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

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 map condition. 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 rings 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 the study of spatial behaviour in ecological 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? This is a key question in the study of human navigation, and yet so far, the existing work within the cognitive sciences has failed to provide a clear answer.

The turn towards real-world approaches in the cognitive sciences has resulted in a renewed attention to the impact of environmental factors on spatial cognition. Wiener and Mallot (2003) found that region-connectivity influences navigation behaviour, in line with hierarchical theories of route planning. In their study of exploration patterns, Brunec et al. (2023) analysed integration, a space syntax measure of how well connected a path is, and found that those participants who spent more time in regions of high integration formed more accurate cognitive maps. However, most existing studies employ only a single or a few environmental metrics. This is a big setback because there is no consensus on which metrics impact navigation behaviour. Moreover, an important aspect in the study of navigation are computational models, which again often involve few environmental metrics (e.g. obstacles in Edvardsen et al., 2019, or information cost at decision points in Lancia et al., 2023). To evaluate whether computational models reproduce human navigational patterns in a given environment, we need to further our understanding of precisely how that environment affects human navigation, and this step requires advancing our knowledge of the impact of different environmental metrics.

Previous research on the navigability of environments has come from a variety of disciplines ranging from psychology to architecture. To date, a series of environmental factors have been hypothesised to impact navigation behaviour, including: 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) and intelligibility of the paths/streets (Hillier 1996, Barton et al., 2014). Farr et al (2012) reviewed existing research on environmental factors that affect navigation and listed city layout, colour and light, maps,signage, visibility, inter-connection density and space syntax measures. Another research study included differentiation, visual access, layout complexity and signage as environmental factors that affect navigation performance (Montello, 2005). Another review article (Wolbers and Hegarty, 2010) identified the following environmental cues: discrete environmental objects, global orientation cues, geometric structure of the environment and symbolic representations were mentioned. Despite the large number of candidates, it is not clear yet which environmental factors help people more or make it harder to complete a navigation task.

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) 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 mapsketching and pointing tasks, these results did not translate to wayfinding performance. 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 (i.e. passing a decision point not required to complete the wayfinding task) and repeat decision point use (i.e. passing the same decision point twice). Also, when participants got lost, they wandered around, thus increasing the exposure to the environment which could have affected their performance in the mapsketching task (Haq & Girotto, 2003). Results of another wayfinding experiment highlighted 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 situations 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 study which environmental factors influence navigation (or wayfinding) performance, one would ideally test a large number of participants in a large number of spaces in which environmental factors are systematically varied. This approach is, of course, very time and resource consuming compared to most prior studies addressing this question. Here, we surmounted these challenges by 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 (SHQ) (Coutrot et al., 2018; Spiers, Coutrot and Hornberger, 2021). The Gamification of experiments is a powerful tool for data acquisition. It has the potential to provide a large data sets especially if the game/experiment is designed to be fun and interactive (De Leeuw et al., 2020). Moreover, gamified studies allows collecting data from large samples from different parts of the world, which is what SHQ was designed for (Morgan, 2016). Previous work has used SHQ to study the relationship between sleep duration and spatial navigation performance (Coutrot et al., 2022), the relationship between gender differences in navigation and countrywide gender inequality (Courtrot et al., 2018), and age-related changes in spatial navigation strategies (Greg et al., 2022). 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). 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 (to see the proportion of the total number of players per level, see Appendix B). 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). 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. Level progression was linear, so participants needed to complete level N in order to access level N+1. 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 of the game. 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 (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.

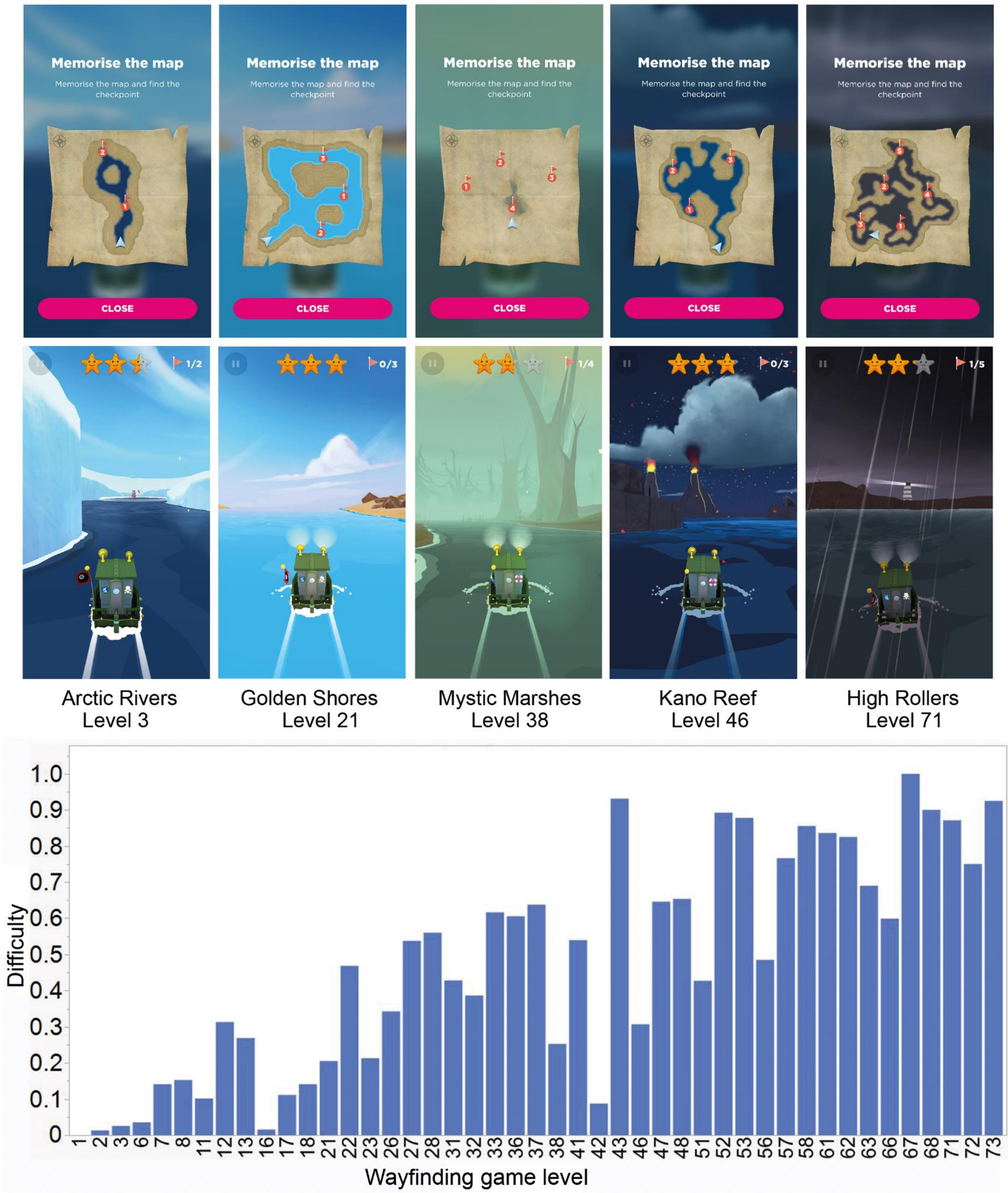

Figure 1. Navigation Task Sea Hero Quest. Top row: Example maps shown to participants at the start of 5 of the 45 wayfinding levels tested. Each map is from a different themed region in the game. Maps show starting location (blue arrow) and checkpoints (red circles) to be navigated to in the order indicated by the numbers in the circles. 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. Middle map (level 38) shows an example of a map where the layout is obscured in the map image.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).

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[1]. 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 simplifying/increasing what was estimated by the design team for complexity of the layout. All our environmental analyses for 58 metrics were completed only after the environment design was finalised and converted into game environments.

2.4) Environment analysis

To analyse the environmental configuration of each of the 45 levels, we employed 58 separate metrics (for a detailed description of each of the metrics, see Appendix A Table A1, and see Appendix A Table A.2. to see the results of our calculation for 58 metrics), which, based on previous studies, were all potentially linked to navigation performance. The metrics fall into four families: task-specific metrics; space syntax relational metrics; space syntax geometric metrics; and general geometric metrics.

[1] The term "difficulty" was used in a previous paper (Coutrot et al., 2019) and we continue to use the term for clarity and consistency.

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 goal locations 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).

Space syntax relational metrics and space syntax geometric metrics were developed using space syntax (see Appendix C.1-C.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 (Figure 2a). 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. 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.

