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DISSECTING VISIBILITY GRAPH ANALYSIS:

THE METRICS AND THEIR ROLE IN UNDERSTANDING WORKPLACE HUMAN BEHAVIOUR

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ABSTRACT

Visibility Graph Analysis (VGA) is one of the main methods of analysis of interior space within the field of Space Syntax, formulated by Turner et al. (2001) by extending Benedikt's work on isovists and isovist fields (1979). It is a means to quantify the configuration of space as regular units which can then be used to identify the relationship of that space to the behaviour of the humans that occupy it. This paper is interested in the application of this method and its related metrics in workplaces, and how it can be used to understand the behaviour of office workers. Such information can then be used as evidence when designing new office spaces. We focus on the main tool used by the Space Syntax community: depthmapX (previously known as Depthmap). There are 25 VGA metrics that depthmapX can currently calculate, a mixture of classic graph-theory metrics, metrics borrowed from the urban-scale Space Syntax theories and some VGA-specific metrics describing local spatial properties. Some of the metrics are also derivatives, permutations and normalisations of other metrics which provide new information in relation to the configuration of space. While some of the metrics were described in previous research, there has never been a comprehensive understanding of all the VGA metrics produced by depthmapX, especially the concepts, formulae and algorithms behind their calculation. This has led researchers to focus on small subsets of these metrics avoiding thus the scattered and opaque nature of the theory and application. In previous research we have used VGA extensively aiming to understand human behaviour in office spaces but specifically only explored those that deal with local and global visibility. This paper first describes and elaborates on the various metrics produced by the current version of depthmapX and also outlines the theoretical considerations for each metric and how these potentially relate to human behaviour. Using a large dataset with VGA and observation data in office spaces we examine how these metrics relate to two kinds of behaviours: movement and interaction. We test how well each metric predicts each behaviour using two aggregations, per-floor and per-metric-quantile-bin. We show that for most of the metrics tested, per-metric-quartile-bin works better than per-floor. The findings suggest that of the two behaviours examined, movement is best predicted, with many of the local and global metrics significant and with high effects. This paper contributes to the general Space Syntax field in relation to indoor spatial analysis, by providing a thorough description of the metrics of VGA. It also aims to highlight how and which of these metrics can be used to specifically understand human behaviour in workplaces. Ultimately, such information can be used to predict this behaviour in newly designed office-spaces and thus allow designers to inform their designs.

KEYWORDS

visibility graph analysis, office space, workspace, office spaces, human behaviour, space syntax

1. INTRODUCTION

Quantifying the qualities and characteristics of interior space is an important part in the process of evidence-based design. It allows both for understanding the features of these spaces but also provides common units of analysis that human behaviour may be studied with. Methods to carry out this process exist within the field of Space Syntax which, while traditionally focused on urban analysis, has a sizeable part of the participating research community focusing on buildings and their interior space.

There are currently three methods available for such an analysis: Line-based (Axial / Segment analysis) which is commonly used for cities, Convex-space analysis and Grid-based (Visibility Graph Analysis). This paper will focus on Visibility Graph Analysis (VGA). VGA was formulated by Turner et al. (2001) by extending earlier work on isovists and isovist fields (Benedikt, 1979). The work by Benedikt allowed researchers to quantify locally visible properties of space, such as its area or perimeter. Turner et al. introduced the concept of depth typically found in the urban scale, which allowed for quantifying global properties of the spatial configuration such as the distance between non-intervisible parts of the space. An implementation of this method was created in parallel in the software application "Depthmap" (Turner, 2001).

VGA and Depthmap were extended and refined in parallel to allow for different elements of the spatial configuration to be quantified, and in 2011 the software was made free and open-source as depthmapX. The application can currently calculate 25 metrics for VGA, some local and some global. While a few of these metrics implement the original and well-known ideas from Benedikt (1979) and Turner et al. (2001), most of them are either permutations of the original metrics or ideas that have been implemented but not fully explored. The lack of a consistent manual specific to VGA also contributes to the fact that they are seldom used by other researchers.

In our previous work (Koutsolampros et al., 2015; Sailer et al., 2016; Koutsolampros et al., 2017; Koutsolampros et al., 2018) we focused on human behaviour in the workplace using a large dataset of office spaces. We have also focused on the very small subset of metrics typically used by the rest of the literature with limited success. This research has shown that a large dataset is insufficient for this task if the methods and metrics are not updated to deal with more complexity.

With this in mind, this paper aims to provide a comprehensive review of all the metrics and how they can be used to enhance our understanding of human behaviour. We will show how each metric relates to two behaviours in office spaces, movement and interaction, both in the level of the floor, but also in the context of the actual space.

The paper is structured as follows: The following chapter will expand on the origin of VGA, as well as the various metrics, and provide details of their current implementation in depthmapX. We will then describe how we constructed the statistical tests required to examine each metric against each behaviour for different contexts. Finally, the paper will present the results of the statistical tests and discuss the implications of the findings in relation to activity in office spaces.

2. LITERATURE REVIEW

Visibility Graph Analysis as it was described by Turner et al. (2001) has its roots in two previous works: The Social Logic of Space by Hillier and Hanson (1984) and To Take Hold of Space: Isovists and Isovist Fields by Benedikt (1979). Hillier and Hanson dealt with a quantitative analytic conceptualisation of space and how that potentially relates to human behaviour when the studied spaces are considered parts of a greater interconnected whole, for example a street within a city or a room within a building. The authors proposed two representations, axial lines and convex spaces to each fit streets or rooms respectively. They also suggested that their adjacencies can be treated as edges of a graph which can then be studied to explore immediate and non-immediate relationships between lines/rooms (treated as the nodes of the graph).

While Hillier and Hanson (1984) did suggest metrics related to each node and its immediate surrounding elements (i.e. how many other lines/rooms each is connected to) they also introduced a more 'global' concept: depth. Depth is defined generally as the effort to get from one point in a city/building to another and may be measured in euclidean distance, number of turns or change of angle. However, these abstract representations do not work well for indoor spaces. Axial lines are better suited for quantifying lines of movement while convex spaces work better for occupancy patterns (number of people in a space). Both these representations may also abstract away important details of the configuration and can not be reconstructed objectively (Peponis et al., 1997) (for further discussion see: Koutsolampros et al., 2018).

To alleviate this problem, Turner et al. (2001) suggested instead a lattice grid laid over the space which provided a regular spatial unit and allowed for more detail in describing the configuration. Turner used the concept of the isovist from Benedikt (1979) to connect the vertices of the grid creating thus a graph, similar to Hillier and Hanson (1984). An isovist is all the points visible from a specific point in space. In two dimensions (in plan view) it can be thought of as a polygon as seen in Figure 1 (b). Apart from providing a way to make the graph, isovists also allowed for the creation of different metrics that described the space that is around a cell, such as its area or perimeter. The graph may also be limited in visible distance when created, in which case the cells that are within the isovist but beyond that limit will not be marked as within the visible area and thus not connected to the cell the isovist was generated from.

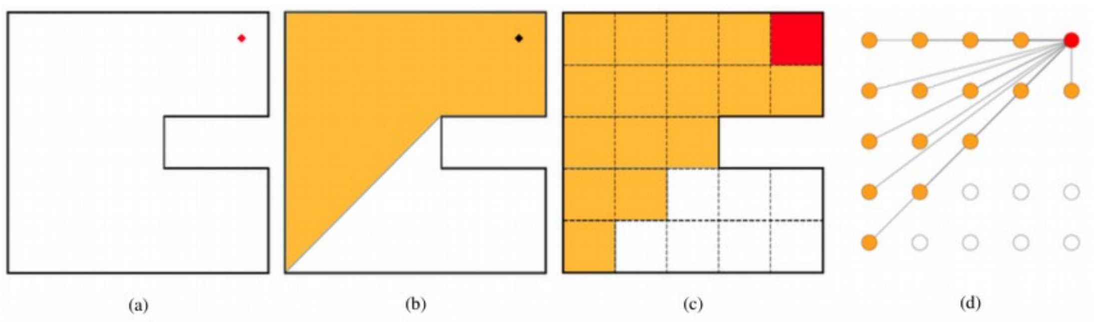

Figure 1: In a sample plan (a), creating an isovists results to a polygon (b). Applying that polygon to a grid to find which cells are inter-visible (c) allows us to treat this as a graph (d)

Most of these ideas were incorporated in a software application called Depthmap, which Turner first described in 2001 (Turner, 2001). As the research progressed Depthmap's capabilities increased (Turner, 2004; Turner, 2007b) until it was finally renamed depthmapX and released as free and open-source by Varoudis (2012) under a GPLv2 license. As an important research tool of the Space Syntax community Depthmap and later depthmapX implemented and slowly accumulated a large amount of knowledge which is now available through its source code and interface.

The current version (depthmapX development team, 2017) allows the user to create a Visibility Graph and carry out VGA, which can eventually provide up to 25 different metrics of the graph. Many of these metrics describe properties of the graph, the isovist, or the configuration, others are permutations and some are normalisations. Many researchers use depthmapX to carry out VGA, but, while the functionality of the program has been described in various forms (Turner, 2001; Turner, 2004; Turner, 2007b; Silva and Turner, 2010; Al-Sayed et al., 2014) there exists no comprehensive manual explaining what each metric does.

3. VISIBILITY GRAPH METRICS

3.1 OVERVIEW

There are 25 different metrics in total as seen in Table 1. In depthmapX they are calculated through six different processes that act as loose groupings, i.e. 1) the properties of the isovist at every pixel, the various relationships between all pixels specifically 2) local and 3) global visibility, 4) metric and 5) angular relationships and finally 6) through-vision. The metrics that are calculations of relationships between pixels are split in three categories depending on the kind of measurement they employ: metric (the euclidean distance in meters), angular (the angular turn in degrees) and visual (the number of turns). Given that the grid also functions as an undirected graph the visual metrics can be thought of as topological distance in steps. In the special cases where the name does not denote the type of metric (Point First/Second moment, *Through Vision*) the metric will be explained in more detail.

A search in google scholar in the form: "isovist min radial" "visibility graph" or "space syntax" or "depthmap" shows that while all the metrics have been used in various research studies, there are clear preferences towards specific metrics (see table 1). Connectivity featured in 365 research papers and is therefore the most used metric, followed by Isovist Area (n = 105) and Visual Control (n = 77). Almost half of the set of possible metrics (12) have fewer than 10 citations. The metrics that measure the size of the isovist are the simplest and are thus used in many of the research papers that also use the more complex ones (occlusivity, control etc.) but potentially also appear in papers where the global metrics are mainly used. The table also highlights the two strands of research in the field, one dealing with the local properties of space and the other with the global ones. *Visual Mean Depth*, the core metric that measures global properties of space is also used as much, or in some cases more than its permutations (the various Integration metrics). This is potentially due to the complexities that accompany the calculation of the Integration metrics which will be discussed later in this paper.

