0.885
Level61	3.40571	0.713	358	170	0.067	445.98	1571.86	2.46	2.85	3795.33	0.835999	0.758596	0.898
Level62	3.344484	0.8875	440	334	0.058	372.75	1739.89	2.3	2.79	4544.457	0.825145	0.746862	0.888
Level63	3.126846	0.8606	209	367	0.008	239.93	863.47	2.21	2.73	8510.356	0.690212	0.696093	0.620
Level66	3.053883	0.7224	324	328	0.04	379.24	1418.69	2.43	2.96	6686.367	0.599263	0.582735	0.602
Level67	3.366829	0.6291	494	556	0.024	716.96	3354.99	2.79	3.37	10297.18	1	1	0.944
Level68	3.354845	0.8797	228	416	0.024	568.04	2199.68	2.7	3.18	5777.199	0.900027	0.823547	0.970
Level71	3.417385	0.7025	598	447	0.016	694.17	3027.17	2.72	3.27	7754.234	0.871114	0.781129	0.963

Appendix Table A.2. Description of each metric used in this study

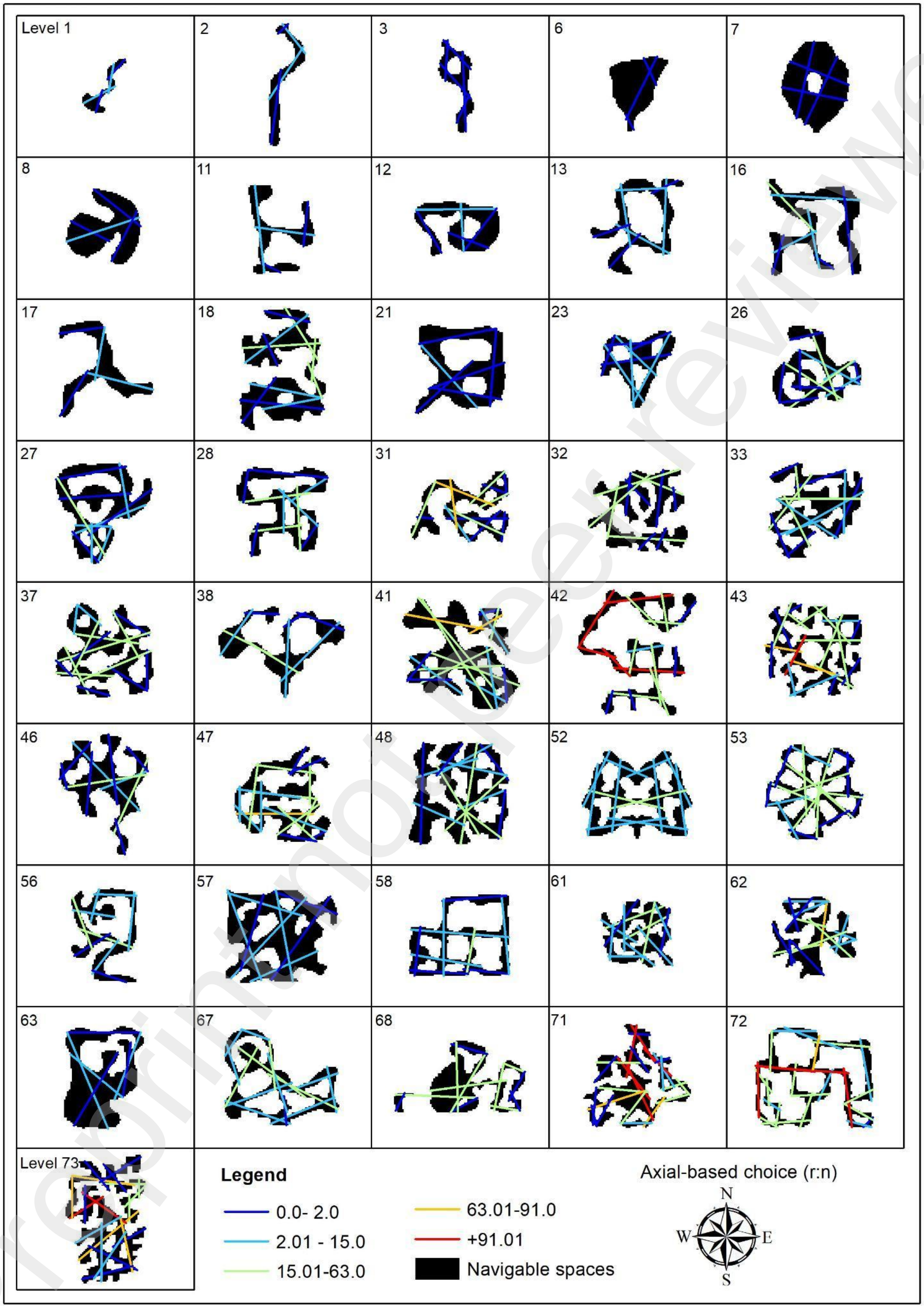
Group	Term	Meaning
Task specific	Destinations	Checkpoints are the locations where a way-finder should reach to complete a wayfinding task successfully.
	Weather	Two weather conditions are coded in this study: foggy or clear weather/visibility condition.
Geometric (general)	Decision point (intersection)	A point where way-finders should make a decision (e.g. turn right or go straight on)
	Area moveable	Navigable area (the area where participants navigate a boat through virtual environments).
	Number of circles	Street segments with a circular shape. As the number of circles increase, the number of navigational choices increases.
	Street network entropy	Unpredictability of a street network. Hence, when the values is low, it is easy to predict the system
Geometric (space syntax)	Axial # of lines	Number of axial lines used to define navigable environments.
	Isovist/total view	Isovist view area that can be seen from the start point/total navigable area
Relational Metrics	Axial choice	Possibility for each axial line to be selected as a part of the shortest route. In this study, we used n*, 2, 3, 5 direction changes.
	Axial integration	Accessibility of axial line from the rest of the system within a specific number of direction changes. We used n, 2, 3, 5 direction changes.
	VGA connectivity	Grids/cells that are connected to each other (similar to connectivity; here the relationship between grids is explored).
	Metric reach (MR)	Total street length that a way-finder can reach up to a set distance threshold. We set 5 thresholds based on the scale of the environments: 10, 25, 50, 75 and 100 meters.
	Segment integration	Accessibility of each segment from the rest of the system within a specific number of direction changes. We used n, 2, 3, 5 direction changes.
Additional metrics used	Segment length	The length of a road segment. While measuring, the distance between two intersections is considered.
	Total segment length	Total length of road segments in each level.
	Average segment length	Average length of road segments in each level.
	Maximum segment length	Maximum length of road segments in each level.
	Dead-end	End of a street segment where there is no possible exits (i.e. cul-de-sac)