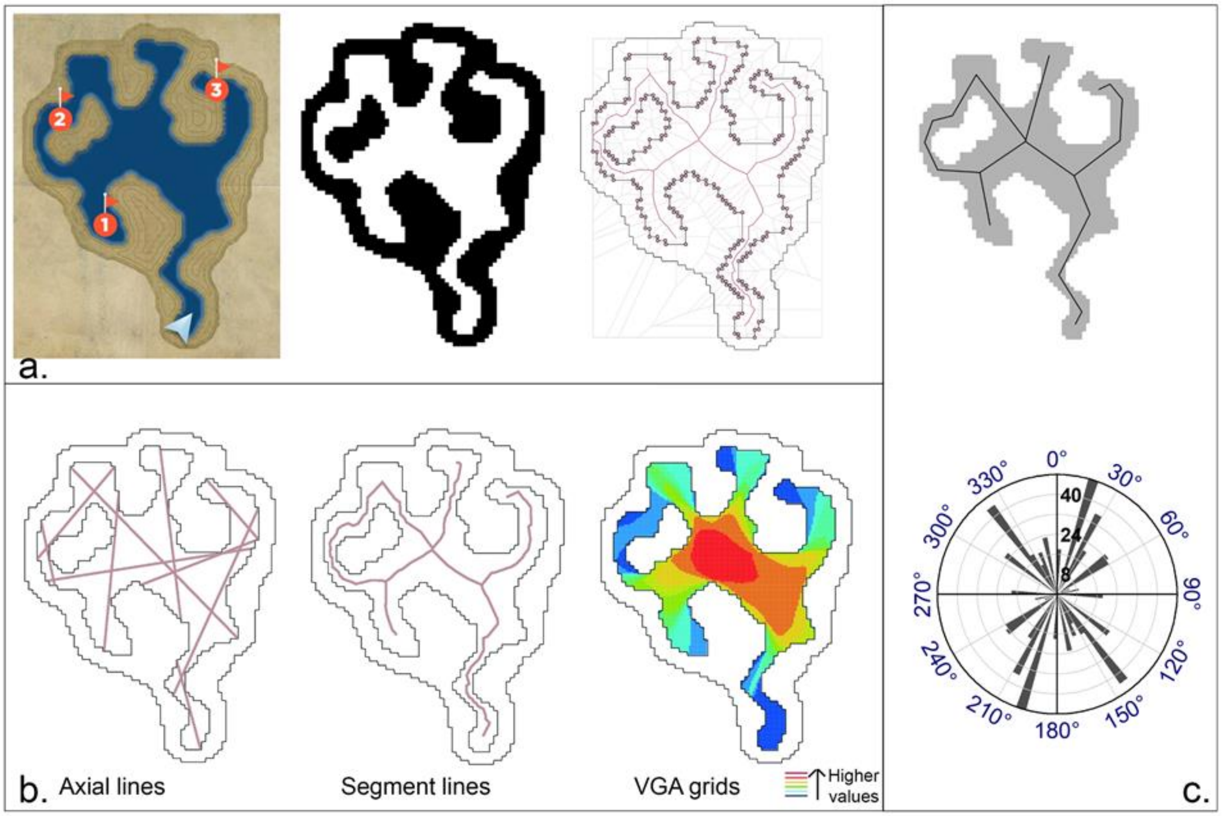

Figure 2. a: The procedure to create segment maps. Images from left to right: screenshot of the map of level 46, black and white image showing navigable spaces (in white), and segment map created from the same file using voronoi polygons b: Illustrations of 3 space syntax analyses. Left and in middle: line-based maps; right: point/grid based analysis, see text for more details c: Simplified segment map and a rose plot of the segments' bearings. The rose plots are used to calculate street network entropy.
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 produced using both line-based analysis (e.g. Seg_Connectivity) and VGA analysis (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 rings* (# of rings), *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, was hypothesised to be important for environmental layout complexity (Boeing, 2018). *Number of rings* corresponds to the number of rings 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. Participants' trajectories, i.e., the path they used, were recorded by sampling the participants' coordinates in the environment with a rate of 2Hz. The length of the trajectory was then calculated. 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. 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.

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

Equation 2. Difficulty score formula

Equipped with the spatial metrics outlined in previous sub-sections 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 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[2] (MR 25).
We then ran a second 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.

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

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

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 (Appendix D). 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 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 ($r=0.76$, $p<.001$), number of circles ($r=0.76$, $p<.001$) and number of destinations ($r=0.74$, $p<.001$). There is a negative correlation between the difficulty and isovist view area from the start/total ($r=-0.54$, $p<.001$), weather ($r=-0.48$, $p<.001$; i.e. worse performance with fog) and segment integration ($r=-0.41$, $p<.05$). The results show that several geometric (general) and task specific features correlated with difficulty.

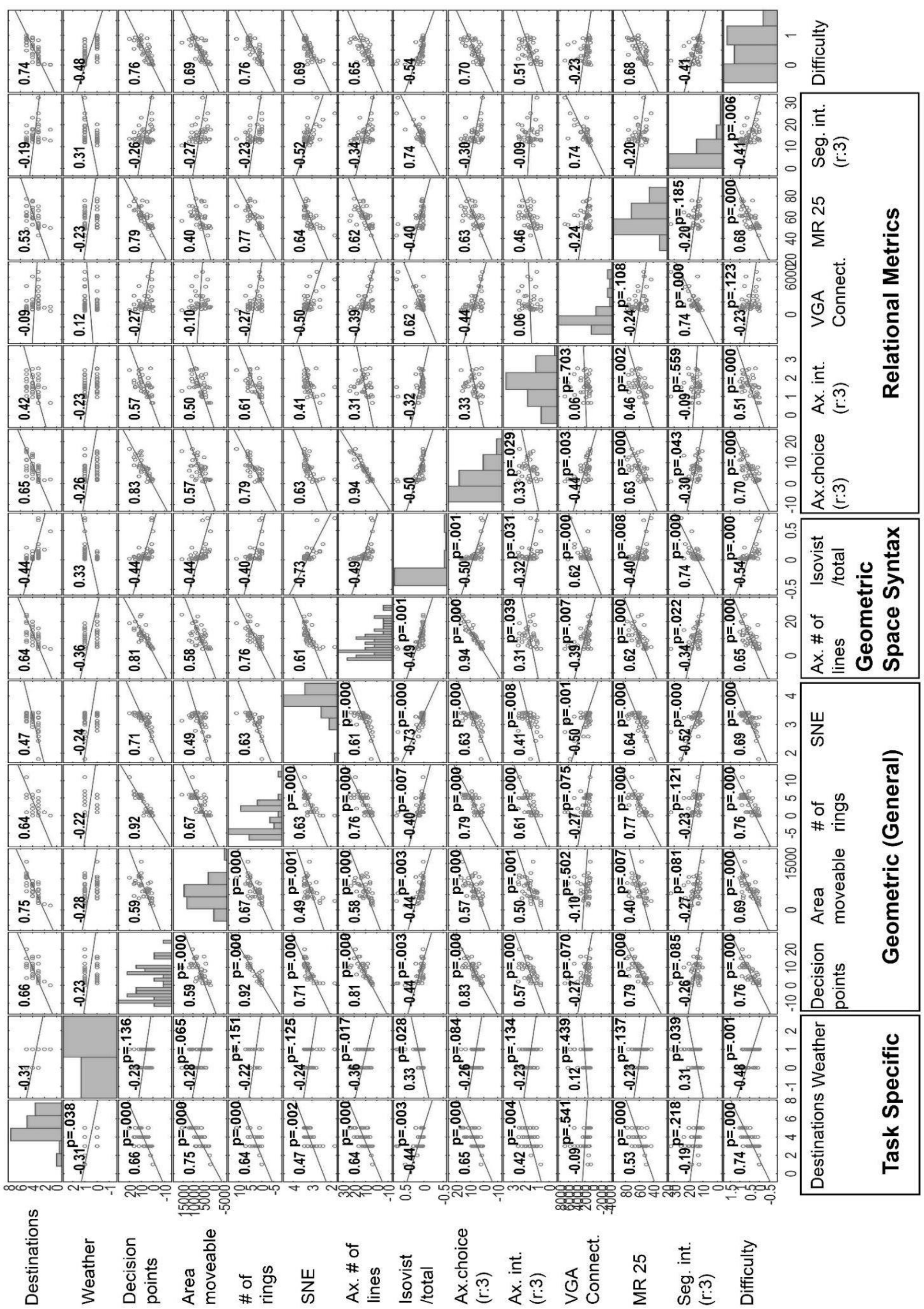

Figure 3. Correlation matrix with all the metrics that met threshold for significant correlation with difficulty using our Lasso approach. Each data point represents a wayfinding level. The line represents the least square regression line, the number next to it the regression coefficient, and the number on the right shows the p values. Histograms show the metrics distribution.

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, but also see Appendix E to see the Lasso coefficients for the selected metrics across age groups). 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.

