

Testing the spatial affordance hypothesis:
Evidence from factor analysis,
mathematical models, and behavioural
analysis

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

This thesis attempts to explain the apparent link between how we navigate the world around us and the physical properties that define that world. Despite a number of works indicating the substantial effect of the layout of the environment – both as a whole and within a viewpoint – no work to date has directly attempted to address how and what physical properties shape our navigation through space. This research question is examined in the context of a direct relationship between the physical environment and our movement choices – an affordance. To test this idea, the question is approached from the ground up using a combination of spatial analysis, mathematical modeling, and behavioural analysis, to reveal that a small family of local perceptual variables, but particularly that of mean surface depth, is capable for accounting for much of our movements in space, even when the environment is largely disorganized. Using Factor Analysis (Chapter Two), three studies using data drawn from both artificial and real-world spaces reveal a critical link between the local perceptual characteristics of the environment and properties and the complexity of space lying outside the local perceptual space. Chapter Three explores the capacity of these specific local perceptual variables to guide navigation behaviour in a way that is consistent with the concept of an affordance. Across all approaches, the variable of mean surface depth is shown to both systematically relate to the layout of the world around us and guide our movement choices within that world. In establishing this affordance – Depth Afforded Navigation – a novel link between studies of local perception and the layout of space can be established and built upon in future work. This work not only sheds new light on how common patterns of navigation behaviour occur, but also allows the often disparate approaches (i.e., space syntax, isovist analysis, angular segment analysis, etc.) used to understand the role of space to be understood under one unifying model.

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Dedication

I would like to dedicate this work to two people. The first is the late Alisdair Turner whose intelligent and insightful body of work has served as an inspiration. The second, my loving wife Carol. Without her support, patience, and encouragement I would not be the same.

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Chapter 1

Understanding How Spatial Variables Shape Movement

1.1 Introduction

For over a century, urban planners and architects have had an intuitive understanding that people navigate the world in common ways – most influenced by how an environment has been configured. One classic example of this can be found in the approach used to design Grand Central Station in Glasgow, Scotland (Matheson, 1909). Matheson noted that a mass of people showed a tendency to move through the space around them like the flow of water, traveling along the lines of least resistance. Resistance could take a number of forms – a reduction of the size of a walkway, the enclosure of an open space with walls, or the presence of other people. Critically, Matheson noted that the flow of water alone (that is, without considering the experience, abilities, or goals of the individual navigators) could accurately predict where people would move and where they would congregate. This observation suggested an essential link between the geometry of an environment and the behaviour of people within such an environment. This initial example was later confirmed in stochastic (Mayne, 1954) and physics-derived (Helbing, Molnar, Farkas, & Bolay, 2001; Helbing, 1993; Helbing, 1992; Henderson & Jenkins, 1974) models that predict the movement of crowds by referencing the shape of surrounding space and momentum of movement.

Recent work within a subfield of architecture and urban planning known as Space Syntax (Hillier, 1996; Hillier & Hanson, 1984) suggests a more complicated picture of how the geometry of an environment might shape people's navigation and behaviour. Space Syntax includes a number of theories and techniques which are meant to quantify the structure of an environment by reducing the environment to simple mathematical descriptions of the unique paths and/or sight lines available within that environment. In contrast to the water flow technique employed by Matheson and the mathematical models derived from physical equations, both of which are greatly influenced by the discrete size and shape of space (such as the distance between two points in space or the area around a specific point) in determining the capacity for movement, the Space Syntax method instead focuses on describing an environment through the relationship between each unique pathway in an environment and all other pathways found nearby. To achieve this, open space in an environment is decomposed into two elementary features: (1) available pathways or lines-of-sight, defined by straight lines (termed: *axial lines*) between each discrete space in an environment and (2) the intersection/choice points created at the intersection of each axial line (Hillier & Vaughan, 2007;

Hillier & Hanson, 1984). This simple description of space – of paths and their intersections – is then examined using graph theory to assess the degree of local (as experienced from a local position in space) and global (drawing upon knowledge about the overall configuration of an environment) complexity of a location in space. For example, *connectivity* (sometimes termed *degree*) is defined as the number of intersections between each axial line and all others found within an environment. As connectivity only considers those lines directly intersecting with an axial line, ignoring all others present in the environment, it is a measure of the local complexity of a space. In contrast, *integration*, the average number of turns (or nodes that must be traversed) to go from one axial line to all other axial lines in environment, is a measure of the global complexity of a space. Figure 1.1 provides a concrete example of how these two measures can be computed for a simple environment.