Measuring	Metric	Extent	Units	Graph/Geometric	Citations
Size	Isovist Area	Local	Metric	Geometric	105
	Connectivity	Local	Topological	Graph	365
	Isovist Perimeter	Local	Metric	Geometric	28
Shape	Isovist Compactness	Local	Metric	Geometric	22
	Point First Moment	Local	Metric	Both	1
	Point Second Moment	Local	Metric	Both	2
	Isovist Min Radial	Local	Metric	Geometric	4
	Isovist Max Radial	Local	Metric	Geometric	8
Potential to explore	Isovist Drift Angle	Local	Metric	Geometric	5
	Isovist Drift Magnitude	Local	Metric	Geometric	7
	Isovist Occlusivity	Local	Metric	Geometric	21
Potential to move	Through Vision	Local	Topological	Both	19
	Visual Clustering Coefficient	Local	Topological	Graph	29
Control	Visual Control	Semi-Global	Topological	Graph	57
	Visual Controllability	Semi-Global	Topological	Graph	19
Global	Angular Mean Depth	Global	Angular	Both	11
	Metric Mean Shortest Path Angle	Global	Metric	Both	1
	Metric Mean Shortest Path Distance	Global	Metric	Both	8
	Metric Mean Straight Line Distance	Global	Metric	Both	3
	Visual Mean Depth	Global	Topological	Graph	39
Normalised depth	Visual Integration [HH]	Global	Topological	Graph	45
	Visual Integration [P-value]	Global	Topological	Graph	8
	Visual Integration [Tekl]	Global	Topological	Graph	5
Complexity	Visual Entropy	Global	Topological	Graph	16
	Visual Relativised Entropy	Global	Topological	Graph	4

Table 1: All the metrics calculated by depthmapX

This paper will examine the metrics in the order seen in Table 1, from local to global. The notation will mostly follow existing papers in the field. [1] For the graph notation the paper mainly follows Turner et al. (2001), where it is defined as G = (V, E) where V(G) (the vertices) are the cells of the grid that are part of the graph:

$$V(G) = \{v_1, v_2, v_3, \ldots, v_n\}$$

and E(G) (the edges) the pairs of mutually visible cells:

$$E(G) = \{e_1, e_2, e_3, \ldots, e_n\}\ where\ e_{ij} \Leftrightarrow e_{ji}$$

For a specific vertex the neighbourhood (the other cells that are visible from it) is defined as:

$$N(v_i) = \{v_j | e_{ij} \in E\}$$

The notation for the isovist on the other hand will mostly follow Benedikt (1979), except where necessary to disambiguate from the properties of the graph. Thus, in continuous space D an isovist is defined as the number of points visible from a generating point g:

[1]Where possible the equations are copied from their originating papers, but in some cases they are extracted from the source code or as they appear typically in graph theory

$$I = \{q \in D : q\ visible from\ g\}$$

and its boundary denoted as ∂I. The vertices of the boundary are defined as V(∂I) while the lines that connect them E(∂I).

3.2 THE SIZE OF SPACES

Given that an isovist is a polygon, the metrics ***Isovist Area*** and ***Isovist Perimeter*** measure those properties for that polygon. Note that isovists are simple polygons, thus for every isovist with n vertices on its boundary and x_i, y_i the coordinates of each vertex depthmapX calculates the above using:

$$Isovist Area = A = \frac{1}{2}\sum_{i=0}^{n-1}(x_i y_{i+1} - x_{i+1} y_i),\ where\ (x_n, y_n) = (x_0, y_0)\ and$$

$$Isovist\ Perimeter = \Pi = \sum_{i=0}^{n-1}\sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2},\ where\ (x_n, y_n) = (x_0, y_0)$$

Isovist Area has been used to apply the theory of Prospect and Refuge to the field of space syntax (Psathiti and Sailer, 2017) by looking at the area of a partial isovist as prospect and the total *Connectivity* as refuge.

Connectivity is a metric that relates to the area of the isovist and defined as the amount of cells visible from a specific cell. In graph theory it is known as the neighbourhood size or degree of the current vertex:

$$Connectivity = deg(v_i) = |N(v_i)|$$

Connectivity is typically very close to a multiple of the *Isovist Area*, depending on the cell size. With smaller cell sizes, more details from the space will be taken into account making *Connectivity* and *Isovist Area* closer in value. The two may only differ substantially if, as mentioned above, the visibility distance of the graph is restricted, for which case *Connectivity* follows the restriction while the *Isovist Area* does not.

3.3 ISOVIST SHAPE

Isovist Compactness is a measure of the shape of the isovist, that is invariant to its area (in contrast to perimeter). More specifically the more an isovist approximates a disk, the higher its compactness, approaching a maximum value of 1. This metric seems to have been developed in order to provide a measure of simplicity of the isovist polygon (and thus the space visible). While it is referred to also as complexity or circularity by Benedikt (1979) and convexity by Batty (2001) it originates from efforts to measure the roundness of grains of sand (Cox, 1927). It is calculated using the formula:

$$Isovist\ Compactness = 4\pi A/\Pi^2$$

where A is the *Isovist Area* and Π the perimeter, and it may take values from 0 (less round) to 1 (more round). depthmapX also provides the metrics ***Isovist Min Radial*** and ***Isovist Max Radial***. These represent the minimum and maximum distances from the generating point to the obstacles that make up the isovist. For the maximum radial, this is simply the maximum distance in the set of all distances from the generating point to the vertices of the boundary:

$$Isovist\ Max\ Radial = \max_{v \in \partial I} d(p, q)$$

Similarly, for the minimum it is the minimum distance in the set of distances from the generating point to the lines of the boundary.

$$Isovist\ Min\ Radial = \min_{l \in \partial I} d(p, q)$$

The minimum radial can potentially be thought of as a way to judge how close a person is to a wall, while maximum radial the longest line of sight from that point. The maximum radial has been used by Zook (2017) to examine travelling patterns in museum spaces.

Two metrics that relate to the shape of the isovist are ***Point First Moment*** and ***Point Second Moment***, as the first and second area moments of inertia of the isovist. They can be thought of as the potential for an isovist to spin around its generating point. More elongated isovists have more potential to spin, and that potential increases if the generating point is towards the edges of the shape. In that sense, the two metrics can be considered the inverse of compactness. These were described by Turner (2004), but whether they are meaningful in a context of spatial analysis was left as an open question. Despite the fact that they are stated to describe the isovist they are actually calculated by adding up the distances and the squares of the distances respectively from one cell to all its other visible cells:

$$Point\ First\ Moment = \sum_{v_j \in N(v_i)} d(v_i, v_j)$$

$$Point\ Second\ Moment = \sum_{v_j \in N(v_i)} d(v_i, v_j)^2$$

The two moments effectively favour spaces with longer visible distances. Elongated spaces such as corridors will thus display higher moments, especially towards their ends as well as where they meet other corridors (see for example figure 8).

3.4 LOCAL POTENTIAL FOR EXPLORATION

A metric for identifying potentials for exploration was described by Benedikt (1979) which relates to the perimeter of the isovist, the ***Isovist Occlusivity***. This metric is calculated by taking parts of the perimeter of the isovist that are not blocked by obstacles. It is a concept referred to by Gibson (1983) and quantified by Benedikt (1979), for pointing out potential stimuli as a person moves in areas “just around the corner”. These potential stimuli can be either visual stimuli (new places to see) or accessible stimuli (new places to go).

The final isovist property provided by depthmapX is a metric suggested by Conroy (2001) called ’Drift’. Drift of an isovist is the vector from the generating point (g) to the centre of gravity of the polygon (c). depthmapX provides two metrics that allow us to fully describe this vector, its magnitude (***Isovist Drift Magnitude***) and its angle from the positive x-axis (***Isovist Drift Angle***). These are calculated in depthmapX as:

$$Isovist\ Drift\ Magnitude = \sqrt{(c_x - g_x)^2 + (c_y - g_y)^2}$$

$$Isovist\ Drift\ Angle = \begin{cases} 2\pi - \arccos(c_x - g_x), & \text{if } (c_y - g_y)<0 \\ \arccos(c_x - g_x), & \text{otherwise} \end{cases}$$

The vector will generally show the direction towards the largest parts of an isovist as these largest paths would drag the centroid more. In this way, Conroy (2001) suggests, we might be able to identify directions towards some minimum path from which the entire world is visible. In some cases *Isovist Drift Magnitude* works like the area moments of inertia (*Point First Moment*) as in elongated rectangular spaces such as corridors its value will increase towards the edges, away from the centroid.

3.5 HIGHLIGHTING AREAS THAT ARE IMPORTANT FOR MOVEMENT

One of the newest metrics ***Through Vision*** was described in 2007 by Turner (2007a) as a way to pinpoint the locations that are crossed-over more often and can thus be considered important for movement. *Through Vision* can be defined as the amount of lines of visibility that pass through a location. In more formal terms, for each cell in the grid, it is the number of times it is crossed by lines drawn between the centroids of all other inter-visible cells. This metric can be used to pinpoint locations most likely to be travelled, given that they are “in the way” to get from one position to another. It is thus expected to relate to movement especially in spaces that have long and straight walkable lines.

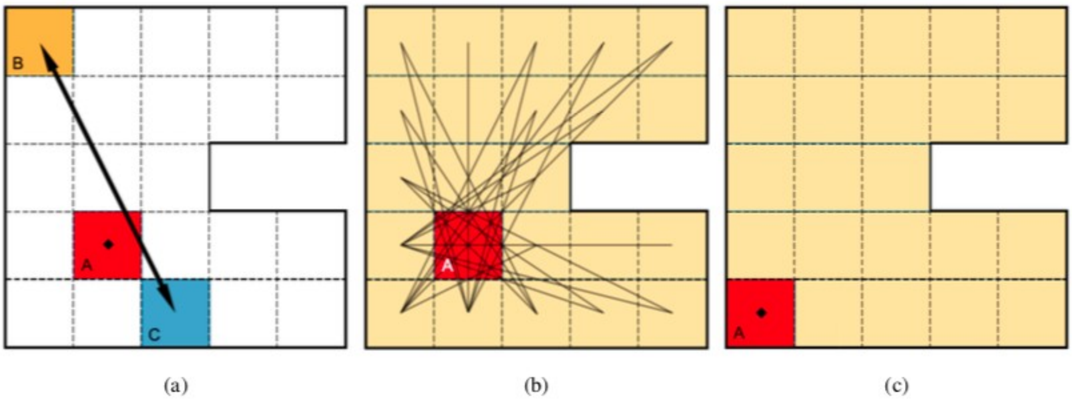

Figure 2: Through vision. a) Lines drawn from inter-visible cells (B to C and C to B) add to Through vision for cell A. In b) cell A has a through vision value of 56, while in c) cell A has a through vision value of 0

A metric called ***Visual Clustering Coefficient*** was defined by Turner et al. (2001) as an adaptation of the Clustering Coefficient from Small Worlds: The Dynamics of Networks between Order and Randomness (Watts, 1999). This was expressed as the ratio of the number of cells in an isovist that can see each other to the total possible connections that could exist between those cells (i.e. all-to-all connections).