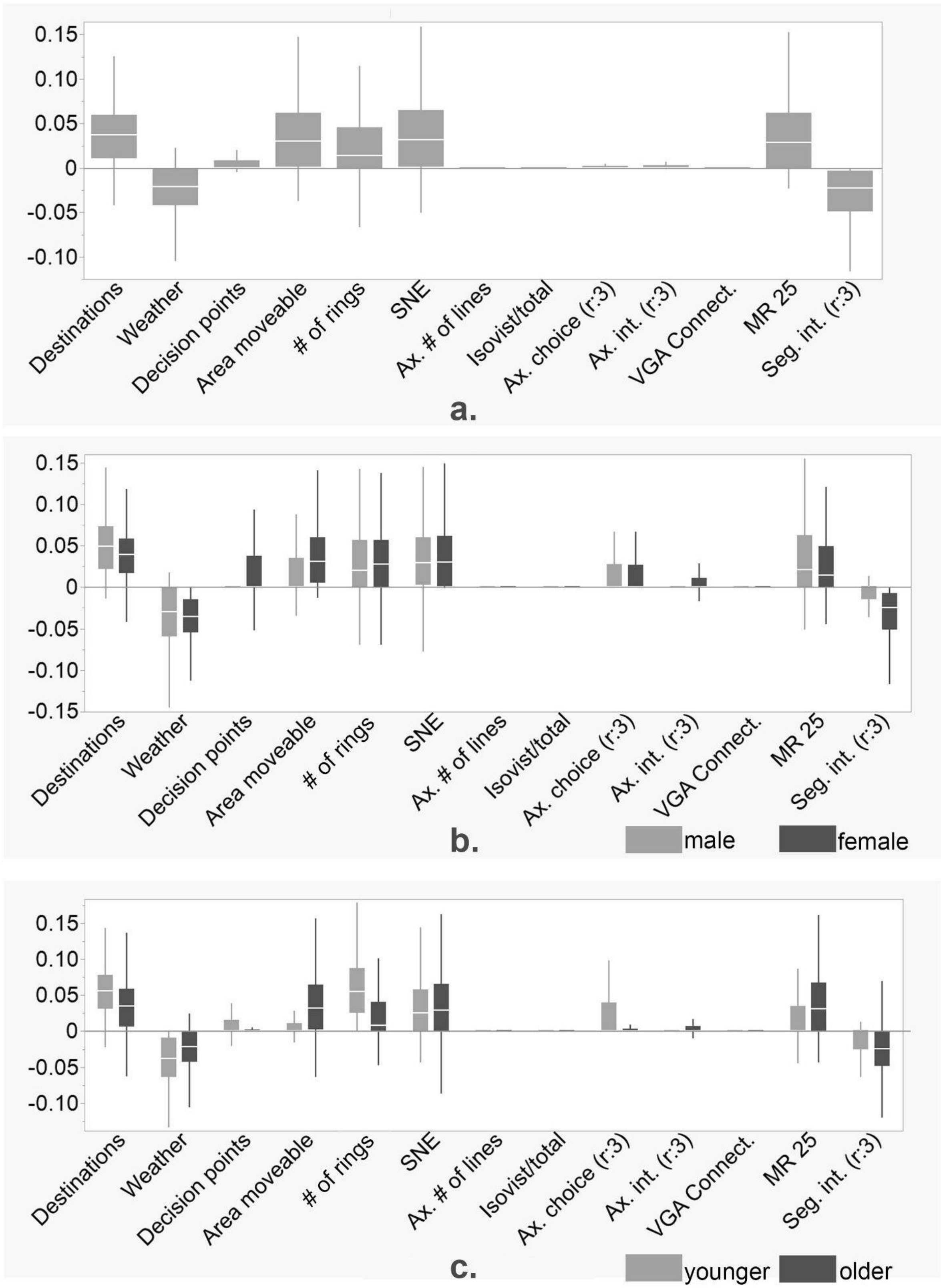

Figure 4. Lasso coefficients for the selected metrics from each family (a), coefficients for Males and Females (b), and coefficients for different Younger and Older participants (c). The Lasso computation was bootstrapped

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 aimed to understand the factors that make an environment hard to navigate. We used 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 navigability. We measured 58 spatial metrics —divided into four families— and, using a Lasso regression, we found the set of metrics from each family that best explained 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 found that several other predicted metrics did not predict difficulty, such as intelligibility. Thus, our results indicate that perceived 'complexity' of an environment is insufficient to predict how hard it will be to navigate. Instead it is important to measure specific geometric features. We also discovered differences between different socio-demographic groups. For example, the number of decision points was more predictive of navigational performance for female participants than for male participants and for younger participants than for older ones. These findings help explain why some environments are harder to navigate than others and provide principles for the design of navigable environments. Below we discuss the theoretical importance of each of the selected metrics. We then discuss an interesting outcome of the present study, which is that some variables (*axial integration* and *number of decision points*) had an impact on difficulty only for certain demographics in our sample. Finally, we discuss limitations of our study related to the use of mobile testing, the inclusion of participants, and the impact of landmarks on navigation.

4.1.) Theoretical import of the selected metrics

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 also predicts wayfinding difficulty (Barhorst-Cates et al., 2021). This is also consistent with results from 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). Our results suggest that growing up in more entropic environments provides greater challenge for wayfinding thus training navigation abilities compared to growing up in environments with more organised grid-like layout.

The impact of entropy on wayfinding difficulty connects the present findings with recent information-theoretic approaches to the study of navigation (Lancia et al., 2023). Previous experimental work has employed information theory measures to model the saliency of different decision points when processing route directions (Takemiya et al 2012), the capacity of grid cells in spatial memory (Mathis et al., 2012), agent-signage interaction (Dubey et al., 2021), or the cognitive cost of shortcuts (Lancia et al., 2023), to name but a few examples. Our findings advance this line of work by showing that the information theoretic measure of street network entropy captures much of what makes an environment difficult to navigate. Moreover, because we have put entropy in competition with other potential predictors through the Lasso regression, our results are more robust than previous studies employing a single environmental metric. Furthermore, as entropy is a measure of unpredictability, this finding links with predictive approaches to spatial cognition. If, as recent models of hippocampal and prefrontal function suggest (e.g. Brunec and Momennejad 2022; Stoianov and et al., 2022), navigation depends on hierarchically nested predictions of the environment, it is congruent that the predictability of the environment (i.e. street network entropy) becomes a key factor in navigation difficulty.

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. *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. Using neuroimaging, we have previously found that the right anterior hippocampus tracked the changes in segment integration of the streets entered during navigation in London (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. One of the reasons for the divergent results can be the environment investigated in the 2001 study. Only one urban area, the area around St Giles Circus in Central London, was analysed rather than multiple layouts. In addition, pedestrian flow was sampled for 5 minute periods within every hour from the morning till the evening. These differences in methods and case study may be the reason for the difference in results.

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 difficulty, 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 ringiness 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. However, 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 without salient objects can cause many locations to 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 ringiness makes an environment harder to navigate. Ringiness in Sea Hero Quest paths provided alternative routes for the participants (e.g., they could take one route to a location and another one to go back). Moreover, when combined with the other factors we had, such as fog or non-existence of salient objects, it might become harder for participants to recover from any wrong decision. Therefore, the more rings 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 rings 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). In addition, if it is foggy, it becomes harder for participants to see environmental clues and use these to inform and navigate. 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. Moreover, prior studies have suggested intelligibility would be an important factor for predicting difficulty (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 difficulty and these can be high in environments which score high on intelligibility.

4.2.) The impact of the variables on different socio-demographic groups

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, but it is also about participants' determination. Even if participants got lost or made wrong decisions during navigation, they could correct their path and complete the navigation tasks. 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.

4.3.) Limitations and future directions

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 while it can be more restricted in virtual environments, which can cause difficulty of spatial learning (Barhorst-Cates et al., 2019). In addition, 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 navigational difficulty 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. It would also be useful to explore how different environmental features impact the performance of participants using different strategies to navigate (e.g. a counting-dependent strategy vs. a landmark-dependent strategy, as in Greg et al., 2022).

5. Conclusion

In conclusion, we find the key elements that determine the navigability of an environment, in other words, navigational difficulty, are: *entropy*, *segment integration* (closeness centrality of paths), *number of decision points*, *number of rings*, *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 visibility. 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 difficulty (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. 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 rings	Street segments with a circular shape. As the number of rings increases, the number of navigational choices increases.
	Dead-end	End of a street segment where there is no possible exits (i.e. cul-de-sac)
	Segment length	The length of a road segment. While measuring, the distance between two intersections is considered.
	Average segment length	Average length of road segments in each level.
	Maximum segment length	Maximum length of road segments in each level.
	Total segment length	Total length of road segments in each level.
	Shortest route	A route between an origin and destination, which is the shortest one based on time needed (in our case)
	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.
	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
	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 lines from the rest of the system within a specific number of direction changes. We used n, 2, 3, 5 direction changes.
	Connectivity	The number of segments intersect with a segment. A higher number of intersection means higher connectivity
	VGA connectivity	Grids/cells that are connected to each other (similar to connectivity; here the relationship between grids is explored).
	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).
	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) .
	Normalised choice	This adjusts choice values according to the depth of each segment in a game level. It gives the opportunity to compare structures across cases/environments.
	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.
	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.
	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.
	Intelligibility	The easiness of understanding an environment from any point a way-finder stands (correlation between axial connectivity-integration)
	Visual intelligibility	The ease 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.

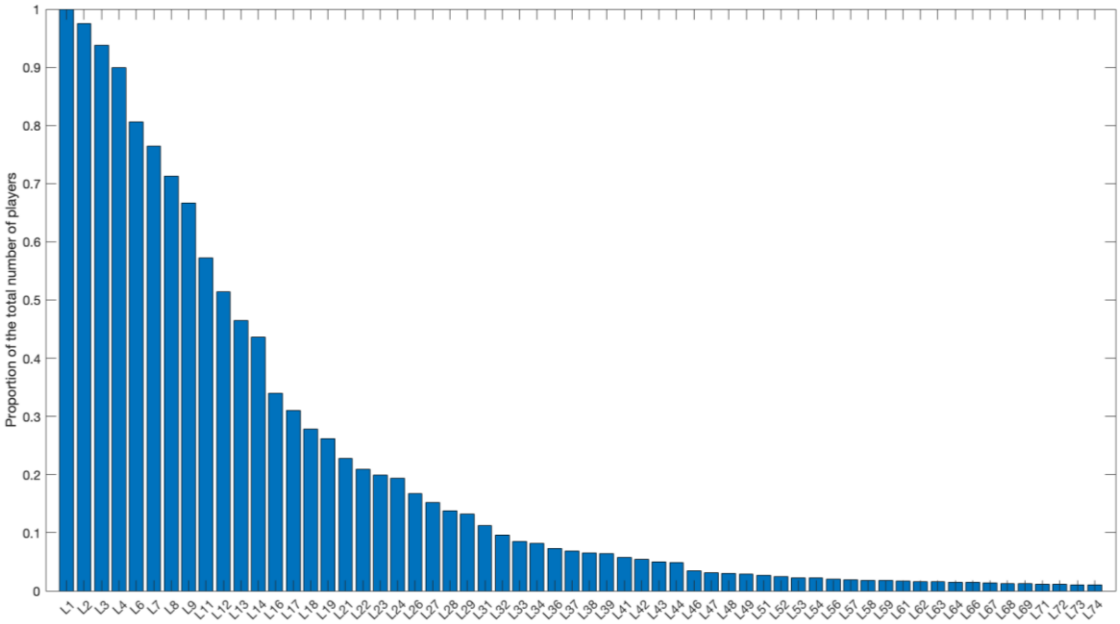
Appendix Table A. 2. Fifty-eight metrics used in this study and the results of each level. Note that task-related conditions are converted to numeric data. Weather and map conditions were shown as 0 or 1. In both conditions, "1" represents clear weather/ map conditions and "0" represents occluded map/ low visibility conditions.