Early behavioural studies applying the Space Syntax approach were interested in how the complexity of an environment can shape how a crowd moves through space. Similar to the water-based and mathematical models, these early studies counted the number of people at each location in an environment at various points of time (this approach is sometimes known as *aggregate* traffic analysis) in various cities and buildings. These studies of aggregate traffic revealed a strong correlation between the number of pedestrians (Hillier, Burdett, Peponis, & Penn, 1987; Hillier, Penn, Hanson, Grajewski, & Xu, 1993; Hillier et al., 1987) or vehicles (Penn, Hillier, Bannister, & Xu, 1998a; Penn, Hillier, Bannister, & Xu, 1998b) passing through a location and the corresponding level of local and global measures derived by Space Syntax. Overall, the strongest correlations between the amount of traffic passing along roads and hallways were noted for the measures of connectivity and integration introduced earlier (see Penn, 2003 for a review). Further, when the overall complexity of an entire environment or neighbourhood was examined – an idea that can be captured by how well the global complexity of an environment correlates with the local complexity of space (termed *intelligibility*) – traffic was shown to follow the expected paths (that is, high connectivity and/or high integration) when the overall correlation between the local and global variables was high (e.g., Penn, 2003). When the correlation between connectivity and integration was reduced in a complex environment, such as the winding streets of Rome or London, the movement of individuals was much more varied. Together, these studies of aggregate movement appear to suggest that individual navigators are driven by these local and global measures of spatial complexity.

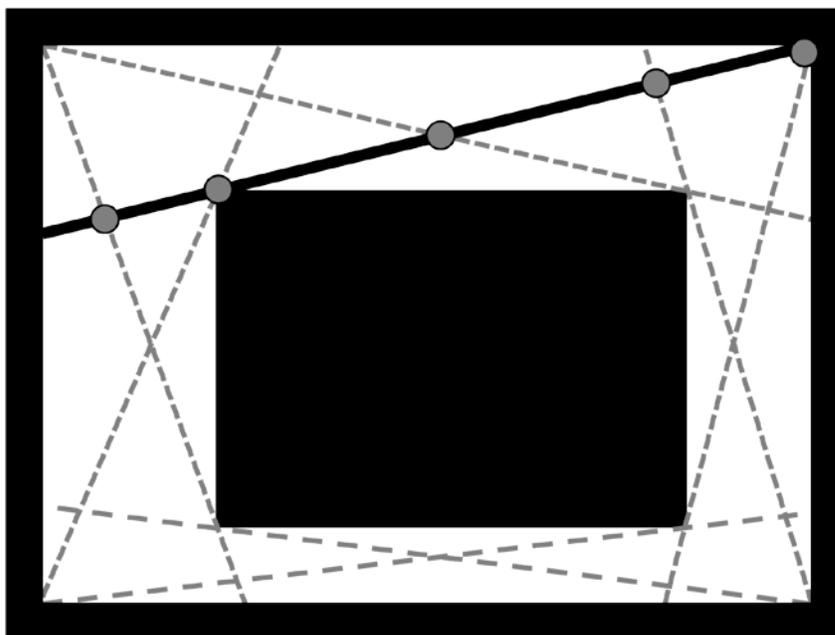


Figure 1.1 A depiction of the Space Syntax method for axial analysis. The dashed lines and solid line represent potential lines-of-sight or available paths (i.e., axial lines) available within the environment. The solid line demonstrates how data is quantified relative to a specific axial line.

Studies of individuals navigating various real (Hillier & Iida, 2005; Haq & Zimring, 2003; Haq, 2003; Peponis, Zimring, & Choi, 1990) and virtual (Barton, Valtchanov, & Ellard, 2014; Conroy Dalton, 2003; Conroy, 2001) environments have shown correspondence with this view. For instance, Conroy (2001) demonstrated that individual navigators followed more direct paths toward a goal and reduced route redundancy in highly intelligible environments versus less intelligible environments. The routes of individuals have also been shown to be more similar to each other in highly intelligible spaces than routes in low intelligibility spaces (Barton et al., 2014; Conroy, 2001). Individuals also show a tendency to follow paths with higher connectivity when they are unfamiliar with an environment, and shift toward using paths with higher integration as their familiarity with an environment increases (Hölscher, Brösamle, & Vrachliotis, 2012; Haq & Zimring, 2003; Haq, 2003). These findings are interesting because they strongly suggest that a considerable portion of human navigation can be accounted for by the complexity of surrounding space, independent of individual goals, spatial knowledge, or individual differences. Without factoring in individual differences, intelligibility and the topological measures of Space Syntax have been shown to account for between 40-50% (Barton et al., 2014) and 60-80% (Penn, 2003) of the variation in individual movement. It is these results that have caused many to argue (summarized in Penn, 2003) that navigation of individuals and crowds is directed by variables that capture the complexity of surrounding space.