	Shortest route	A route between an origin and destination, which is the shortest one based on time needed (in our case)
	Axial map	A map that is drawn based on line-of-sight (straight lines in which people have unobstructed vision)
	All lines map	Line complex that results from drawing every straight line (all possible line-of sights).
	Segment map	A map where the space between two junctions is represented with one line
	Visibility graph analysis (VGA)	Analysing an environment considering the visual relations and using grids
	Connectivity	The number of segments intersect with a segment. A higher number of intersection means higher connectivity
	Normalised choice	This adjusts choice values according to the depth of each segment in a game level. It gives opportunity to compare structures across cases/environments.
	Mean depth	Calculated by defining a depth value to each space considering the number of spaces it is away from other spaces. We sum these values and divide by the number of spaces in the system less one (showing how deep or shallow a line is) .
	Intelligibility	The easiness of understanding an environment from any point a way-finder stands (correlation between axial connectivity-integration)
	Directional reach	Total street length that a way-finder can reach using a set specific number of direction changes. We used 10 degrees and 0 and 2 direction changes and 20 degrees and 0 and 2 direction changes in this study.
	Visual integration	Accessibility of each grid from the rest of the system within a specific number of steps (here the relationship between grids is explored).
	Visual intelligibility	The easiness of understanding an environment from any point a way-finder stands (correlation between visual connectivity-integration).

* Global measure that shows the relationship between a line towards all other lines in the system.