This metric seems to have been developed to measure convexity and compactness as it points out the spaces where all are visible to all (coefficient is 1), but it also seems to be able to point out junctions (low coefficient: standing on a corner where one can see two spaces but the spaces can't see each other).

$$Visual\ Clustering\ Coefficient = C_i = 2e/n(n-1)$$

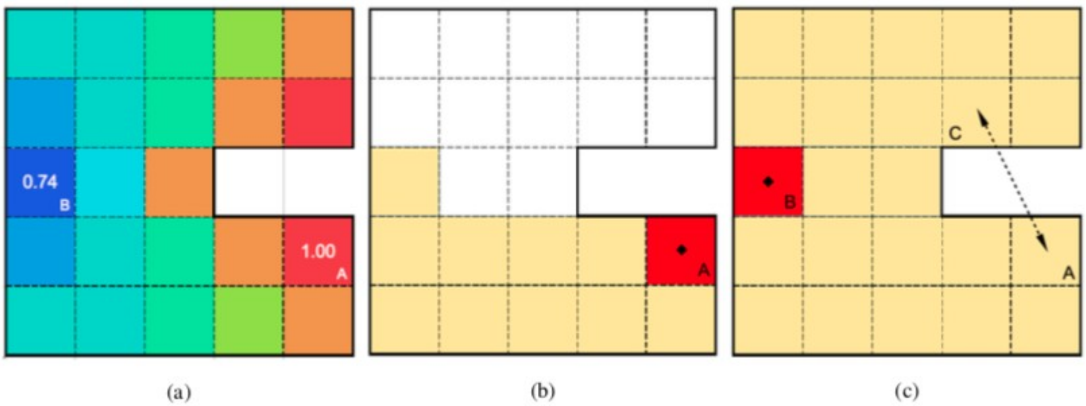

Figure 3: a) Clustering coefficient for every cell. b) Cell A has a value of 1 as all its visible cells can see each other, while c) cell B has a lower value as not all the visible pixels can see each other (i.e. A and C)

3.6 VISIBILITY AS A MATTER OF CONTROL

There are two metrics provided by depthmapX that can be considered semi-global because instead of capturing properties of the space that are immediate to the visual field they capture properties that relate to the immediate space extended by one visual step. These are *Visual Control* and *Visual Controllability*.

Visual Control was first described by Turner (2001) as the VGA implementation of the 'Control' metric described by Hillier and Hanson (1984). It is calculated by "summing the reciprocals of the neighbourhood sizes adjoining the vertex" (Turner, 2001, p. 31.4, eq. 3).

$$Visual\ Control = c_i = \sum_{v_j \in V(\Gamma_i)} 1/k_j$$

It essentially defines whether the space visible from a cell in relation to other directly visible cells is more ($c_i > 1$) than what they see or less ($c_i < 1$). Turner (2004) suggested the example of Bentham's panopticon where the central location can see in every cell (high control) while from within the cells not much is visible (low control).

Visual Controllability works in reverse, showing how controllable a location is. This was also described in the first Depthmap paper (Turner, 2001), although it was not given a name (shown as equation 4). It is calculated as the ratio between the number of visible cells (immediate neighbours) and the sum of all the cells visible from the immediate neighbours.

$$Visual\ Controllability = c_i' = \frac{k_i}{\cup N(v_j) : v_j \in N(v_i)}$$

Low controllability means that a cell has a visual field that is narrower (smaller) than its neighbours combined, while high controllability means that the cell and its neighbours have approximately the same or equal (value of 1) visual field.

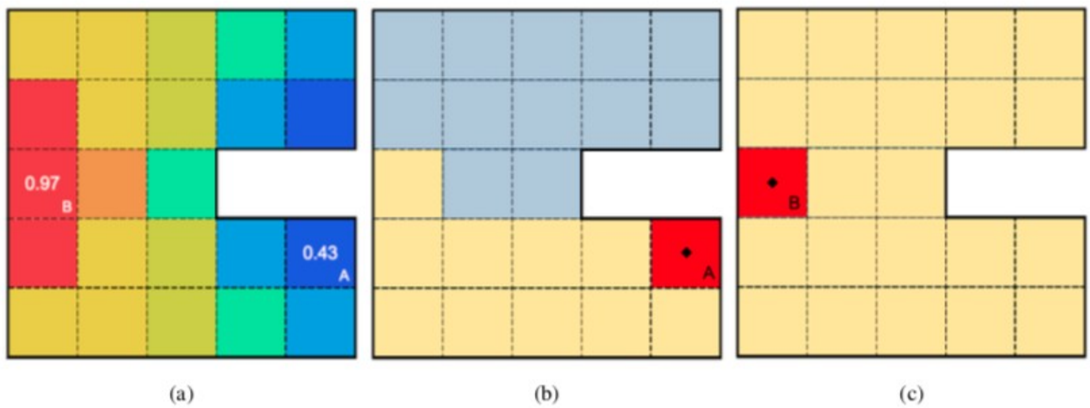

Figure 4: a) Visual Controllability. b) Cell A can see 10 cells directly and 13 through its neighbours (including cell A) thus having a controllability of 10/(10 + 13) = 0.43. c) Cell B can see all 22 cells and so can all the neighbours (but also including cell B) and thus has a controllability of 22/23 = 0.97

3.7 SPACE AS A GRAPH - GLOBAL POTENTIAL

Finally, depthmapX provides a set of global metrics, those that, for each cell, the values are affected by every other cell in the set. The aspect that provides this connection is 'depth', defined as the effort to follow the shortest path to get from one cell to another. The concept exists in graph theory but for VGA it was borrowed from Hillier and Hanson (1984) by Turner and Penn (1999) and adapted accordingly. The effort required to travel the shortest path can be measured in various ways, three of which are implemented in VGA: visual, metric and angular. Visual depth is the least amount of visual steps (a step from a cell to any other immediately visible cell) required to reach another point in the space. Metric and angular depths are the least amount of absolute euclidian distance or angular change required to reach a point.

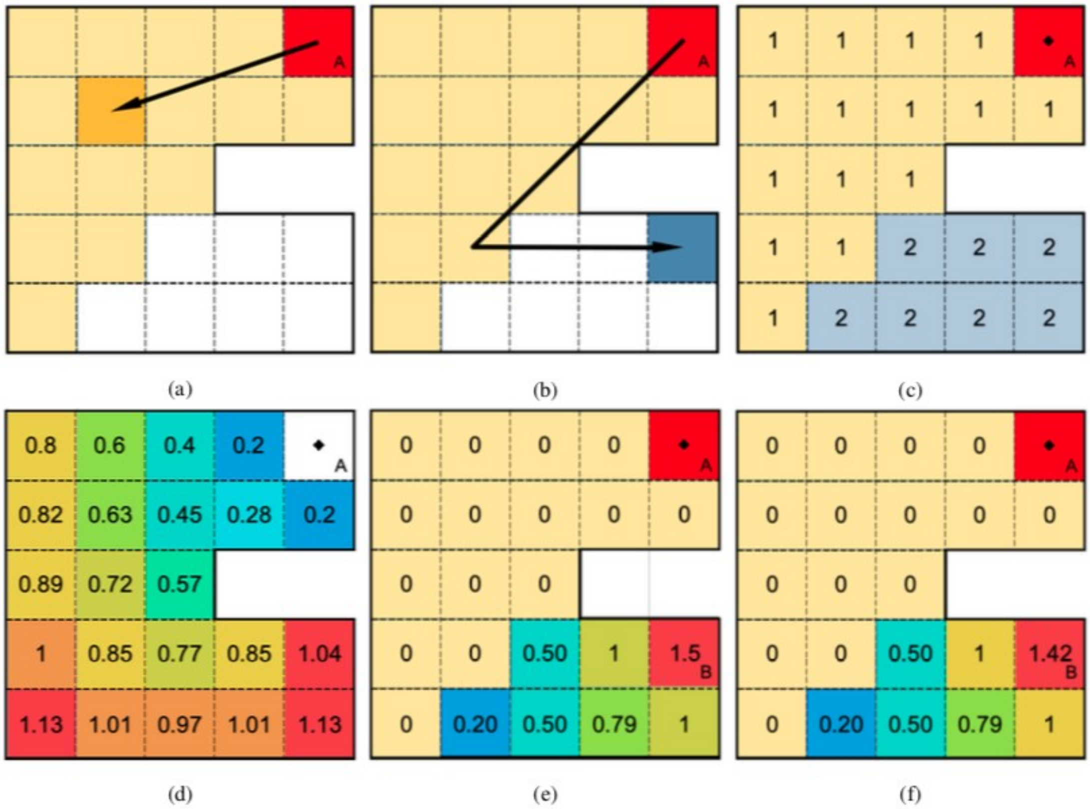

Figure 5: Shortest distances from cell A. a) It takes one step to reach the cells that are directly visible (in light yellow), and b) two steps to the rest. c) The number of steps required to reach any other cell may thus be calculated. d) Metric distance to get to any cell and e) the accumulated angle on the metric paths. f) Angular distance to get to every cell

For each of the different depth types depthmapX provides one metric as the average depth to get from one cell to any other cell in the set. ***Visual Mean Depth*** is the average number of visual steps required to reach every other cell in the system. ***Metric Mean Shortest Path Distance*** is the average metric distance required and ***Angular Mean Depth*** is the average amount of angular change required to reach every other cell in the system. It should be noted that finding the shortest path and measuring that path are not necessarily done using the same kind of depth. For example, depthmapX also provides a related metric the ***Metric Mean Shortest Path Angle*** which is the average accumulated angular change when taking the shortest metric path to reach every cell in the set. This metric is very similar to *Angular Mean Depth* except, as evident in figures 6e and 6f, except in cases where the shortest angular path is shorter (in accumulated angle) than the metric path (i.e. cell B in the same figure)

Also calculated is a metric called ***Metric Mean Straight Line Distance***, the average euclidean distance (ignoring any obstacles) from a cell to every other cell in the system. This metric could be useful in pinpointing the centroid of a system, but should only be used in single-floor instances, as it may fluctuate depending on the way that floors are set along the continuous 2D space.

3.8 NORMALISING DEPTH

The main average depth used in literature is *Visual Mean Depth*, but as with its line-graph counterpart (known simply as Mean Depth) its value tends to grow with the system, thus making the comparison between systems problematic. Hillier and Hanson (1984) suggested ways to normalise Mean Depth further so as to alleviate this problem and thus created a new concept called 'Integration'. To calculate Integration another intermediary metric had to be calculated, 'Relative Asymmetry' (RA), itself a normalisation of Mean Depth to the number of cells in the system in order to make shallow and deep systems comparable.

As stated by Hillier and Hanson (1984, p. 108):

> "The measure of relative asymmetry generalises [mean depth] by comparing how deep the system is from a particular point with how deep or shallow it theoretically could be - the least depth existing when all spaces are directly connected to the original space, and the most when all spaces are arranged in a unilinear sequence away from the original space, i.e. every additional space in the system adds one more level of depth"

RA was then normalised again, against the RA of the root node in an idealised system to allow for "comparisons across systems which differ significantly in size" (Hillier and Hanson, 1984, p. 109). The name of the final metric was coined 'Real Relative Asymmetry' (RRA). Two idealised systems were suggested in The Social Logic of Space a diamond graph as seen in figure 7a and a pyramid graph. The RA values of the root node for each idealised graph were coined d-value and p-value respectively.