Taken as a whole, Space Syntax suggests that the ease with which a space can be perceived and represented strongly influences how we navigate. This position is supported by evidence that suggests that more directed and linear forward motion is observed when an environment is predictable, that is highly intelligible (Conroy, 2001). Across a person's route through an environment, each turn has been shown to conserve linearity, minimizing the angle with which the route deviates at intersections or choice points (Conroy Dalton, 2003). Together, these studies suggest that we move toward locations that offer increased connectivity and integration as they conserve forward motion. Consequently, the influence of the complexity of space on behaviour is achieved by directly perceiving information about the configuration of space (both locally and globally) in the surrounding environment, an idea known as *exosomatic visual architecture* (Turner, 2006; Penn, 2003; Turner & Penn, 2002). Fundamentally, the influence of the local and global configuration of space must be found in the *local* environment in order to observe consistent, characteristic, patterns of movement.

However, to date, little direct evidence exists to link the perception of local spatial information with the tendencies to follow paths that reduce local and global complexity such as in intelligibility

analysis (Montello, 2007). Despite this, many authors (e.g., Emo, Hölscher, Wiener, & Dalton, 2012; Wineman & Peponis, 2010; Maier, Fadel, & Battisto, 2009; Turner, 2006; Penn, 2003; Turner, Doxa, O'Sullivan, & Penn, 2001; Hillier, 1999) have attempted to account for consistencies in how people navigate or behave in space by proposing that a direct relationship must exist between the perception of visual space and the action of locomotion. Crucially, the basis for this relationship has been proposed to be *direct*, taking on the form of an *affordance*, part of the *ecological theory of perception* (Gibson, 1979). It is this presumption that my thesis will seek to examine to determine the sufficiency of the position that affordance and exosomatic visual architecture is capable of explaining how we move through complex urban environments. To achieve this, my thesis will examine whether common patterns of movement fit the constraints outlined by the *ecological theory of perception*.

1.2 Ecological Perception and the Theory of Affordances

The *theory of perception* was first put forward by J.J. Gibson (1950) as an explanation of the close fit between our perceptions of the world and our actions within the world. Gibson noted that there are stable characteristics of the physical world that provide useful information, allowing an organism to act upon the world. Gibson (1950) posited that this was achieved by an organism sampling the structure of the world around them for patterns, gleaned from consistencies in how light (or other sensations) are perceived as the organism moves and acts upon the world. In the case of light perceived through the visual system, the patterns formed by the texture that composes a surface and the contours that define its dimensions provide critical information about the arrangement of the physical world around the organism. In identifying systematic patterns in how the visual field appears, the organism can therefore identify the layout of surrounding space in a systematic way – the *optic array*. One reason for believing this was found in early observational studies of World War II pilots (Gibson, 1950). Gibson observed that pilots tended to orient themselves (and their aircraft) based on visual characteristics of the ground rather than based on other types of sensory feedback (such as the vestibular system). From this, he reasoned that the optic array was critical in determining how to orient and act upon the world, even when other forms of sensory information are available.

The systematic patterns that are observed in nearby space and that compose the *optic array* were later elaborated to be the product of the perception of *invariants* (Gibson, 1978; Gibson, 1966). At the most basic level, vision can be thought of as a combination of static (viewing a specific location in space from a specific point) and dynamic (changes in the visual field observed through movement and action) information. Static viewing of the world, perceiving properties like texture, luminance,