Levels	Theme	Type	Difficulty	Weather	Weatherif	Map	Mapif	axintelligibility	axnumberoflines	axconnectivity	axchoicen	axchoicer2	axchoicer3	axchoicer5	axchoicenormn	axchoicenormr2	axchoicenormr3	axchoicenormr5	lnhh	lnhhr2	lnr3	lnr5	axlinelength	axMeanDepth	alllinesconnectivity	alllineschn	alllinesnormchn	alllineslnn	VGAConnectivity	VisualIntegrationHH
Level1	Arctic Rivers	Simple	Super Easy	<undefin	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 Easy	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 Easy	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	Checkpo	Easy	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	Checkpo	Easy	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	1063.59	0.0007	13.74	6839.33	37.85
Level8	Arctic Rivers	Checkpo	Easy	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	1297.69	0.001	10.05	4447.21	27.43
Level11	Arctic Rivers	Checkpo	Easy	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	Checkpo	Easy	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	1232.82	0.003	5.45	2215.61	12.85
Level13	Arctic Rivers	Checkpo	Easy	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	1942.71	0.002	5.57	1202.05	7.98
Level16	Golden Shores	Checkpo	Easy	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	2105.95	0.002	4.95	1662.07	6.82
Level17	Golden Shores	Checkpo	Easy	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	1051.03	0.001	9.33	2330.21	14.83
Level18	Golden Shores	Checkpo	Easy	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	4151.98	0.002	3.75	2955.52	5.34
Level21	Golden Shores	Checkpo	Easy	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	1309.06	0.001	9.71	3727.27	15.88
Level22	Golden Shores	Checkpo	Easy	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	1942.71	0.002	5.57	1202.05	7.98
Level23	Golden Shores	Checkpo	Medium	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	Checkpo	Medium	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	1604.87	0.001	7.07	1436.87	9.59
Level27	Golden Shores	Checkpo	Medium	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	2709.93	0.001	7.15	1830.82	9.8
Level28	Golden Shores	Checkpo	Medium	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	1568.17	0.003	5	1211.39	6.49
Level31	Mystic Marshes	Checkpo	Medium	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	3523.32	0.002	4.28	922.41	5.5
Level32	Mystic Marshes	Checkpo	Medium	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	3233.48	0.001	5.21	1484.24	7.04
Level33	Mystic Marshes	Checkpo	Medium	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	2986.72	0.001	6.04	1672.64	8.76
Level36	Mystic Marshes	Checkpo	Easy	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	1942.71	0.002	5.57	1202.05	7.98
Level37	Mystic Marshes	Checkpo	Medium	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	3720.61	0.001	6.17	1592.54	7.99
Level38	Mystic Marshes	Checkpo	Medium	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	Checkpo	Easy	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	4741.96	0.001	6.22	2995.79	9.57
Level42	Mystic Marshes	Checkpo	Medium	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	6808.24	0.003	2.47	867.64	2.94
Level43	Mystic Marshes	Checkpo	Medium	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	5053.47	0.001	4.16	768.89	5.01
Level46	Kano Reef	Checkpo	Easy	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	2145.73	0.001	8.53	2938.01	13.24
Level47	Kano Reef	Checkpo	Medium	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	4230.72	0.001	5.06	1271.08	6.84
Level48	Kano Reef	Checkpo	Hard	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	3196.52	0.001	6.1	2186.82	8.45
Level51	Kano Reef	Checkpo	Easy	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	1942.71	0.002	5.57	1202.05	7.98
Level52	Kano Reef	Checkpo	Hard	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	Checkpo	Hard	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	3803.54	0.001	6.17	732.79	7.04
Level56	Kano Reef	Checkpo	Hard	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	2190.35	0.002	4.92	884.15	5.89
Level57	Kano Reef	Checkpo	Hard	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	2933.67	0.0005	10.39	4564.93	15.3
Level58	Kano Reef	Checkpo	Hard	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	1439.12	0.002	5.78	1128.02	7.8
Level61	High Rollers	Checkpo	Easy	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	Checkpo	Medium	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	2150.37	0.001	6.02	1615.68	8.89
Level63	High Rollers	Checkpo	Medium	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	1487.54	0.001	8.16	6094.49	24.92
Level66	High Rollers	Checkpo	Easy	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	1942.71	0.002	5.57	1202.05	7.98
Level67	High Rollers	Checkpo	Hard	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	3615.47	0.001	5.29	1081.73	6.57
Level68	High Rollers	Checkpo	Medium	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	2636.84	0.002	5.59	2421.75	7.99
Level71	High Rollers	Checkpo	Hard	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	5357.67	0.002	3.97	1175.55	5.13
Level72	High Rollers	Checkpo	Hard	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	3687.89	0.003	3.11	685.55	3.98
Level73	High Rollers	Checkpo	Hard	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	4421.64	0.002	3.95	920.47	4.28

Appendix Table A.2. (Continued)