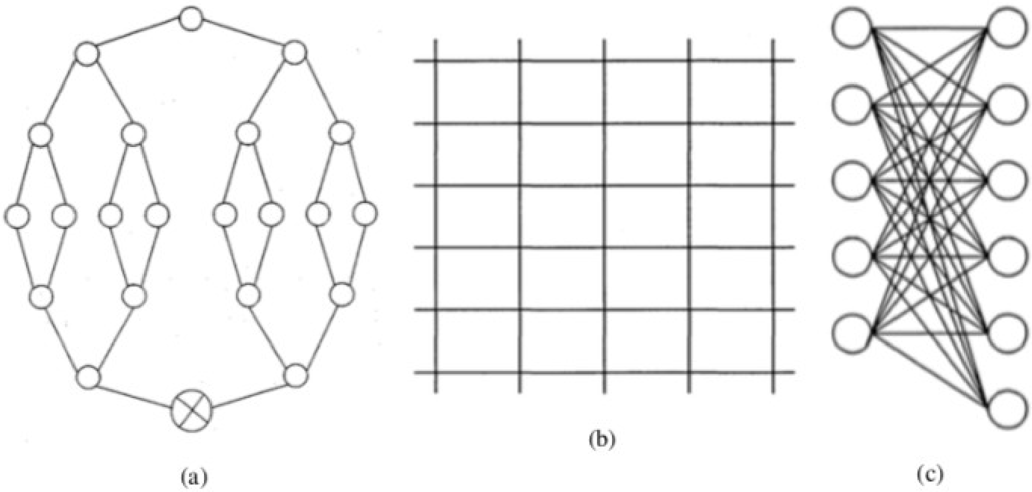

Figure 6: a) Diamond Graph, b) Axial Grid map and c) its equivalent bipartite graph (Teklenburg et al., 1993)

Another normalisation called 'Integration Score' was suggested by Teklenburg et al. (1993), which can be calculated in depthmapX and appears as 'Integration [Tekl]'. Teklenburg et al. aimed to produce a normalisation that would be less dependent on the number of nodes in the system and based on a grid map (figure 7b) and which is a complete bipartite graph (figure 7c).

Turner transferred these ideas to VGA and applied them to Visual Depth. Thus, ***Visual Integration [HH]*** (for Hillier and Hanson) is calculated by calculating RA:

$$RA = \frac{2D_M}{k-2}$$

where DM is the *Visual Mean Depth* and k is the number of cells in the system. The formula to calculate the RA of the idealised diamond system (d-value) was provided by Krüger (1989) and used as such in depthmapX:

$$D = \frac{2(k(\log_2(k+2)/3)-1)}{(k-1)(k-2)}$$

Finally, RRA can be calculated as:

$$RRA_D = RA/D$$

The formula for the RA of the pyramid idealised system (P-value) required to calculate ***Visual Integration [P-value]*** has not been published but can be found in depthmapX as:

$$P = \frac{2(k-\log_2(k)-1)}{(k-1)(k-2)}$$

and the relevant RRA:

$$RRA_P = RA/P$$

It is worth noting that, while the literature typically considers integration to be the same as RRA, depthmapX in fact inverses both values. Thus:

$$Visual\ Integration\ [HH] = 1/RRA_D$$

and

$$Visual\ Integration\ [P\text{-}value] = 1/RRA_P$$

While *Visual Integration [P-value]* is used in a few papers, one specifically mentions how it is calculated (Turner, 2004) and one its effects (de Arruda Campos and Fong, 2003), no published study offers a clear explanation on how the formula in depthmapX is derived.

Finally, the formula to calculate ***Visual Integration [Tekl]*** (or Integration Score) is given by Teklenburg et al. (1993) as:

$$Visual\ Integration\ [Tekl] = \ln(\frac{k-2}{2})/\ln(D_T - k + 1)$$

where D_T is the total depth of the system

3.9 COMPLEXITY OF TRAVEL

The last two metrics that can be calculated by depthmapX are *Visual Entropy* and *Visual Relativised Entropy*. ***Visual Entropy*** (or Point Depth Entropy) was also suggested by Turner (2001) in order to capture the global complexity of a space without having to deal with its size and it is also borrowed from the larger-scale analysis (Hillier et al., 1987). Its value for a VGA cell is essentially Shannon's entropy of information applied to the distribution of depths to any other cell and expressed as:

$$Visual\ Entropy = s_i = \sum_{d=1}^{d_{max}} -p_d log(p_d)$$

where d_{max} is the maximum depth from vertex v_i and p_d is the frequency of visual depth d from the vertex. *Visual Entropy* for a cell increases when the choices ahead (if the whole space is to be traversed) are many and varied. For example a workplace where most of the desks are in separate cellular spaces is more likely to be considered complex to traverse than an open plan office space.

Turner (2001) also suggested a normalised version of entropy called ***Visual Relativised Entropy*** that takes into account the fact that deeper spaces will have higher entropy despite the fact that from a specific point the options might be limited. In other words, if the number of choices available (in regards to steps to traverse a space) are the same in a deep or shallow space, the deeper space will present a higher *Visual Entropy*. To calculate *Visual Relativised Entropy* the probability of a specific depth is divided by the expected frequency of locations at that depth.

$$Visual\ Relativised\ Entropy = r_i \sum_{d=1}^{d_{max}} -p_d log(\frac{p_d}{q_d})\ where\ q_d = \frac{{L_i}^d}{d!}e^{-L_i}$$

Figure 7: All metrics for case 60 for Accessibility (top) and Visibility (bottom)

4. DATA

To evaluate how well each metric corresponds to activity data we examine a dataset of office-spaces provided by Spacelab, an architectural office and consultancy in London, UK. The sample contains 41 different cases (sites), from 34 companies across the UK, compiled from 2012 to 2017. The companies examined vary in size (50 to 2700 desks) and come from different industries, such as Media, Advertising, Technology, Legal and Finance. They comprise a total of 159 floors with the smallest being 28m² and the largest 4500m², though most of the sample is close to 1000m².

There are two types of data for each case: observation data collected by participant observation snapshots (Vaughan, 2001) and visibility graph analysis. The observation data is collected usually over a period of five days, every one hour for eight hours, and it contains information of where people sit, stand, walk and interact as points on a plan. Visibility graph analysis has been carried out with the command-line interface (CLI) version of depthmapX 0.6.0 (depthmapX development team, 2017) at a grid of 45x45cm at both eye-level (visibility) and knee-level (accessibility).

5. METHODOLOGY

In previous work we examined this dataset from the perspective of only two metrics: *Connectivity* and *Visual Mean Depth*. In this case we examine all metrics and how well each can help us understand two behaviours: movement and interaction. We test this on two levels, as measurement of the configuration of floors, and as measurements of the configuration of space in general.

For testing the configuration of floors we aggregate each metric per floor, by calculating the mean of the values of the VGA cells in that floor. This value is then compared to the density of people observed moving or interacting in that floor, controlled by the number of snapshots taken. The density of people moving or interacting is the number of people observed moving or interacting divided by the number of snapshots and the area of the floor. Specifically for interaction we are only considering people interacting in groups smaller or equal to five people so as to avoid capturing extraordinary events in which case larger groups of people may interact.

Testing for the space itself is more complex. Capturing the number of people in a 45x45cm cell results in many empty cells, but also relies on the accurate recording of the actual positions of people. (for an extended discussion on this topic refer to our previous work: Koutsolampros et al., 2018) Thus, to allow for larger areas that can capture more people and do not suffer from such issues of accuracy we create discrete bins for every metric. This process creates patches of continuous space in which the binned metric has similar values and where numbers of people may be counted. More specifically, binning is done with quantiles per metric across all studies. Quantiles allow for approximately equal number of cells to be within one bin, removing the need for the counts of people to be normalised by the area of each bin. The metric *Metric Mean Straight-Line Distance* is ignored, given its dependence on the positioning of each floor in the various plans.

For both floors and bins we carried out linear regression against each activity. One observation for each analysis is either one floor or one bin, the average value of the relevant metric and the number of people found within that floor/bin. Given that the distribution of the density of people in the analysis per floor is heavily skewed to the right, for these tests the natural logarithm of the activity data is taken instead.

Finally, we tested the binning method on each site separately. This allowed us to examine whether the results we find on the global dataset can be used on a per-site basis, and thus enable the use of this method in predicting activities on newly designed buildings. For this test we also examined whether external knowledge (the binning of the whole dataset) works better than re-creating the bins for each site. We took the values of each metric to the extents that it appears in the whole site and split that into 'local' quartiles (in contrast the 'global' quartiles from the whole dataset). For example it might be possible that *Visual Mean Depth* affects movement in a global way i.e. spaces where everything else is two steps away on average always have a specific amount of movement, regardless of the size or number of floors in that building. In this case, when examining a new building, it will be better to use the known global bins, than to re-create them for that building, as relative to the available values there (i.e. if the building is very deep on average and has no two-step average depth).

6. RESULTS

The results of the analysis per-floor are seen in figure 8 and tables 2 and 3 for accessibility and visibility respectively. Given that the variables are log-transformed, to get the adjusted change we need to adjust the coefficient for each metric (c_m) to get a percentage change in the activity:

$$100(e^{c_m} - 1)$$

For accessibility, six of the metrics show a highly significant relationship to density of movement (p-value less than 0.01) while for interaction only three metrics are significantly related. The coefficient of determination (R^2) is low for all apart from *Visual Mean Depth* (R^2=0.28) and *Visual Relativised Entropy* (R^2=0.22).

The high effect of *Visual Mean Depth* shows that floors that are more segregated have fewer people moving. This is in line with previous work by the us (Koutsolampros et al., 2018) and others (Penn et al. 1999), and contradicts older studies that showed the opposite (Hillier and Grajewski, 1990).

More specifically it seems that as *Visual Mean Depth* of accessibility of a floor increases by 1 (average step depth), movement density drops by 20.5%. The results are similar for visibility, though the effects are less strong. For visibility (Table 3) *Metric Mean Shortest Path Angle* is also highly significant and has an effect of R^2=0.21. In fact, it appears that as the accumulated angle of all traversed paths in a floor increases by one degree, there is a 42.74% reduction in movement density. A similar effect can be observed for *Angular Mean Depth* which, as stated earlier, is very similar to *Metric Mean Shortest Path Angle*.

In the case of interaction, there are fewer significant results and it appears that *Visual Mean Depth* is also influential, though to a lesser degree. In this case the metric only explains 11% of the variability for accessibility and 10% for visibility.

For completeness we also tested the overall presence (the total number of people found per floor) against each metric, as well as the ratios of each activity against that presence. We observed that the aforementioned metrics (*Visual Mean Depth*, *Metric Mean Shortest Path Angle* and *Angular Mean Depth*) are also significant to varying degrees with the overall presence (the total number of people found per floor) which may drive both movement and interaction We also observe that the relationships between the movement and interaction and the metrics become insignificant when taken as percentages of the presence. This suggests that there are factors that we have not considered in our analysis that could potentially separate movement and interaction from the overall presence. Thus, it appears that, for this method, these metrics are more useful in detecting the distribution of people, less what they do.