contour, et cetera, can describe the *perspective structure* of the world around us. However, the usefulness of perspective structure is limited because it does not describe how the world is made up of objects but rather it simply describes visible surfaces. In contrast, each time you take a step in any direction, the perspective structure changes, sometimes quite radically, providing very different (but supplementary) information about the structure of the world around us. This is because as we move, certain consistencies can be perceived when examining how the perspective changes with each movement that were not available in the static perspective structure alone. These consistencies compose the *invariant structure* of the world around us. That is, we can understand the layout of the world around us (and its component objects) by perceiving those properties that remain stable, independent of our actions. Gibson reasoned that these stable characteristics of the world, termed *invariants*, are what guide behaviour and action, an idea that would form the basis of the theory of *direct perception* and *ecological perception* (Gibson, 1978; 1966). Many invariants have been identified, including perceived continuity, rectilinearity, margins between illuminated patches, and relative layout of surface structure, to name a few. In each case, one or more invariants provide a description of the location and shape of physical objects through the persistence of each visual property throughout action. Invariants are able to drive action by the organism mapping a physical capability that it has on to the structure of the world as defined by the perceived invariants. Certain perceived invariants, such as the size of an object or surface, will constrain the actions that are available to the organism. Gibson termed this idea *affordance*. A relatively simplistic example of these ideas can be understood by describing the affordance of grasping. The size and shape of a rock can be described by a number of invariant properties, independent of the perspective a person takes at viewing the rock. By mapping the invariants of size and shape onto action capabilities of a person, such as the diameter of your hand and the number of digits, you can determine whether that rock can or cannot be grasped. Thus, at the most fundamental level, the invariants of size and shape afford the act of grasping. This bottom-up view of action selection, where low-level visual information rather than top-down or cognitive processing drive action, are fundamental to *affordance* and *direct perception* (Gibson, 1978).

The idea of affordance has been well studied outside of the field of human navigation. One classical example of this is in the visual cliff paradigm. In this paradigm, infants are placed in front of an apparent drop-off and their behaviour is passively observed. Infants that are not yet able to walk independently often will move toward the apparent drop-off. In contrast, infants that have acquired the capability to walk independently avoid the apparent drop-off. This suggests that the action

possibility of movement must be matched with the perception of the apparent cliff for the affordance of falling to be understood (and acted upon) by infants (Adolph, Ketch, & LoBue, 2014). Adults have also been shown to reference physical capabilities when performing actions. In one example, adults have been shown to climb stairs by referencing the fit between the length of their legs and the height of the riser, choosing stairs with the optimal fit between riser height and the length of their legs (Warren Jr., 1984). A similar affordance has been demonstrated for shoulder width and the diameter of a doorway (Warren Jr & Whang, 1987). In each case, affordance has been shown to be useful in understanding how relatively simplistic choices of actions are made by referencing the properties of the invariant structure in the surrounding world.

To date, however, despite the presumption that affordance is guiding more complex behaviour – in this case, spatial navigation – no studies have examined whether affordance is a reasonable explanation for how we choose to move through urban spaces. In the present work, I will develop an account of navigation behavior from the ground up using an approach motivated by Gibson's theory of direct perception and affordance. To achieve this, and determine fit with the aforementioned implicit hypothesis that spatial information is directly perceived prior to navigating through the world, the space around a navigator will be described by isovists.

1.3 Isovists As Capturing Directly Perceived Visual Properties

Isovists were first conceived by Hardy (1967), and later named *isovist analysis* by Tandy (1967), as a method of describing the shape of nearby landscape features from a specific viewpoint. At the most basic level, isovist analysis provides a means to systematically describe the structure of surrounding space. This is achieved by casting rays out from the position of interest and recording points in space where the nearest physical (that is, occluding) surface is encountered. An isovist, therefore, reduces visible space to a description of space that is the product of relatively low-level visual features: the edges of surfaces and the textural gradients that define their position and shape in space. These features are considered easily perceivable by humans and were thoroughly investigated by Gibson (1979) in his theory of *direct perception* (and, indeed, *ecological perception*). As such, the isovist can be considered analogous to the perspective structure provided by the optic array. One example of an isovist and how it captures the structural properties of space is provided in Figure 1.2. Similar techniques to that of isovist analysis exist in other fields, such as viewshed analysis (Lynch, 1976; focusing on elevation of nearby landscape geometry) and geometric analysis (Gallagher, 1972; interested in intervisibility of two or more locations), are less parsimonious with an optic array.

FIRST-PERSON VIEW



CORRESPONDING ISOVIST

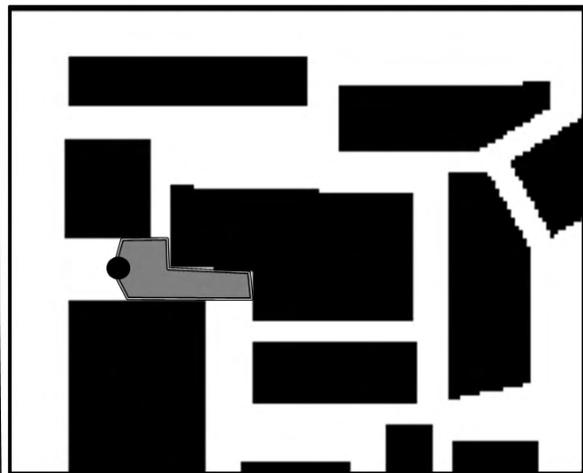


Figure 1.2 A depiction of how an isovist described nearby space. The left pane shows a typical view of the world around a person. Black lines have been added at the base of the lower contour of each building to represent how the walls of each building constrain vision. The right pane presents how each of these edges corresponds to an edge in the visibility polygon, the part of the isovist lying within the viewing angle of the observer, depicted in grey.