Appendix B. Images prepared to illustrate some of the space syntax metrics for each level

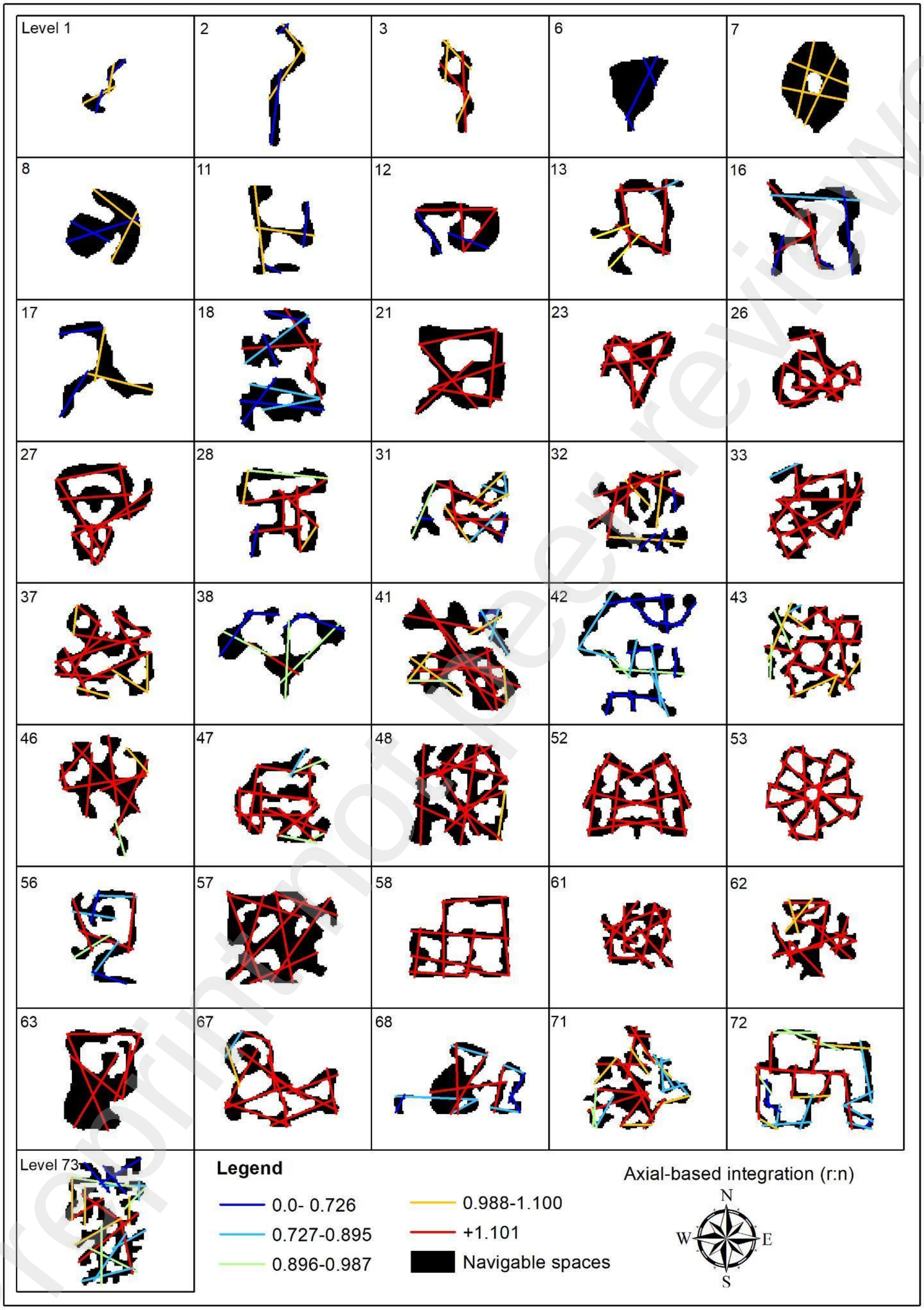
Appendix B.1. Axial based choice (r:3) for all wayfinding levels