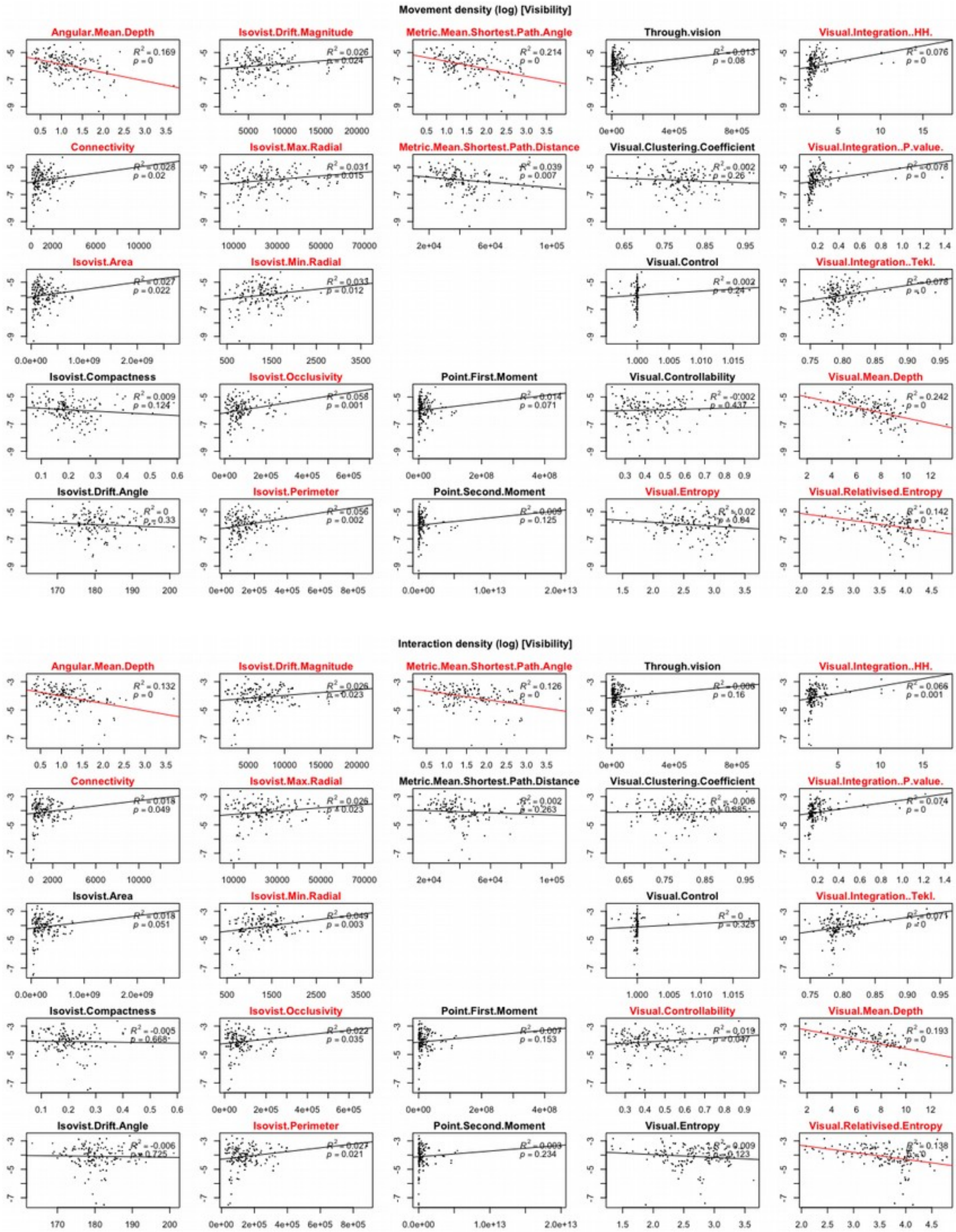

Figure 8: Movement (top) and interaction (bottom) density per floor and against each accessibility metric

	Movement density (log)			Interaction density (log)			Total observed density (log)			Movement percentage			Interaction percentage		
Metric	R^2	p-val	adj coeff	R^2	p-val	adj coeff	R^2	p-val	adj coeff	R^2	p-val	adj coeff	R^2	p-val	adj coeff
Isovist Area		0.82			0.09			0.56			0.40			0.16	
Connectivity		0.84			0.10			0.55			0.40			0.16	
Isovist Perimeter		0.46			0.14			0.46			0.97			0.06	
Isovist Compactness		0.22			0.58		0.06	0.00	-95.97		0.09			0.10	
Point First Moment		0.18			0.29			0.40			0.23			0.06	
Point Second Moment		0.04			0.70			0.13			0.09			0.10	
Isovist Min Radial		0.40			0.09		0.05	0.00	-0.12		0.08			0.86	
Isovist Max Radial		0.12			0.17			0.18			0.58			0.01	
Isovist Drift Angle		0.27			0.06			0.20			0.67			0.52	
Isovist Drift Magnitude		0.30			0.19			0.34			0.77			0.02	
Isovist Occlusivity		0.32			0.32			0.20			0.82			0.10	
Through Vision		0.16			0.32			0.35			0.22			0.06	
Visual Clustering Coefficient	0.04	0.01	-98.65		0.16		0.07	0.00	-98.25		0.63			0.67	
Visual Control		0.23			0.04			0.62			0.06			0.21	
Visual Controllability	0.04	0.01	-81.98		0.74		0.05	0.00	-77.37		1.00			0.08	
Angular Mean Depth		0.01			0.51		0.05	0.00	-25.57		0.63			0.81	
Metric Mean Shortest Path Angle		0.03			0.41			0.04			0.99			0.34	
Metric Mean Shortest Path Distance		0.01			0.08			0.04			0.71			0.05	
Visual Mean Depth	0.28	0.00	-20.72	0.11	0.00	-15.45	0.23	0.00	-15.10		0.09			0.07	
Visual Integration [HH]	0.13	0.00	72.18		0.01		0.09	0.00	43.75		0.21			0.08	
Visual Integration [P-value]	0.14	0.00	NA	0.07	0.00	NA	0.12	0.00	NA		0.22			0.02	
Visual Integration [Tekl]		0.03			0.83			0.17			0.66			0.85	
Visual Entropy		0.25			0.33			0.32			0.88			0.17	
Visual Relativised Entropy	0.22	0.00	-59.09	0.08	0.00	-46.40	0.16	0.00	-44.72		0.07			0.06	

Table 2: All accessibility metrics tested against movement and interaction in the analysis per-floor. Significant results are printed in red

	Movement density (log)			Interaction density (log)			Total observed density (log)			Movement percentage			Interaction percentage		
Metric	R^2	p-val	adj coeff	R^2	p-val	adj coeff	R^2	p-val	adj coeff	R^2	p-val	adj coeff	R^2	p-val	adj coeff
Isovist Area		0.02			0.25		0.07	0.00	0.00		0.63			0.01	
Connectivity		0.02			0.26		0.07	0.00	0.01		0.65			0.01	
Isovist Perimeter	0.06	0.00	0.00		0.64		0.10	0.00	0.00		0.97		0.04	0.01	-0.00
Isovist Compactness		0.12			0.79			0.05			0.92		0.06	0.00	0.12
Point First Moment		0.07			0.15			0.02			0.94			0.05	
Point Second Moment		0.13			0.13			0.07			0.76			0.09	
Isovist Min Radial		0.01			0.80		0.12	0.00	0.05		0.09			0.01	
Isovist Max Radial		0.01			0.58		0.10	0.00	0.00		0.20		0.06	0.00	-0.00
Isovist Drift Angle		0.33			0.71			0.49			0.22			0.60	
Isovist Drift Magnitude		0.02			0.40		0.11	0.00	0.01		0.10		0.06	0.00	-0.00
Isovist Occlusivity	0.06	0.00	0.00		0.77		0.08	0.00	0.00		0.61			0.02	
Through Vision		0.08			0.15			0.02			0.99			0.04	
Visual Clustering Coefficient		0.26			0.30			0.72			0.56			0.96	
Visual Control		0.24			0.27			0.31			0.73			0.67	
Visual Controllability		0.44			0.89			0.01			0.18			0.44	
Angular Mean Depth	0.17	0.00	-46.20		0.15		0.23	0.00	-40.67		0.77			0.56	
Metric Mean Shortest Path Angle	0.21	0.00	-42.74	0.05	0.00	-28.48	0.26	0.00	-35.76		0.56			0.91	
Metric Mean Shortest Path Distance	0.04	0.01	-0.00		0.03			0.07			0.32			0.03	
Visual Mean Depth	0.24	0.00	-17.66	0.10	0.00	-13.73	0.28	0.00	-14.04		0.44			0.10	
Visual Integration [HH]	0.08	0.00	12.43		0.16		0.07	0.00	8.32		0.35			0.47	
Visual Integration [P-value]	0.08	0.00	222.18		0.06		0.07	0.00	126.81		0.42			0.30	
Visual Integration [Tekl]	0.08	0.00	NA		0.10		0.08	0.00	NA		0.81			0.49	
Visual Entropy		0.04			0.09			0.05			0.61			0.14	
Visual Relativised Entropy	0.14	0.00	-40.94	0.06	0.00	-32.83	0.13	0.00	-30.49		0.29			0.05	

Table 3: All visibility metrics tested against movement and interaction in the analysis per-floor. Significant results are printed in red

The following scatterplots (figure 10) and tables (4 and 5) show the results of the analysis per-bin. The activity axis in figure 10 differs for each plot as the position and shape of the aggregating space (and thus number of people within that space) fluctuates per metric. With this method activity is aggregated per square meter and hour. As this results in extremely small values it is multiplied by 100 (i.e. per 100 square meters) to make the effect more apparent.

Movement seems to be related to almost all the metrics, though at different levels, with the strongest effects for the accessibility metrics. The metrics that measure the size of accessible space, *Isovist Area*, *Connectivity*, *Isovist Perimeter*, are highly correlated with the movement density with R^2=0.90, R^2=0.89 and R^2=0.98 respectively. The highest score of the *Isovist Perimeter* seems to be related to the fact that it also describes the shape of the space, potentially what *Isovist Max Radial* (R^2=0.95) also describes, the longest straight walkable lines. *Isovist Max Radial* also correlates highly with movement in visibility (R^2=0.82) showing that the longest lines of visibility also play a part.

The metrics that highlight potential for exploration (*Isovist Drift Magnitude* with R^2=0.96, *Isovist Occlusivity* with R^2=0.99), potential for movement (*Through Vision* with R^2=0.99) as well as *Visual Control* (R^2=0.82) seem to also be related to observed movement, especially in accessibility.

Visual Mean Depth is once again a very good movement predictor for accessibility and visibility (R^2=0.92 and R^2=0.94 respectively). In this case, an increase of *Visual Mean Depth* by one quantile reduces the density of people moving (number per 100m2 and hour) by 0.16.

From the three permutations of integration, the one that responds best is *Visual Integration [Tekl]* (R^2=0.81) for accessibility and *Visual Integration [P-value]* for visibility. Finally, it appears that the normalised version of entropy (*Visual Relativised Entropy*) which shows the complexity of the space ahead for a walker is also important. More specifically, it seems that as the space ahead becomes more complex movement decreases.

Most tests with metrics that relate to movement retain their strength even when compared to presence, suggesting that binning overall works better.

Interaction seems to relate more to global properties of the space. The best predictors are *Visual Integration [P-value]* (R^2=0.92) and *Visual Relativised Entropy* (R^2=0.89) for accessibility, but also *Visual Integration [HH]* (R^2=0.83) for visibility. In this case the results are similar when interaction is taken as the percentage to overall presence, with *Visual Integration [P-value]* (R^2=0.90) and *Visual Relativised Entropy* (R^2=0.92) holding their values in accessibility, but not for the metrics in accessibility.