Isovists, therefore, represent a reasonable way to approximate how the world is perceived by individuals. Additionally, as the isovist is simplified to describe the location and size of *unique* incident surfaces, it effectively captures the invariant features of the surrounding world. This is because the layout of nearby surfaces relative to an organism is precisely what the optic array and patterns of invariance capture.

Having established the isovist as an adequate tool for capturing how an organism may perceive the world, the question of how a person may perceive this information is made apparent. There are many different ways that a person may perceive the structure of their surrounding world, ranging from those capturing the approximate shape or size, to those describing how enclosed a space is. Benedikt (1979) proposed that the isovist polygon can be decomposed into the distinct properties, such as *area*, *perimeter*, *occlusivity* (the total perimeter lying in open space), and *circularity* (the ratio of the area of the isovist to the area of a circle with identical perimeter), each of which were demonstrated to be perceivable by individuals. Subsequent to this early work, a much wider variety of perceived spatial properties have been found to influence both spatial preference and navigation choice. For example, *compactness* (termed jaggedness by the authors) and *openness* (ratio of occlusivity to total perimeter) have been shown to be associated with locations that offer the best hiding place and best overview of a room, respectively (Franz & Wiener, 2008; Wiener et al., 2007). Other work derived from principal components analysis (PCA) suggest that many isovist measures effectively describe how space conserves or restricts the viewing of nearby space (Stamps III, 2005). PCA has also been used to classify intersections based on their isovist shape. Meilinger, Franz, & Bühlhoff (2012) found a higher level of disorientation and poorer spatial memory performance at T-intersections versus non-T intersections, as categorized by PCA. These data suggest that the *shape* of local visual space is both perceived and may be an important determinant in how we interact with the space around us.

A number of studies place emphasis on measures of spatial extent as being a key determinant in spatial behaviour. *Area* has been found to be associated with a person's preferred route in both virtual (Emo, 2014; Franz & Wiener, 2008) and real urban environments (Dzebic, Perdue, & Ellard, 2013; Wineman & Peponis, 2010; Batty, 2001) environments. People have also been shown to prefer to move in the direction of longest sight lines (Wiener, Hölscher, Büchner, & Konieczny, 2012). That is, in making decisions about where to move, the size and not simply the shape of space appears to be influential.

Together, these findings provide sufficient evidence to consider measures derived from isovists to represent systematic properties in space that can be easily perceived as a function of the size and shape of space around a viewpoint. Consistent with *affordance* and *direct perception*, isovists appear to meaningfully capture the properties of space represented by the optic array and therefore may, critically, afford movement through urban environments.

1.4 The Capacity of the Brain to Encode the Geometry of Space

While a theoretical fit between an isovist's depiction of space and the optic array has been presented, navigation has traditionally been viewed as the product of a more complex network of systems in the brain. For example, spatial memory is considered crucial for finding one's way successfully between landmarks and in identifying which locations define landmarks, heavily influencing the type of strategy used to navigate the world (e.g., Golledge, 1999). However, often receiving less attention is the capacity for the brain to represent and understand space in purely geometric terms (such as those described by the shape of an isovist polygon) in the absence of spatial memory or strategic biases. This type of perception/encoding is both critical to the argument that affordances may drive navigation choice but also is essential to understanding how navigation behaviour may be driven in unfamiliar environments.