Levels	SegConnectivity	SegChoicen	SegChoice2	SegChoice3	SegChoice5	SegInn	SegIn2	SegIn3	SegIn5	avrgsegmntlength	maxsgmntlength	DR100	DR102	DR200	DR202	MR10	MR25	MR50	MR75	MR100	decisionpoints	destinations	deadends	ofdeadendssegmap	circles	EntropySNE	VGAintelligibility	segmentlength	shortestroute	isovisttotal	segchoice50m	segchoice100m	segchoicenorm50m	segchoicenorm100m	areamoveablespaces	normdifficulty	normdifficulty_f	normc culty_
Level1	1.95	494	33	64.25	141.8	9.38	13.37	12.74	11.67	60	60	2.7	12.54	2.7	12.54	20	50	60.27	60.27	60.27	0	1	1	1	0	NaN	0.5477	60	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0	0.00647	
Level2	1.97	2106.67	66.02	154.56	400.69	14.46	18.49	17.79	17.03	138	138	3.83	8.61	3.88	14.08	20	50	100	138	137.99	0	1	1	1	0	NaN	0.6435	138	138	0.489	NaN	NaN	NaN	NaN	1452.183	0.01311	0	0.018
Level3	2.06	552.09	30.45	74.09	231.03	13.11	13.89	13.44	13.49	38.5	58	3.82	12.73	4.03	17.09	20	52.01	109.6	140.9	152.42	2	2	2	2	1	NaN	0.9296	154	107	0.175	304.9	560.65	2.35	2.59	1912.475	0.025299	0.019847	0.036
Level6	1.87	70	65.18	70	70	25.25	25.32	25.25	25.25	32.3	47	11.05	26.7	19.89	39.89	19.84	42.81	49.05	49.05	49.05	1	3	1	3	0	1.791759	0.0705	97	106	0.712	70	70	1.68	1.68	2831.622	0.035398	0.034645	0.05
Level7	2.03	167.96	227.72	507.76	167.96	32.44	32.03	32.32	32.44	85.5	158	5.92	36.91	15.21	61.4	23.49	53.65	103.7	153.7	170.95	1	3	0	1	1	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	584.49	98.2	241.75	558.28	22.62	24.19	22.33	22.56	47.3	58	7.46	19.36	16.02	42.94	20	49.77	100.4	138.6	141.38	1	3	3	3	0	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	2060.93	32.57	77.75	232.933	12.57	13.64	13.21	13	68	76	3.5	15.41	6.83	19.28	21.47	52.14	104.4	154.4	197.53	1	3	3	3	0	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	1.97	2730	68.84	151.43	404.34	13.86	18.03	17.55	16.85	115	129	5.95	22.28	6.01	33.98	20	50	99.53	128.4	153.35	1	3	1	1	1	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	2.01	3378.33	24.03	59.73	184.43	12.36	12.06	11.87	11.83	54	103	3.41	16.23	5.34	22.37	20.25	50.84	107.7	168.4	221.72	3	3	3	3	1	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	2.02	5813.61	54.1	128.49	373.81	15.18	16.81	16.71	16.66	48.1	165	4.3	13.81	6.46	22.8	20.87	51.97	105.9	155.9	200.39	3	3	4	5	0	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	1589	81.57	179.57	498.45	18.52	19.69	19.31	18.69	71.3	87	1.95	11.99	10.35	37.66	20	50	100.2	150.2	197.02	1	3	3	3	0	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	2.07	4727.48	50.75	125.72	367.47	12.67	16.41	16.46	16.54	28.8	97	6.52	25.22	7.62	35.85	21.63	54.83	108.3	160.8	207.93	7	3	4	7	1	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	2.07	531.93	76.05	202.56	686.4	24.3	19.35	20.23	22.49	69.6	171	3.66	23.66	5.66	41.56	24.48	61.69	141.2	228.5	292.96	2	3	1	1	2	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	2.01	3378.33	24.03	59.73	184.43	12.36	12.06	11.87	11.83	54	103	3.41	16.23	5.34	22.37	20.25	50.84	107.7	168.4	221.72	4	3	3	3	1	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	2.1	577.56	33	95.14	364.79	19.58	13.54	14.24	16.42	41.2	84	5.1	19.57	6.17	28.19	19.59	59.09	146	241.8	285.54	5	3	1	1	3	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	2.15	576.32	57.43	145.68	525.48	26.21	16.87	17.57	20.03	30.7	90	4.07	16.85	5.85	25.38	24.08	75.82	201.6	333.8	408.33	9	4	1	1	5	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	2.06	7179.98	40.91	97.51	296.86	16.26	14.8	14.8	15.04	29.9	131	4.6	14.84	6.26	22.39	20.84	58.82	133.8	208.4	273.27	10	4	1	2	5	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	2.06	1167.7	25.4	66.01	213.73	14.89	12.15	12.2	12.67	55.2	201	5.49	21.09	6.09	25.98	21.08	62.83	148.6	236.5	310	5	4	1	1	3	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	2.06	5966.37	32.43	80.56	252.46	15.96	13.26	13.42	13.81	33.5	75	2.82	11.86	3.56	13.6	22.26	61.27	126.4	183.4	246.69	8	3	2	2	4	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	2.09	4879.12	67.1	160.5	432.17	17.26	17.56	18.1	18.56	21.9	56	4.1	17.11	5.42	26.09	21.39	60.16	129.9	190.1	247.51	8	4	10	10	0	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	2.07	7751.9	34.02	85.5	279.95	15.8	14.06	14.16	14.68	29.9	81	5.05	19	7.72	28.62	21.28	59.43	135.8	224.1	292.95	11	4	2	3	5	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	2.01	3378.33	24.03	59.73	184.43	12.36	12.06	11.87	11.83	54	103	3.41	16.23	5.34	22.37	20.25	50.84	107.7	168.4	221.72	3	3	3	3	1	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	2.07	5334.54	135.74	301.73	819.23	27.24	22.61	23.19	24.05	33.1	93	3.9	14.64	5.47	25.88	22.67	64.65	147.6	234.4	322.78	10	4	2	2	5	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	2.05	4770.28	50.02	111.28	291.31	14.38	15.39	15.69	15.56	26.6	71	4.44	22.11	4.88	30.59	23.54	60.06	123.9	188.7	254.72	5	4	2	5	1	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	2.13	3396.43	48	129.59	478.7	24.46	15.66	16.51	18.91	24.2	49	4.9	21.91	7.49	33.19	22.45	66.51	164.4	276.3	388.69	16	3	4	5	7	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	2.03	15745.7	35.45	80.98	256.64	12.76	13.84	13.66	13.78	29.4	83	4.35	18.48	5.42	23.55	20.6	53.19	111	159.2	201.03	6	4	5	5	2	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	2.08	7967.31	31.87	83.24	283.44	21.98	13.4	13.71	14.7	25.8	98	4.2	14.05	5.21	19.6	22.86	67.29	158.9	264.8	369.14	15	4	6	5	6	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	2.02	5454.03	58.83	153.14	443.4	15.09	16.86	16.83	17.13	32.7	77	4.91	20.11	8.91	34.43	20	52.26	106.7	161.7	214.48	4	3	4	4	1	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	2.09	7021.11	40.37	108.1	360.12	20.87	14.73	15.21	16.48	29.4	58	3.56	14.2	4.52	20.56	23.24	69.39	168.9	278.5	393.08	12	4	2	2	6	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	2.13	3332.64	32.63	89.48	309.86	22.49	13.85	14.27	15.68	30.1	96	5.69	19.44	7.3	28.26	21.55	64.99	167.3	293.3	416.1	12	5	4	4	5	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	2.01	3378.33	24.03	59.73	184.43	12.36	12.06	11.87	11.83	54	103	3.41	16.23	5.34	22.37	20.25	50.84	107.7	168.4	221.72	3	3	3	3	1	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	2.11	1368.47	48.19	121.56	415.11	27.66	16.06	16.49	17.82	40.9	72	3.24	14.25	4.71	23.22	20.69	60.93	161	301.6	430.19	11	5	1	1	6	3.292949	0.5848	614	451	0.019	885.71	4098.85	2.89	3.53	10752.46	0.892544	0.776335	
Level53	2.1	10910.6	31.95	83.02	285.89	23.64	13.22	13.59	14.6	24.1	58	3.24	11.36	3.49	13.24	22.2	70.72	186.9	312.8	447.82	20	5	0	0	11	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	2.02	6436.72	32.08	76.37	223.92	12.01	13.52	13.2	13.07	42.2	130	2.29	13.53	2.96	16.08	19.87	49.15	97.04	149.6	196.88	4	5	5	4	1	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	2.08	5024.07	72.12	180.15	557.68	24.29	18.96	19.68	20.91	28.4	82	5.32	21.81	11.33	45.58	22.31	62.2	147.7	231.3	313.38	12	5	3	4	5	3.276325	0.9622	568	516	0.211	407.54	1839	2.45	3.06	10614.53	0.766321	0.739926	0.732
Level58	2.06	8271.16	26.4	66.6	210.03	14.3	12.14	12.27	12.65	39.8	144	2.69	13.66	3.22	17.92	24.3	70.81	178.4	314	431.54	10	5	0	0	6	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	2.14	3107.25	23	60.07	169.17	12.55	11.87	12.23	12.61	18.8	67	3.45	15.38	4.23	19.06	22.87	70.49	169.7	251.5	299.85	12	3	4	4	5	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	2.21	1663.73	27.8	78.34	252.81	17.86	12.62	13.46	15.3	16.2	38	3.68	18.36	4.33	24.66	24.46	75.28	156.8	248.8	351.3	16	4	6	6	6	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	2.03	3468.11	36.32	84.2	204.6	8.77	14	13.69	13.02	45.3	171	9.46	31.94	12.74	46.78	19.68	53.01	103.3	137.2	172.12	4	4	1	4	1	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	2.01	3378.33	24.03	59.73	184.43	12.36	12.06	11.87	11.83	54	103	3.41	16.23	5.34	22.37	20.25	50.84	107.7	168.4	221.72	3	3	3	3	1	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	2.07	6280.79	26.43	63.98	204.26	17.65	12.25	12.27	12.57	38	127	4.06	16.35	4.45	19.03	21.48	61.58	151.3	263.4	386.71	10	5	2	2	3	3.366829	0.6291	494	556	0.024	716.96	3354.99	2.79	3.37	10297.18	1	1	0.944
Level68	2.04	7910.74	34.75	89.03	221.56	11.67	12.86	13.17	13.8	62	157	3.75	30.49	5.79	46.36	25.76	74.85	171.2	264.8	325.4	5	4	1	1	3	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	2.09	8428.59	28.27	73.04	230.95	16.9	12.79	12.69	13.12	33.2	83	4.47	15.15	5.21	19.73	22.19	61.85	136.7	216	308.21	11	5	5	3	5	3.417385	0.7025	598	447	0.016	694.17	3027.17	2.72	3.27	7754.234	0.871114	0.781129	0.963