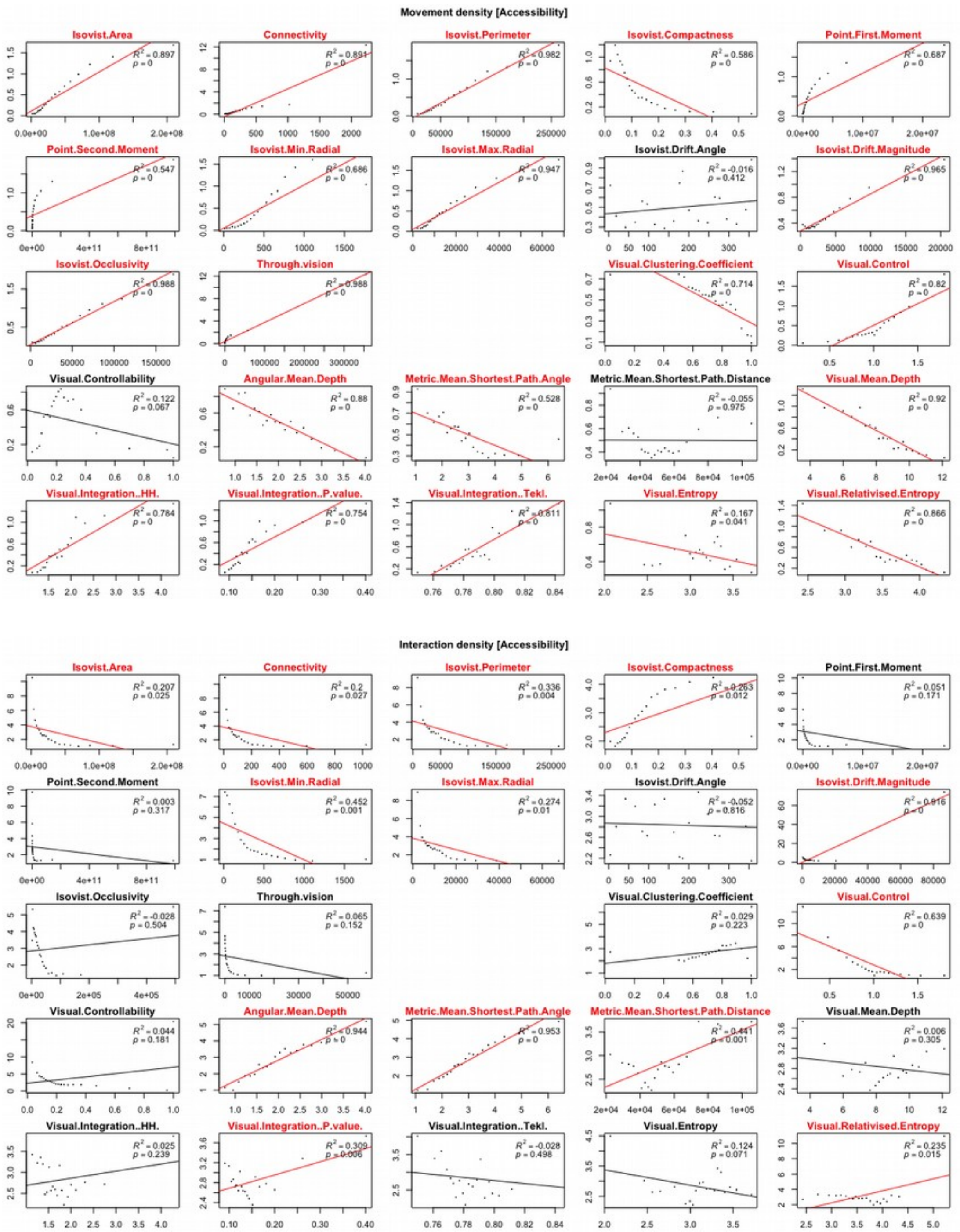

Figure 9: Movement (a) and interaction (b) density per bin and against each accessibility metric. Activity measured in numbers of people per 100 m2 and hour

	Movement density			Interaction density			Total observed density			Movement percentage			Interaction percentage		
Metric	R^2	p-val	coeff	R^2	p-val	coeff	R^2	p-val	coeff	R^2	p-val	coeff	R^2	p-val	coeff
Isovist Area	**0.90**	0.00	0.00		0.03			0.02		**0.88**	0.00	0.00	0.52	0.00	0.00
Connectivity	**0.89**	0.00	0.00		0.03			0.52		**0.91**	0.00	0.00	0.58	0.00	0.00
Isovist Perimeter	**0.98**	0.00	0.00		0.02		0.36	0.00	-0.00	**0.97**	0.00	0.00		0.01	
Isovist Compactness	0.59	0.00	-2.00	0.48	0.00	0.52		0.06		0.44	0.00	-0.34	0.71	0.00	0.04
Point First Moment	0.69	0.00	0.00		0.30			0.16		0.67	0.00	0.00	0.57	0.00	0.00
Point Second Moment	0.55	0.00	0.00		0.54			0.30		0.52	0.00	0.00	0.41	0.00	0.00
Isovist Min Radial	0.69	0.00	0.00	0.49	0.00	-0.00	0.36	0.00	-0.01	0.75	0.00	0.00		0.43	
Isovist Max Radial	**0.95**	0.00	0.00		0.05			0.22		**0.95**	0.00	0.00	0.55	0.00	0.00
Isovist Drift Angle		0.41			0.91			0.72			0.64			0.55	
Isovist Drift Magnitude	**0.96**	0.00	0.00	0.33	0.00	-0.00	**0.87**	0.00	0.00	**0.96**	0.00	0.00	0.46	0.00	0.00
Isovist Occlusivity	**0.99**	0.00	0.00	0.38	0.00	-0.00		0.03		**0.97**	0.00	0.00		0.03	
Through Vision	**0.99**	0.00	0.00		0.38			0.60		0.60	0.00	0.00		0.04	
Visual Clustering Coefficient	0.71	0.00	-0.73		0.10			0.14		0.35	0.00	-0.11		0.31	
Visual Control	**0.82**	0.00	1.10	0.62	0.00	-0.46	0.57	0.00	-23.51	0.79	0.00	0.42	0.31	0.01	0.01
Visual Controllability		0.07			0.95			0.40			0.03		0.29	0.01	0.05
Angular Mean Depth	**0.88**	0.00	-0.25		0.07		**0.95**	0.00	4.47	0.67	0.00	-0.08	0.63	0.00	-0.02
Metric Mean Shortest Path Angle	0.53	0.00	-0.10	0.75	0.00	-0.03	**0.99**	0.00	2.81	0.59	0.00	-0.04	0.73	0.00	-0.01
Metric Mean Shortest Path Distance		0.98		0.42	0.00	-0.00	0.63	0.00	0.00		0.01		0.51	0.00	-0.00
Visual Mean Depth	**0.92**	0.00	-0.16	0.67	0.00	-0.06		0.40		**0.85**	0.00	-0.02	0.78	0.00	-0.01
Visual Integration [HH]	0.78	0.00	0.48	0.48	0.00	0.17		0.88		0.51	0.00	0.05	0.57	0.00	0.02
Visual Integration [P-value]	0.75	0.00	4.36	**0.92**	0.00	2.17		0.60		0.57	0.00	0.45	**0.90**	0.00	0.22
Visual Integration [Tekl]	**0.81**	0.00	15.49		0.97			0.19		0.56	0.00	1.98		0.84	
Visual Entropy		0.04			0.07			0.45			0.10			0.16	
Visual Relativised Entropy	**0.87**	0.00	-0.60	**0.89**	0.00	-0.26		0.21		0.72	0.00	-0.07	**0.92**	0.00	-0.03

Table 4: All accessibility metrics tested against movement and interaction. Significant results are printed in red, and bold when $R^2 > 0.8$

	Movement density			Interaction density			Total observed density			Movement percentage			Interaction percentage		
Metric	R^2	p-val	coeff	R^2	p-val	coeff	R^2	p-val	coeff	R^2	p-val	coeff	R^2	p-val	coeff
Isovist Area	0.30	0.01	0.00		0.06		0.43	0.00	0.00		0.34			0.30	
Connectivity	0.31	0.01	0.00		0.05		0.44	0.00	0.00		0.37			0.29	
Isovist Perimeter	0.75	0.00	0.00		0.05		0.60	0.00	0.00		0.03			0.28	
Isovist Compactness	0.68	0.00	-1.02		0.09		**0.95**	0.00	-9.83	0.58	0.00	-0.09	0.74	0.00	0.11
Point First Moment		0.02		0.29	0.01	0.00		0.03			0.81			0.99	
Point Second Moment		0.02		0.42	0.00	0.00		0.11			0.20			0.61	
Isovist Min Radial		0.77		0.48	0.00	0.00	0.66	0.00	0.00	0.72	0.00	-0.00		0.02	
Isovist Max Radial	**0.82**	0.00	0.00		0.97		0.58	0.00	0.00	0.45	0.00	0.00		0.03	
Isovist Drift Angle		0.32			0.77			1.00			0.41			0.80	
Isovist Drift Magnitude	0.78	0.00	0.00		0.46		0.37	0.00	0.00		0.39			0.09	
Isovist Occlusivity	0.79	0.00	0.00		0.01		0.53	0.00	0.00	0.43	0.00	0.00		0.59	
Through Vision		0.05		0.39	0.00	0.00	0.28	0.01	0.00		1.00			0.67	
Visual Clustering Coefficient	0.75	0.00	-1.08		0.02			0.10			0.01		0.33	0.00	0.11
Visual Control	0.66	0.00	0.38		0.59		0.59	0.00	3.93		0.07			0.07	
Visual Controllability	0.39	0.00	-0.28	0.37	0.00	0.25		0.40		0.54	0.00	-0.07	0.35	0.00	0.25
Angular Mean Depth	0.60	0.00	-0.15		0.10		**0.86**	0.00	-1.59	0.35	0.00	-0.01		0.34	
Metric Mean Shortest Path Angle	0.78	0.00	-0.13	0.45	0.00	-0.12	**0.88**	0.00	-1.23	0.61	0.00	-0.01	0.37	0.00	-0.01
Metric Mean Shortest Path Distance		0.23		0.48	0.00	-0.00	0.30	0.01	0.00	0.31	0.01	-0.00	0.55	0.00	-0.00
Visual Mean Depth	**0.94**	0.00	-0.08	0.50	0.00	-0.05	0.77	0.00	-0.65	0.80	0.00	-0.01	0.38	0.00	-0.00
Visual Integration [HH]	0.42	0.00	0.04	**0.83**	0.00	0.04	0.29	0.01	0.29	0.29	0.01	0.00	0.49	0.00	0.00
Visual Integration [P-value]	**0.82**	0.00	4.11	**0.86**	0.00	0.54	0.57	0.00	2.67	**0.82**	0.00	0.32	0.72	0.00	0.05
Visual Integration [Tekl]	0.67	0.00	34.56	0.31	0.01	2.50	0.80	0.00	27.00	0.67	0.00	2.73		0.50	
Visual Entropy		0.02			0.01			0.04			0.17			0.03	
Visual Relativised Entropy	**0.91**	0.00	-0.25	0.40	0.00	-0.15	0.64	0.00	-1.49	**0.82**	0.00	-0.02		0.02	

Table 5: All visibility metrics tested against movement and interaction. Significant results are printed in red, and bold when $R^2 > 0.8$

Finally, in table 6 it is shown how well the binning method works for each site. Each cell in the table displays the percentage of sites that are significant significant ($p < 0.01$) for each metric and each activity and have effects $R^2 > 0.2$, $R^2 > 0.5$ or $R^2 > 0.8$. These are tested for Accessibility and Visibility, for the global quantile bins and the local quantile bins (LQ).