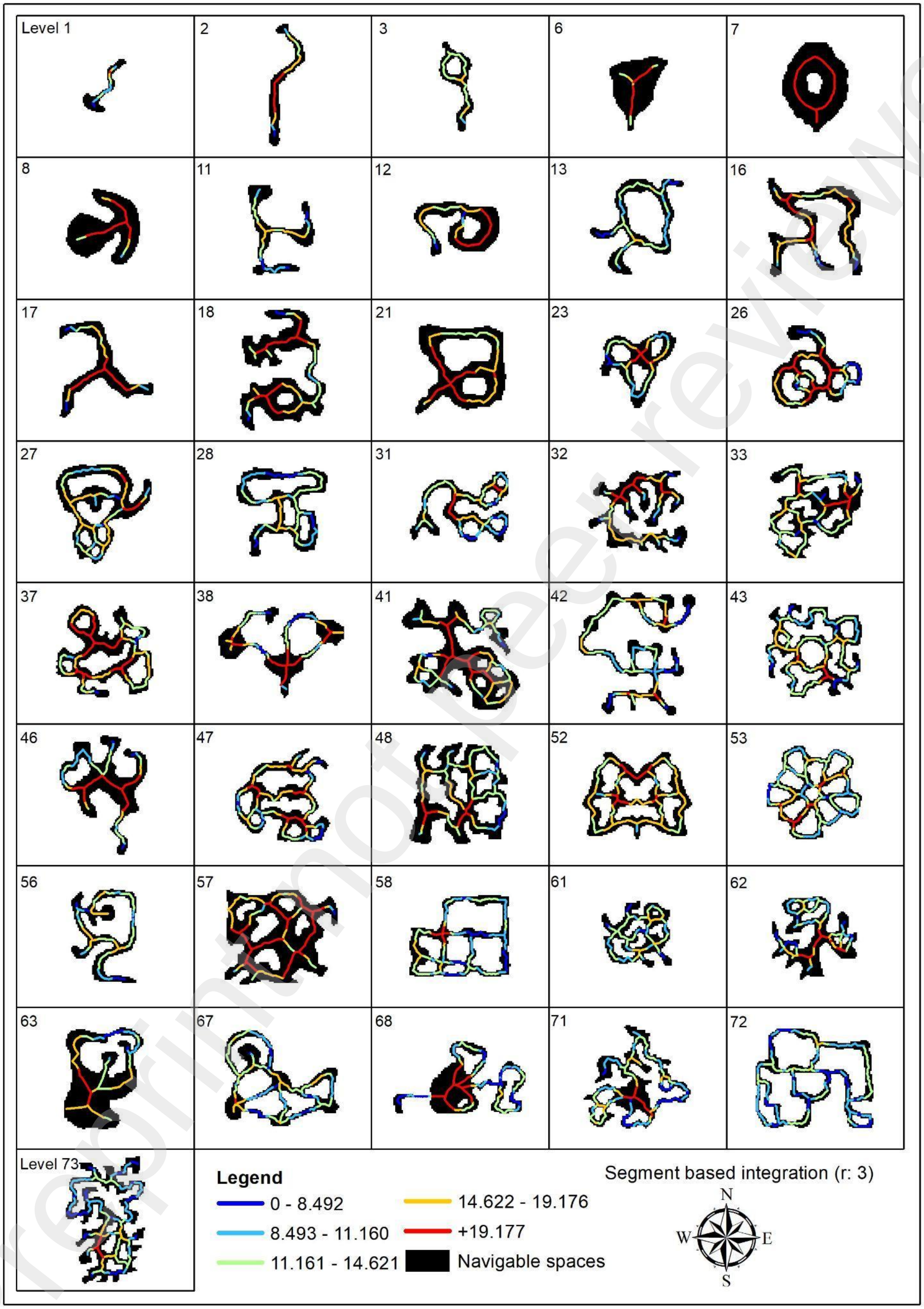
Appendix B.2. Axial based choice (r:n) for all wayfinding levels