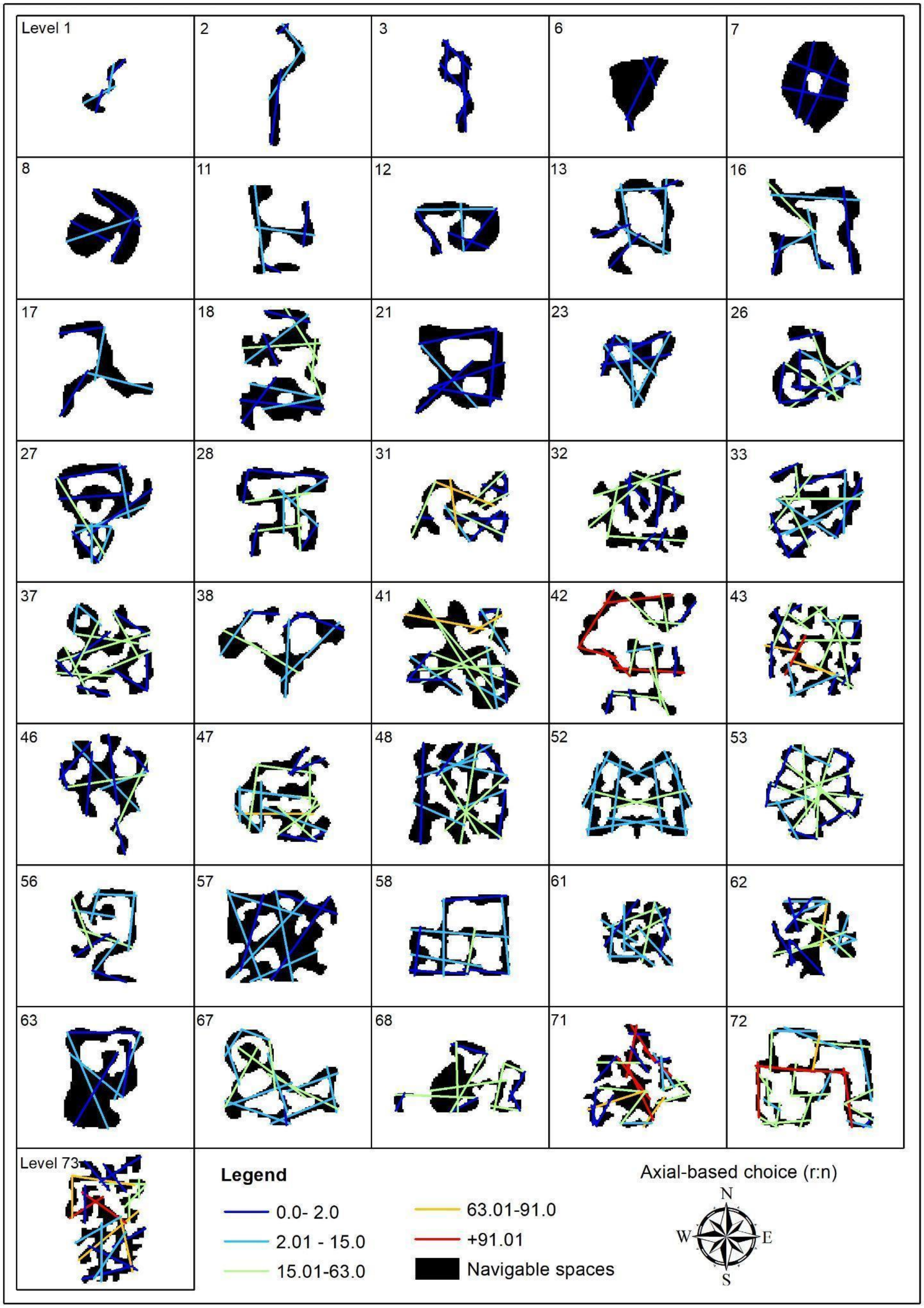
Appendix B- Image prepared to show the distribution of the number of players



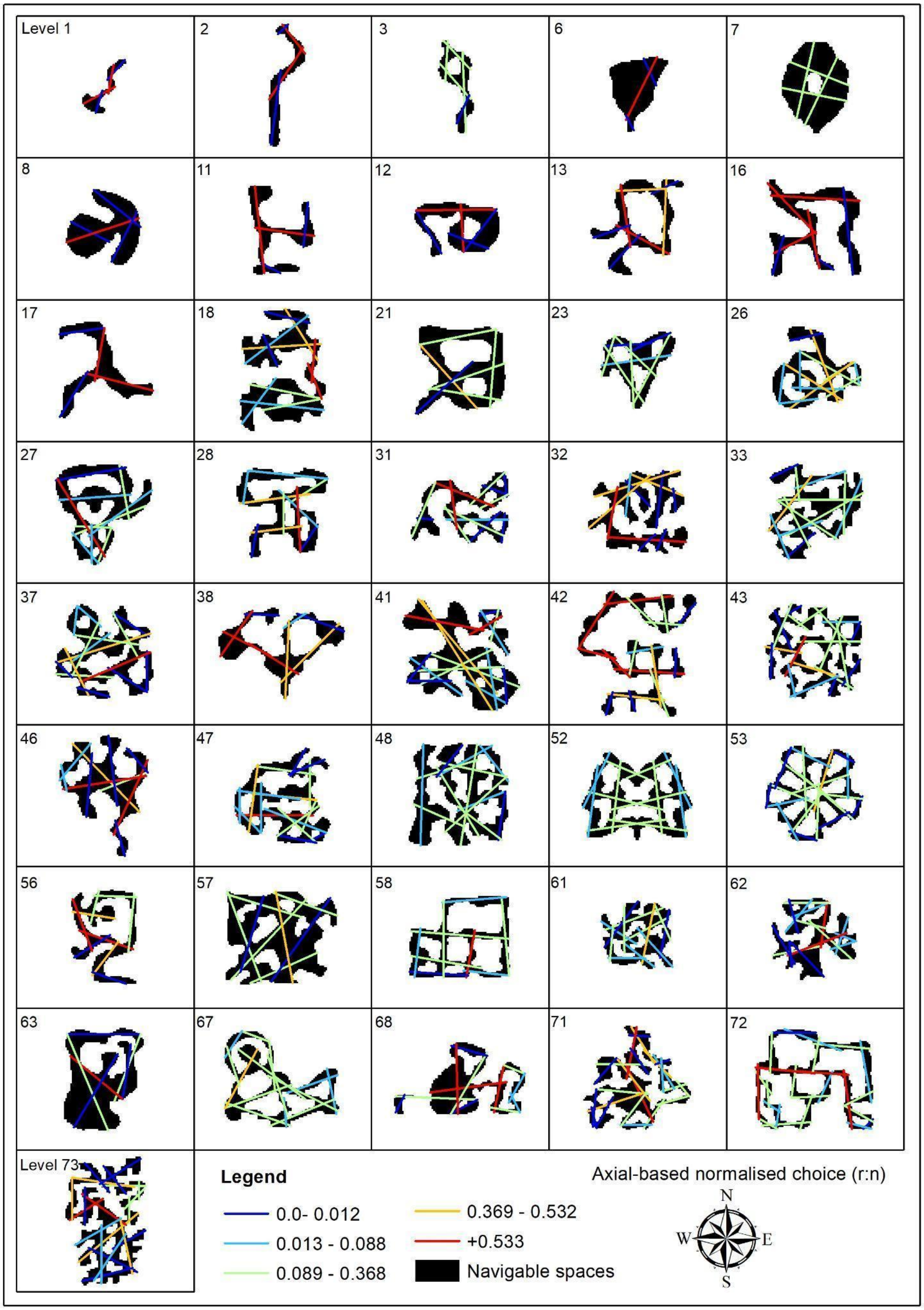
Appendix B. 1. Proportion of the total number of players.

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

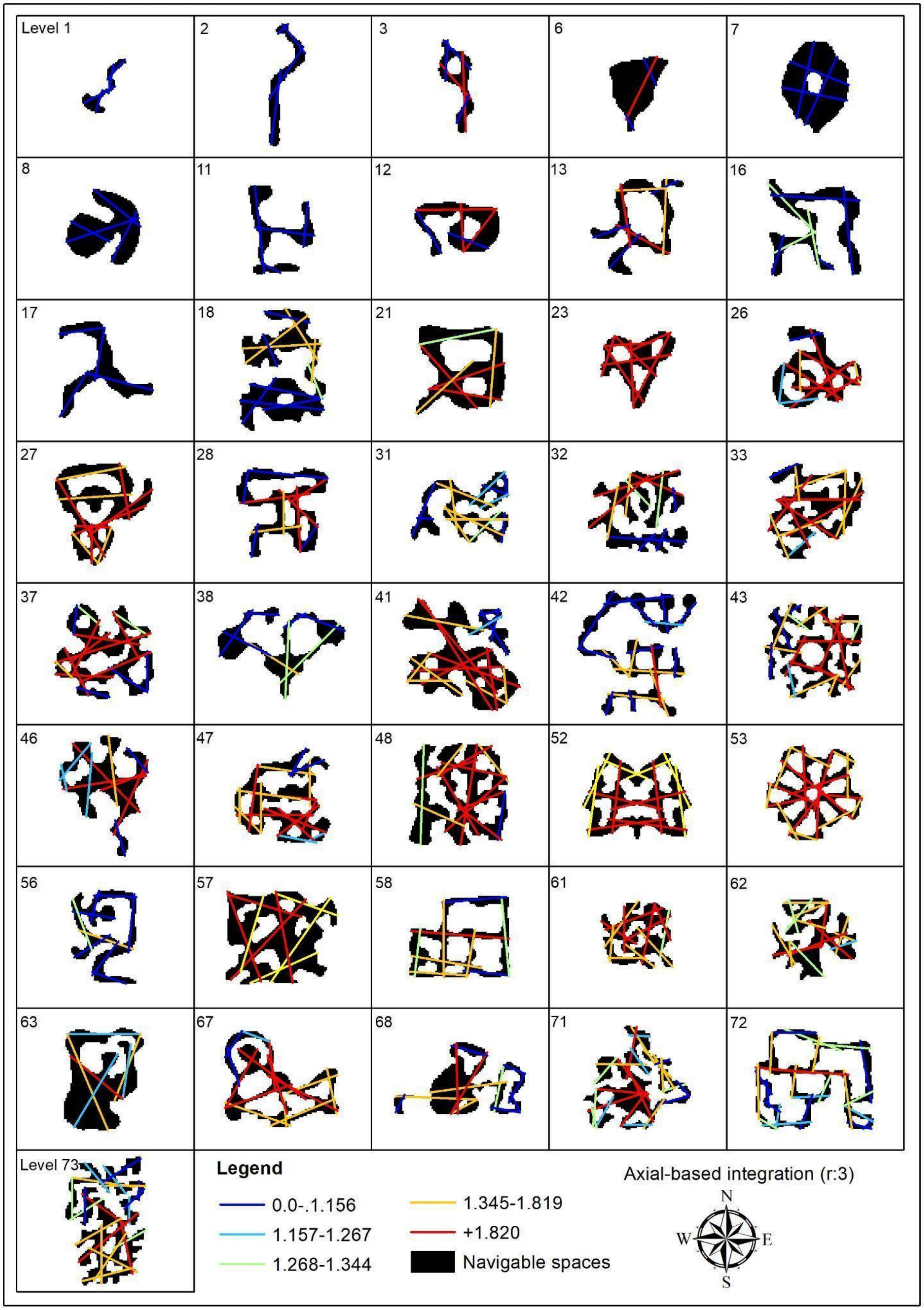
Appendix C.1. Axial based choice (r:3) for all wayfinding levels