metric	Acc.Movement.0.2	Acc.Movement.0.5	Acc.Movement.0.8	Vis.Movement.0.2	Vis.Movement.0.5	Vis.Movement.0.8	Acc.Interaction.0.2	Acc.Interaction.0.5	Acc.Interaction.0.8	Vis.Interaction.0.2	Vis.Interaction.0.5	Vis.Interaction.0.8	Acc.Movement.LQ.0.2	Acc.Movement.LQ.0.5	Acc.Movement.LQ.0.8	Vis.Movement.LQ.0.2	Vis.Movement.LQ.0.5	Vis.Movement.LQ.0.8	Acc.Interaction.LQ.0.2	Acc.Interaction.LQ.0.5	Acc.Interaction.LQ.0.8	Vis.Interaction.LQ.0.2	Vis.Interaction.LQ.0.5	Vis.Interaction.LQ.0.8
Isovist Area	80.5	65.9	39.0	12.2	9.8	0.0	34.1	9.8	0.0	12.2	9.8	0.0	82.9	75.6	31.7	17.1	4.9	0.0	41.5	7.3	0.0	24.4	4.9	0.0
Connectivity	80.5	63.4	34.1	12.2	4.9	2.4	34.1	4.9	0.0	12.2	9.8	0.0	82.9	80.5	31.7	19.5	4.9	0.0	48.8	9.8	0.0	17.1	2.4	0.0
Isovist Perimeter	82.9	80.5	51.2	34.1	22.0	2.4	46.3	17.1	0.0	12.2	9.8	0.0	87.8	82.9	46.3	41.5	14.6	0.0	51.2	7.3	0.0	26.8	7.3	0.0
Isovist Compactness	68.3	29.3	0.0	39.0	14.6	0.0	26.8	17.1	2.4	4.9	0.0	0.0	70.7	41.5	0.0	51.2	19.5	0.0	26.8	26.8	0.0	17.1	2.4	0.0
Point First Moment	65.9	48.8	24.4	12.2	9.8	0.0	12.2	0.0	0.0	9.8	7.3	2.4	78.0	68.3	19.5	31.7	14.6	0.0	14.6	0.0	0.0	24.4	7.3	0.0
Point Second Moment	51.2	39.0	9.8	14.6	12.2	2.4	2.4	0.0	0.0	12.2	12.2	2.4	70.7	43.9	9.8	26.8	9.8	0.0	2.4	0.0	0.0	17.1	7.3	0.0
Isovist Min Radial	85.4	70.7	29.3	9.8	2.4	0.0	73.2	22.0	0.0	14.6	9.8	2.4	90.2	65.9	26.8	7.3	4.9	0.0	70.7	17.1	0.0	26.8	9.8	2.4
Isovist Max Radial	80.5	65.9	29.3	31.7	12.2	0.0	29.3	7.3	0.0	14.6	9.8	0.0	82.9	78.0	29.3	34.1	22.0	0.0	46.3	7.3	0.0	17.1	2.4	0.0
Isovist Drift Angle	4.9	0.0	0.0	9.8	4.9	0.0	2.4	0.0	0.0	0.0	0.0	0.0	2.4	0.0	0.0	7.3	2.4	0.0	2.4	0.0	0.0	2.4	0.0	0.0
Isovist Drift Magnitude	65.9	36.6	14.6	41.5	9.8	2.4	34.1	4.9	0.0	26.8	14.6	2.4	61.0	48.8	9.8	39.0	17.1	4.9	34.1	4.9	0.0	14.6	2.4	0.0
Isovist Occlusivity	80.5	73.2	48.8	29.3	19.5	4.9	34.1	9.8	0.0	19.5	14.6	2.4	85.4	80.5	46.3	46.3	26.8	0.0	43.9	12.2	0.0	36.6	12.2	0.0
Through Vision	80.5	80.5	39.0	36.6	24.4	9.8	9.8	0.0	0.0	22.0	17.1	2.4	82.9	82.9	43.9	36.6	22.0	7.3	22.0	2.4	0.0	26.8	12.2	4.9
Visual Clustering Coefficient	48.8	36.6	7.3	48.8	26.8	0.0	17.1	0.0	0.0	4.9	0.0	0.0	56.1	41.5	7.3	56.1	31.7	0.0	22.0	0.0	0.0	4.9	2.4	0.0
Visual Control	87.8	80.5	31.7	58.5	26.8	0.0	95.1	68.3	0.0	7.3	0.0	0.0	85.4	80.5	31.7	58.5	34.1	0.0	97.6	68.3	0.0	14.6	2.4	0.0
Visual Controllability	14.6	7.3	0.0	12.2	9.8	0.0	43.9	19.5	0.0	2.4	2.4	0.0	12.2	2.4	0.0	17.1	4.9	0.0	51.2	19.5	0.0	7.3	4.9	0.0
Angular Mean Depth	58.5	34.1	0.0	17.1	7.3	0.0	56.1	34.1	2.4	17.1	12.2	0.0	75.6	46.3	2.4	24.4	7.3	0.0	63.4	48.8	9.8	17.1	0.0	0.0
Metric Mean Shortest Path Angle	56.1	41.5	2.4	19.5	12.2	0.0	51.2	29.3	9.8	14.6	7.3	2.4	68.3	53.7	4.9	34.1	4.9	2.4	65.9	39.0	12.2	17.1	4.9	2.4
Metric Mean Shortest Path Distance	39.0	31.7	12.2	19.5	12.2	4.9	2.4	2.4	0.0	12.2	7.3	2.4	73.2	43.9	2.4	56.1	29.3	0.0	17.1	2.4	0.0	7.3	0.0	0.0
Visual Mean Depth	36.6	31.7	7.3	19.5	19.5	4.9	9.8	4.9	0.0	7.3	7.3	2.4	68.3	34.1	0.0	34.1	9.8	0.0	29.3	9.8	0.0	12.2	4.9	0.0
Visual Integration [HH]	43.9	41.5	4.9	24.4	22.0	2.4	7.3	0.0	0.0	0.0	0.0	0.0	70.7	56.1	4.9	41.5	22.0	0.0	17.1	4.9	0.0	7.3	2.4	0.0
Visual Integration [P-value]	43.9	39.0	7.3	24.4	22.0	7.3	2.4	0.0	0.0	2.4	2.4	0.0	73.2	56.1	4.9	41.5	22.0	0.0	17.1	4.9	0.0	7.3	2.4	0.0
Visual Integration [Tekl]	43.9	26.8	4.9	24.4	17.1	2.4	9.8	9.8	2.4	2.4	2.4	0.0	70.7	46.3	0.0	41.5	17.1	0.0	22.0	7.3	0.0	9.8	2.4	0.0
Visual Entropy	14.6	12.2	0.0	7.3	4.9	2.4	0.0	0.0	0.0	4.9	4.9	2.4	19.5	4.9	0.0	9.8	2.4	0.0	4.9	2.4	0.0	2.4	2.4	0.0
Visual Relativised Entropy	24.4	24.4	2.4	14.6	9.8	0.0	2.4	0.0	0.0	2.4	2.4	0.0	51.2	24.4	0.0	29.3	4.9	0.0	26.8	14.6	0.0	4.9	2.4	0.0

Table 6: Percentages of the sites each metric is significant ($p < 0.01$) for each activity and has effect $R^2 > 0.2$, $R^2 > 0.5$ or $R^2 > 0.8$. Tested for Accessibility and Visibility, for the global quantile bins and the internal quantile bins (LQ)

We can see that for movement the results are similar to the globally observed. The local metrics for the size of the visual field, the potential for exploration, movement and and control all predict at least 20% of the result in 60-80% of the sites. *Isovist Occlusivity* and *Isovist Perimeter* predict more than 80% of the variability in nearly half the cases.

Where local quartiles are used the results are almost universally better than the global results when the barrier for variability is set low (0.2 and 0.5). All the local metrics have slightly higher chances of predicting 20% or 50% of the variability while those chances increase by a large margin when global metrics are concerned. In the case of R^2=0.8 the results for local quartiles seem to get worse than the global ones.

The results for interaction are not as similar as the ones for the whole-sample analysis in tables 5 and 4. There is one result that stands out quite significantly, *Visual Control* which predicts the variability of interaction higher than 20% for 95.1% of the cases, but also *Isovist Min Radial* which does so for 73.2% of the cases. Both these metrics were significant in the whole-sample analysis but did not have as strong an effect as the global ones. On the other hand, the global visual metrics that were quite significant on the large sample, here explain variability for a very small sample of the cases. Instead, we find variability over 20% explained for almost approximately half the cases by the angular depth metrics (*Angular Mean Depth* and *Metric Mean Shortest Path Angle*)

7. DISCUSSION

From the two methods, binning the metrics seems to work best as a tool for predicting the activities of people in office spaces. While in the literature (for example in Hillier and Grajewski (1990)) aggregating by floor has been the default it is apparent here that aggregating by larger patches of space predicts both activities better. This might be due to the fact that a floor as a whole very likely contains high and low values of each metric which may cancel each other out in the aggregation. This is especially true for local metrics and it becomes apparent from tables 2 and 3, where only the global metrics have some significance. For such global metrics as *Visual Mean Depth*, different floors might get different values, depending on how far they are from the central floor.

In general, for the per-floor analysis, movement was better predicted than interaction, and mainly by global metrics. However it seems that it is actually the overall presence of people and not what they are doing that can be predicted by these metrics, as the results in the last two columns of table 2 show.

The results of the binning method seem much more robust. Movement was found to be well predicted by many local and global metrics, but mainly in accessibility. Overall it seems that people are mainly found walking in larger areas, and in areas where the potentials for movement, exploration and control are higher. This might point to a preference for movement that is highly connected to visibility. The metrics that relate to the size of spaces and control of the visual field potentially allow people to survey many other people in the office. For example someone may prefer to take a certain path if it goes through areas where other people are sitting, as it creates the potential to talk to other people. The high effect of *Isovist Min Radial* for visibility is potentially present for the same reasons. The appearance of more movement in more integrated spaces is potentially due to the centrality of the configuration afforded by the relevant metrics. Reaching a centrally-located space is more is more likely to unlock the shortest paths everywhere else.

Interaction on the other hand does not appear to be as predictable as movement, even with the binning method. It seems to be driven mainly by visual global metrics and from those more specifically, the various integrations. Visual Integration [P- value] seems to have a persistent effect for interaction in both accessibility and visibility and should thus be studied further.

As is apparent from the scatterplots of the binning method, especially for interaction, most local metrics show patterns that are related to the regression line but could potentially be approximated best with curvilinear regression. This visual effect points to the existence of a process that has not been taken into account and potentially related to the isovist.

The large number of highly effective correlated tests in binning suggests that many of the metrics measure similar properties of the space. A simple example is the high R^2 of *Isovist Area* and *Connectivity* when tested against movement in accessibility (table 4), which, as explained earlier measure almost the same property of the configuration, the amount of visible space. This might also be the case with *Isovist Drift Magnitude* and *Isovist Max Radial* in the same table, which for accessibility will rank the edges of corridors very high.