Appendix B.3. Axial based normalised choice (r:n) for all wayfinding levels

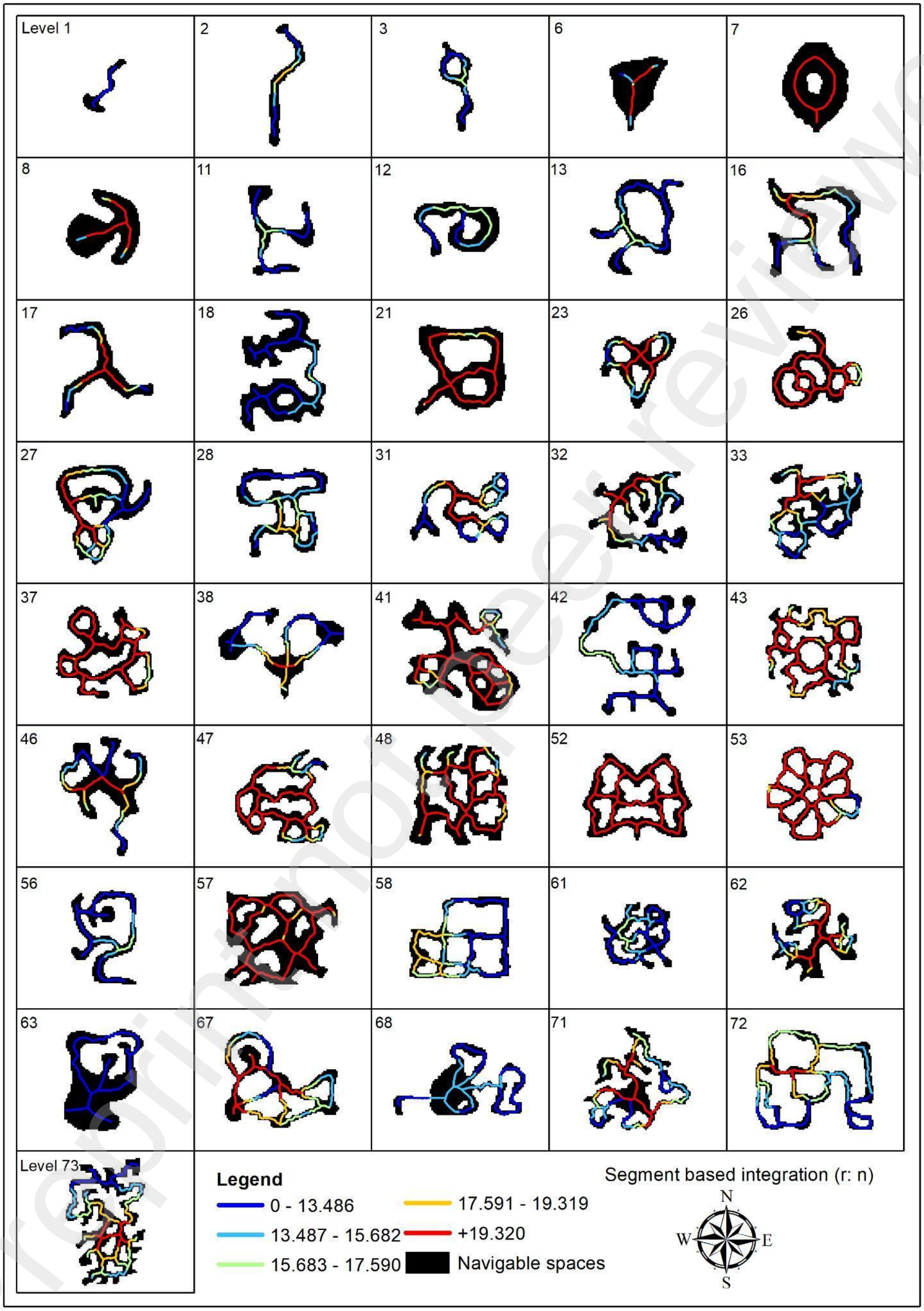
Appendix B.4. Axial based integration (r:3) for all wayfinding levels



Appendix B.5. Axial based integration (r:n) for all wayfinding levels



Appendix B.6. Segment based integration (r:3) for all wayfinding levels



Appendix B.7. Segment based integration (r:n) for all wayfinding levels

Appendix B.8. Metric reach for all wayfinding levels

Appendix B.9. Directional reach for all wayfinding levels

Appendix B.10. Visual connectivity for all wayfinding levels

Appendix B.11. Visual integration for all wayfinding levels

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