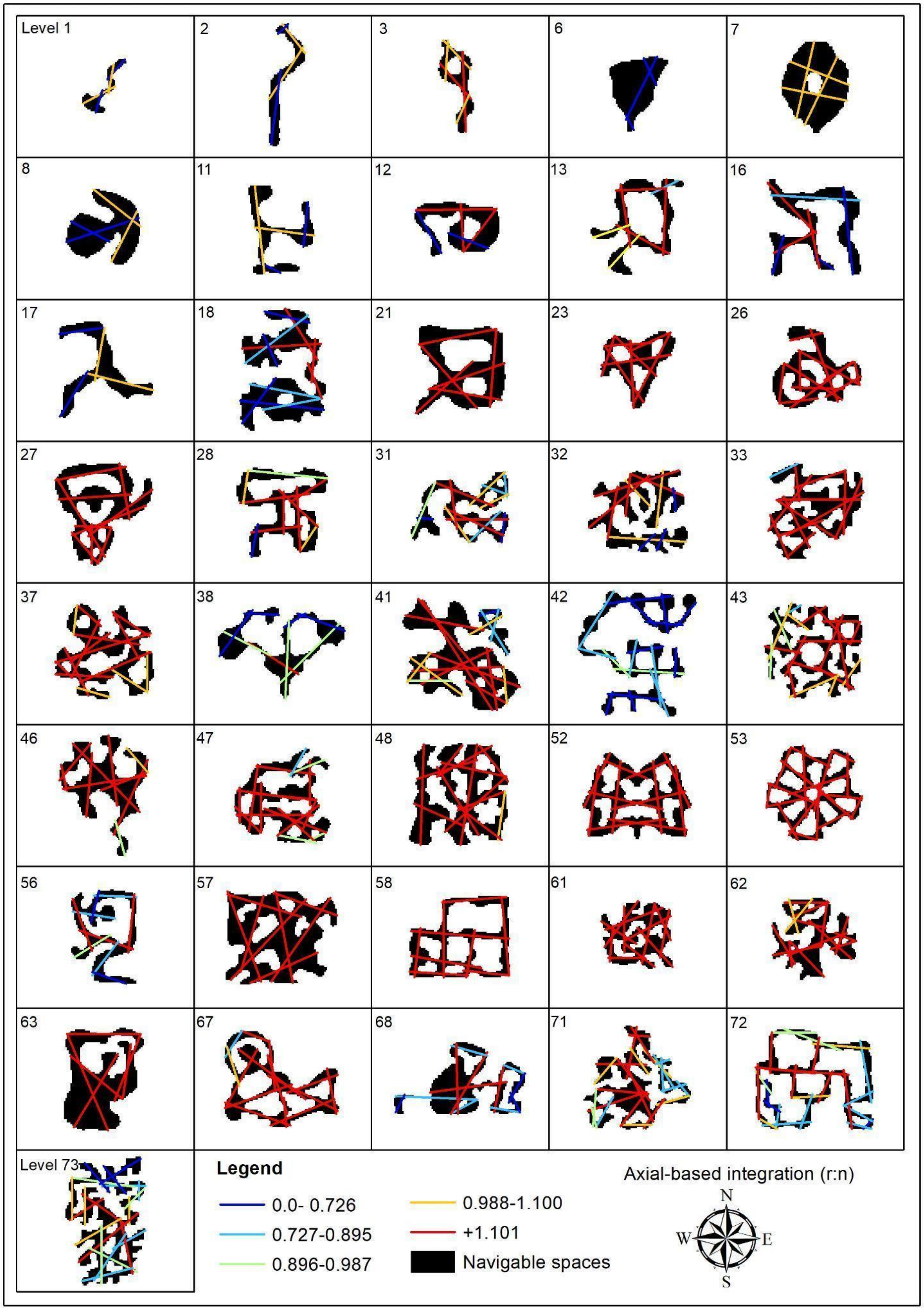
Appendix C.2. Axial based choice (r:n) for all wayfinding levels



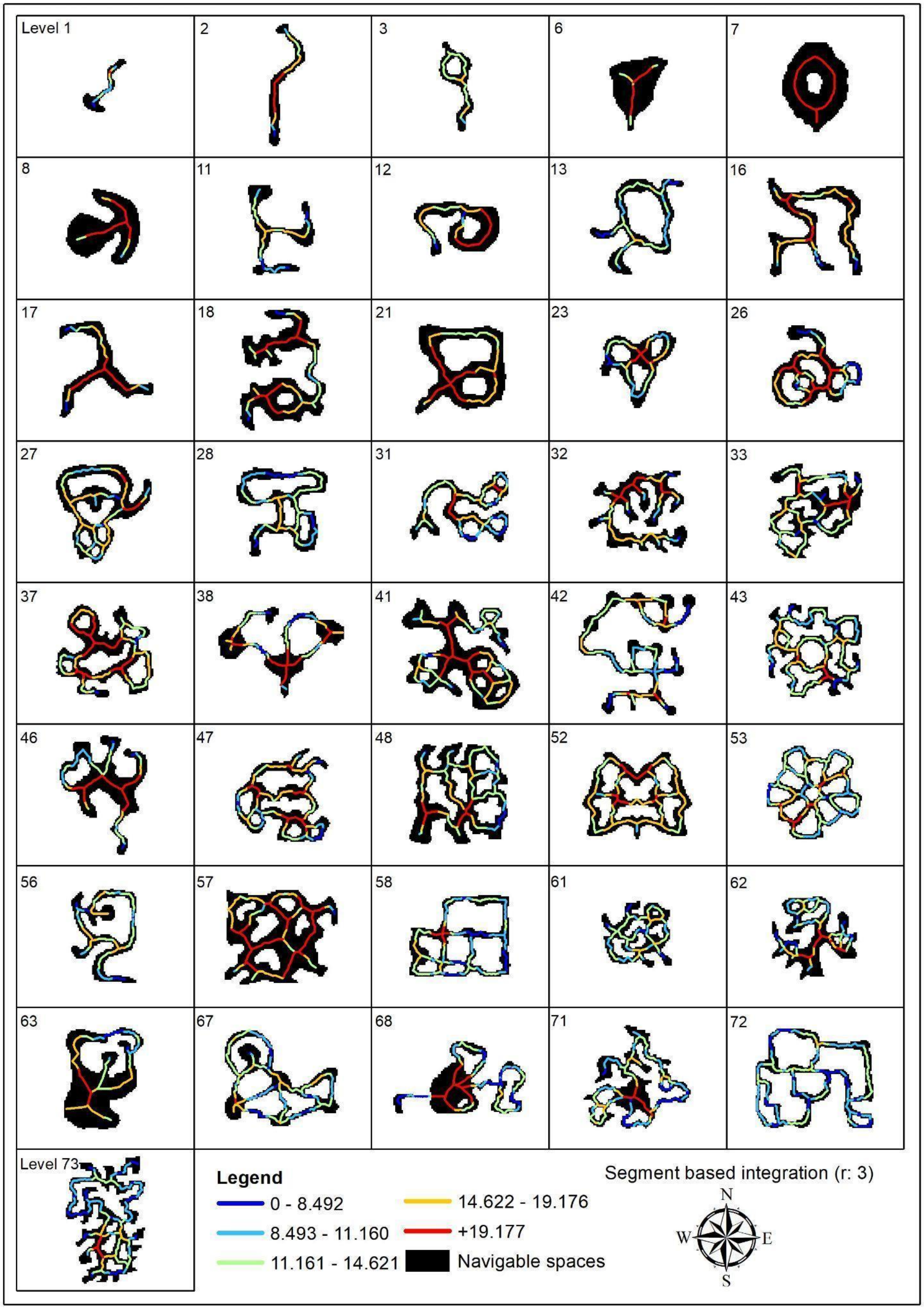
Appendix C.3. Axial based normalised choice (r:n) for all wayfinding levels