Movement seems to be the most predictable even when the analysis is carried by site. The fact that the results are very similar to the whole-sample analysis suggests that there are universal characteristics of spatial configurations that attract movement. This could potentially be attributed to the fact that movement is primarily a utilitarian activity and mainly happens in corridors or corridor-shaped spaces, a configuration that some of the metrics were made to capture (for example *Through Vision* and *Isovist Max Radial* for accessibility). There are though global properties of movement that are not captured particularly well as far as each site is concerned and should potentially be studied for each site. This is apparent from the fact that the prediction for the each site was higher when the binning was done on a per site-basis.

The discrepancies for interaction between the whole-sample and the per-site analyses show us that this specific activity should potentially be studied at both levels. There seem to be elements of the configuration that trigger interactions that are universal and others that depend on parameters that differ per site. A possible explanation could be the workplace culture of each company or the industry that company belongs to, which might tolerate interactions in the workplace or not. It is for example more likely that if the workplace culture frowns upon interactions close to workspaces, then those interactions might be moved to places that are deeper to get to (more segregated) in order to avoid disturbing others.

Binning non-normalised global metrics such as *Visual Mean Depth* requires more exploration, as when it is carried out across the whole range of values in a diverse dataset it can have unexpected side-effects. As seen in Figure 11 (a), binning a metric for a multi-floor study creates high values and separates the cells into many different groups, but in a single-floor studies (b), the binning may put the whole floor in a single bin. This might work as the centre of a building functions as a core, while in single-floor instances there is no other part apart from the core and may thus also attract more movement

Of the permutations of integration presented it has become apparent that the simpler measure of Visual Integration [Tekl] is a better predictor for movement than *Visual Integration [HH]* and *Visual Integration [P-value]*.

6. CONCLUSION

In this paper we examined the origins of Visibility Graph Analysis, from the combination of ideas from the Social Logic of Space and isovists by Turner et al. (2001), to its current implementation in depthmapX. We identified the 25 metrics that depthmapX can generate, where they come from and how they are calculated, as well how to potentially use each of them to understand human behaviour in office spaces.

We tested each of the metrics across a large sample of office spaces to unearth their relationship to two specific human behaviours: movement and interaction. We found that some metrics such as *Visual Mean Depth* play an important role for understanding the effects of movement, more specifically that more segregated floors and spaces tend to attract less movement. We also found that of the two activities movement is the easiest to predict, with many of the results applicable both to large-scale analysis but also on a per-site level.

The research presented has a few limitations to be noted. The size and variety of the dataset creates large variability in the analysis. This is highlighted in the tests where activity is aggregated by floor in which the normalisation (by floor area) does not aid the prediction as much as the total number of people is. In this case, a better normalisation metric is required to account for the effect of floor size. This is also true for the VGA metrics, especially the ones that measure global properties of the space. Although there have been normalisations, they have been created for different contexts (typically urban line analysis), and in our tests they usually perform worse than the raw metric. Finally, here we have only examined each metric on its own against each activity. While this is typically the case in the literature, it is more likely that a combination will yield better results as it will allow for taking into account different properties of space at the same time, each of which contributes a part in the prediction.

Thus, the next step for this analysis will specifically focus on methods using multiple variables. This will initially take the form of multi-collinearity analysis where the metrics that truly add new information will be identified and become parts of multiple-regression models to test how well they predict activities in combination. As some activities were found to affect each other (overall presence affects movement) they should also be tested in a multi-variate model which will take them and the metrics into account at the same time. Eventually, the models that best predict the various activities will be tested against newly designed plans.

This paper contributes to the current discourse in multiple ways. It collects, explains and visualises the various VGA metrics that are currently available in depthmapX and thus has the potential to become a useful reference for future work. We tested each metric against observational data giving explanations for how well they predict or do not predict the activities in office spaces. We used two methods for the comparisons to observation data, one similar to the existing ones which helps validate old results and the other a new method that allows for more fine-grained analysis. Finally, this work is a step towards better predicting activity in office spaces which can eventually provide designers with new tools to allow for human-centric evidence-based design.

REFERENCES

Batty, M. (Feb. 2001). "Exploring Isovist Fields: Space and Shape in Architectural and Urban Morphology". In: Environment and Planning B: Planning and Design 28.1, pp. 123–150. ISSN: 0265-8135, 1472-3417. DOI: 10.1068/b2725. URL: http://journals.sagepub.com/doi/10.1068/b2725 (visited on 08/13/2018).

Benedikt, M. L. (1979). "To Take Hold of Space: Isovists and Isovist Fields". In: 6.1, pp. 47–65. ISSN: 0265-8135. DOI: 10.1068/b060047. URL: http://dx.doi.org/10.1068/b060047.

Conroy, R. (2001). "Spatial Navigation in Immersive Virtual Environments". PhD thesis. UCL (University College London).

Cox, E. P. (1927). "A Method of Assigning Numerical and Percentage Values to the Degree of Roundness of Sand Grains". In: Journal of Paleontology 1.3, pp. 179–183. ISSN: 0022-3360. URL: https://www.jstor. org/stable/1298056 (visited on 01/16/2019).

De Arruda Campos, M. B. and Fong, P. S. (2003). "A Proposed Methodology to Normalise Total Depth Values When Applying the Visibility Graph Analysis". In: Proceedings of the Fourth International Space Syntax Symposium. Fourth International Space Syntax Symposium. London, UK. URL: http://www.spacesyntax. net/symposia-archive/SSS4/fullpapers/35Campos-Fongpaper.pdf (visited on 05/18/2016).

depthmapX development team (2017). depthmapX. Version 0.6.0. URL: https://github.com/SpaceGroupUCL/ depthmapX/.

Gibson, J. J. (1983). The Senses Considered as Perceptual Systems. Westport, Conn: Greenwood Press. 335 pp. ISBN: 978-0-313-23961-8.

Hillier, B. and Grajewski, T. (1990). "The Application of Space Syntax to Work Environments inside Buildings: Second Phase: Towards a Predictive Model". In: Unit for Architectural Studies. London: The Bartlett School of Architecture and Planning, University College London.

Hillier, B. and Hanson, J. (1984). The Social Logic of Space. Cambridge University Press (CUP). ISBN: 978-0- 511-59723-7. URL: http://dx.doi.org/10.1017/cbo9780511597237.

Hillier, B., Hanson, J., and Graham, H. (1987). "Ideas Are in Things: An Application of the Space Syntax Method to Discovering House Genotypes". In: 14.4, pp. 363–385. ISSN: 0265-8135. DOI: 10.1068/b140363. URL: http://dx.doi.org/10.1068/b140363.

Koutsolampros, P., Sailer, K., and Varoudis, T. (2018). "Partitioning Indoor Space Using Visibility Graphs: Investigating User Behaviour in Office Spaces". In: p. 13.

Koutsolampros, P. et al. (2015). "Spatial Databases: Generating New Insights on Office Design and Human Behaviours in the Workplace". In: Proceedings of the 10th International Space Syntax Symposium. 10th International Space Syntax Symposium. London.

Koutsolampros, P. et al. (2017). "Big Data and Workplace Micro-Behaviours: A Closer Inspection of the Social Behaviour of Eating and Interacting". In: Proceedings of the 11th International Space Syntax Symposium. Vol. 11. Instituto Superior Tecnico Departamentode Engenharia Civil, Arquitetura e Georrecursos, pp. 149–1. URL: http://discovery.ucl.ac.uk/1568210/ (visited on 09/20/2017).

Krüger, M. J. T. (Sept. 1989). "On Node and Axial Grid Maps: Distance Measures and Related Topics". In: Presented at: European Conference on the Representation and Management of Urban Change, Cambridge, UK. (1989). European Conference on the Representation and Management of Urban Change. London, UK: Bartlett School of Architecture and Planning, UCL. URL: http://discovery.ucl.ac.uk/1011/ (visited on 01/03/2019).

Penn, A., Desyllas, J., and Vaughan, L. (1999). "The Space of Innovation: Interaction and Communication in the Work Environment". In: Environment and Planning B: Planning and Design 26.2, pp. 193–218. ISSN: 0265- 8135, 1472-3417. DOI: 10.1068/b4225. URL: http://discovery.ucl.ac.uk/931/ (visited on 07/16/2015).

Peponis, J. et al. (1997). "On the Description of Shape and Spatial Configuration inside Buildings: Convex Partitions and Their Local Properties". In: 24.5, pp. 761–781. ISSN: 0265-8135. DOI: 10.1068/b240761. URL: http://dx.doi.org/10.1068/b240761.

Psathiti, C. and Sailer, K. (2017). "A Prospect-Refuge Approach to Seat Preference: Environmental Psychology and Spatial Layout". In: p. 16. URL: http://discovery.ucl.ac.uk/1568213/.

Sailer, K. et al. (2016). "Measuring Interaction in Workplaces". In: Architecture and Interaction. Ed. by Dalton, N. S. et al.

Al-Sayed, K. et al. (2014). Space Syntax Methodology. Bartlett School of Architecture, UCL. URL: http:// discovery.ucl.ac.uk/1415080/ (visited on 10/14/2017).

Silva, J. P. and Turner, A. (2010). "Introduction to Depthmap 10". URL: http://www.academia.edu/ 15667098/Introduction_to_Depthmap10_SC2010 (visited on 01/16/2019).

Teklenburg, J. A. F., Timmermans, H. J. P., and Wagenberg, A. F. van (1993). "Space Syntax: Standardised Integration Measures and Some Simulations". In: 20.3, pp. 347–357. ISSN: 0265-8135. DOI: 10.1068/b200347. URL: http://dx.doi.org/10.1068/b200347.

Turner, A. (2001). "Depthmap: A Program to Perform Visibility Graph Analysis". In: Proceedings of the 3rd International Symposium on Space Syntax, p. 9. URL: http://www.ucl.ac.uk/bartlett/3sss/papers_pdf/31_turner.pdf.

Turner, A. (2004). "Depthmap 4: A Researcher's Handbook". In: URL: http://discovery.ucl.ac.uk/2651/ (visited on 05/31/2016).

Turner, A. (2007a). "To Move through Space: Lines of Vision and Movement". In: Proceedings, 6th International Space Syntax Symposium, 12 - 15 June, 2007. 6th International Space Syntax Symposium. URL: http:// eprints.ucl.ac.uk/4111/ (visited on 11/02/2018).

Turner, A. (2007b). "UCL Depthmap 7: From Isovist Analysis to Generic Spatial Network Analysis". In: pp. 43– 51.

Turner, A. and Penn, A. (1999). "Making Isovists Syntactic: Isovist Integration Analysis". In:

Turner, A. et al. (Feb. 2001). "From Isovists to Visibility Graphs: A Methodology for the Analysis of Architectural Space". In: Environment and Planning B: Planning and Design 28.1, pp. 103–121. ISSN: 0265-8135, 1472- 3417. DOI: 10.1068/b2684. URL: http://journals.sagepub.com/doi/10.1068/b2684 (visited on 03/04/2017).

Varoudis, T. (2012). depthmapX - Multi-Platform Spatial Network Analyses Software. OpenSource.

Vaughan, L. (2001). Space Syntax Observation Manual (2001 Unpublished Revised Edition).

Watts, D. J. (1999). Small Worlds: The Dynamics of Networks between Order and Randomness. Princeton University Press. ISBN: 0-691-11704-7 978-0-691-11704-1.

Zook, J. B. (2017). "Spatial Schemata in Museum Floorplans". In: Proceedings of the 11th International Space Syntax Symposium. 11th International Space Syntax Symposium.