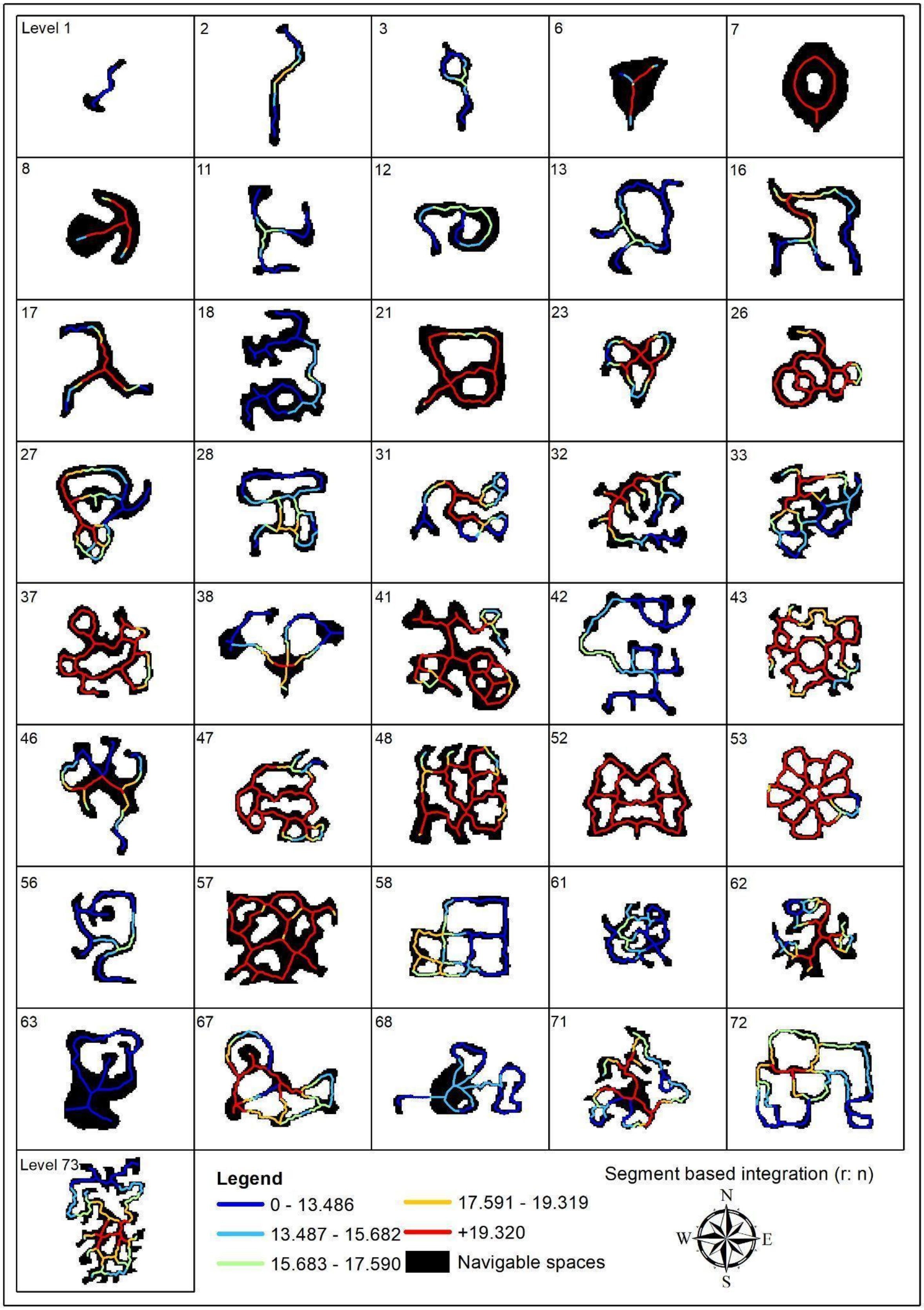
Appendix C.4. Axial based integration (r:3) for all wayfinding levels



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



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



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

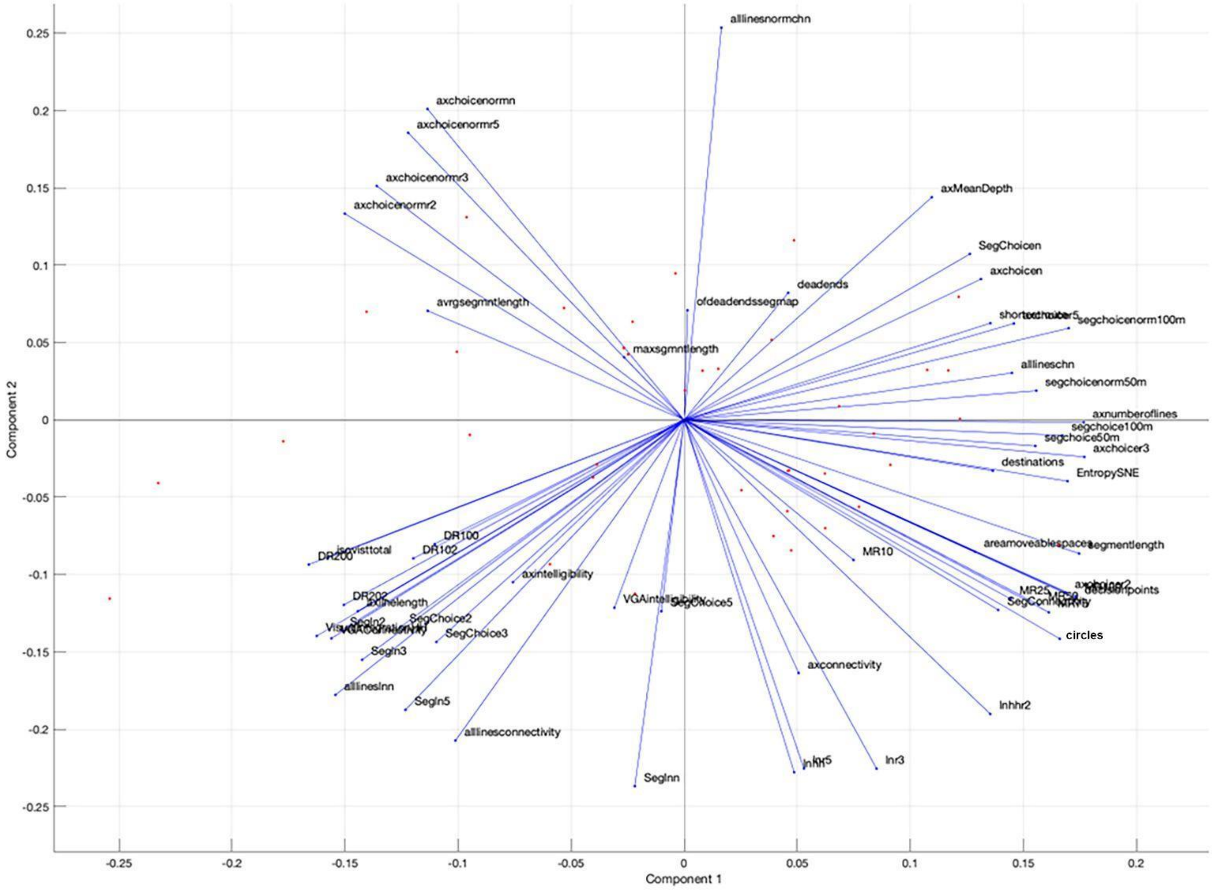
Appendix C.8. Metric reach for all wayfinding levels

Appendix C.9. Directional reach for all wayfinding levels

Appendix C.10. Visual connectivity for all wayfinding levels

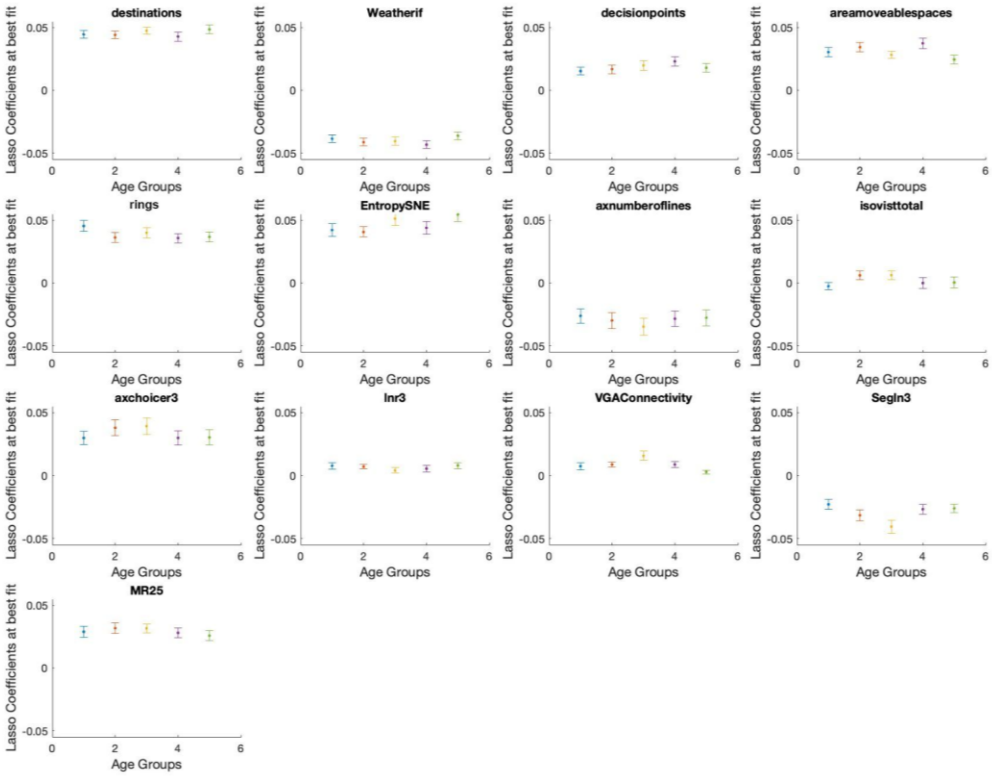
Appendix C.11. Visual integration for all wayfinding levels

Appendix Figure D. Results of the principle component analysis



Appendix D.1: Results of the PCA analysis and the two components (C1 and C2)

Appendix Figure E. Lasso coefficients for the selected metrics across age groups.



Appendix E.1: Lasso coefficients for the selected metrics from each family across age groups. Age group 1 = [20 29], 2=[30 39], 2=[40 49], 2=[50 59], 2=[60 69] years old. The Lasso computation was bootstrapped 100 times and error bars represent the standard errors.

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