Fundamentally, an isovist can be considered an abstraction of surrounding space into simple descriptions of the surrounding geometry alone, as in the optic array underlying affordance. The first evidence for the brain's capacity to encode purely geometric features of space was presented by Ken Cheng (1986). In one study, rats were trained in a rectangular enclosure with small panels in each corner, identifiable by texture and colour. Each rat was trained to find a reward that was located at one of the four corner panels through repeated exposure to food reward at specific locations. Interestingly, when the food reward was not placed at the learned locations, the rats were found to search for food at the corner where the food was previously located *and* the corner that was diagonally opposite to this position. This finding provided initial evidence that the geometry of the space was being encoded by the brain and, in Cheng's procedure, even seemed to supersede purely visual or textural landmarks. Other work has demonstrated that the inclusion of a more explicit landmark feature did not reduce these errors, suggesting preferential encoding of geometric information in guiding navigation (e.g., Wall, Botly, Black, & Shettlesworth, 2004). This finding has also been demonstrated in experiments using monkeys, suggesting that the use of geometry to find a location is generalized beyond experiments with rats (e.g., Gouteux, Thinus-Blanc, & Vauclair,

2001). Furthermore, the influence of the geometry of space has been demonstrated to be independent of distant visual cues lying outside the experimental apparatus and to persist in the presence of other types of landmark information, such as that of the angle of the corner (Margules & Gallistel, 1988). This pattern of results has been demonstrated across a variety of different types of environments and paradigms, including the Morris water maze (Benhamou & Poucet, 1998), triangular maze (Pearce, Ward-Robinson, Good, Fussell, & Aydin, 2001) and hidden platform task (Hayward, McGregor, Good, & Pearce, 2003). The tendency to use geometric cues has, however, found to be diminished in aversive conditions (Golob & Taube, 2002; Gibson, Shettleworth, & McDonald, 2001) suggesting that the importance of geometric information is only observed under appetitive conditions (i.e., exploring a novel environment or effortfully wayfinding to a goal location). The strength of these findings have caused some to argue that the brain must possess a *geometric module* for encoding geometric information (Cheng & Newcombe, 2005; Cheng, 1986).

Rats have also been shown to be influenced by the overall configuration of an environment in a manner resembling experimental outcomes from manipulations of the space syntax measure of intelligibility. In one example, rats freely navigating an open field apparatus that contained a number of objects (uniform in shape) arranged in a uniform grid (evocative of high intelligibility environments) or a deformed grid (i.e., low intelligibility) were found to travel further, examine more objects, and follow a more orderly path when the overall environment was uniformly arranged than when it was deformed (Onsat, Portugali, & Eilam, 2011). This finding bears close similarity to the movement of humans in intelligible and unintelligible spaces (Penn, 2003) and suggests that both local and global geometry are important in guiding behaviour.

Studies of human participants have also shown an influence of geometric cues. In a series of studies based on the earlier animal models, children have been shown to search either the correct or geometrically equivalent corner for a target item after becoming disorientated (Hermer, 1997; Hermer & Spelke, 1994). In a square room with one wall painted a distinctive colour, children were found to frequently examine geometrically equivalent corners regardless of how much experience they had with other types of cues that were also present in the room, such as the colours of the walls (Wang, Hermer, & Spelke, 1999). This result has also been replicated in a triangular shaped environment (Huttenlocher & Vasilyeva, 2003). Interestingly, adults who were normally able to make use of landmarks were found to revert to a geometric strategy when engaging in a verbal shadowing task but not a non-verbal shadowing task (Hermer-Vazquez, Spelke, & Katsnelson, 1999). Together, these

results suggest that both adults and children encode geometric and landmark information separately, with purely geometric information representing a default strategy.

The encoding of geometric information has been demonstrated to be independent of self-motion information, suggesting that it is the direct perception of geometry itself that is encoded by the brain. Adults who performed a spatial updating task in a variety of virtual environments differing in their rotational symmetry (e.g., square, rectangle, trapezoid) were found to point more accurately toward the location of a learned landmark as a function of the number of corners of an environment. In a second experiment, the shape of the room was manipulated such that the angle of the walls behind the participant was changed when the participant moved away from them, thus preserving self-motion information but distorting visual information about the geometry of the space. A significant relationship was observed between the number of path segments made by the participant and a reduction in pointing accuracy. As self-motion in the forward plane was maintained, the authors contended that geometric information must have been encoded to support pointing-task performance (Kelly, McNamara, Bodenheimer, Carr, & Rieser, 2008). These and other results have subsequently been argued to suggest a capacity to encode local geometric space through purely visual means (Gallistel, 1990; Gallistel, 1980).

The studies of both animals and humans outlined here (and many others in the literature) support the idea that we can encode the geometric properties of the environment as characterized by the isovist, quickly and efficiently. Isovists are therefore considered a plausible way to describe how people encode or perceive space.

1.5 The Present Work

Given the considerable body of evidence that supports the role of affordance and/or exosomatic visual architecture on navigation, the present work attempts to establish the sufficiency of *direct perception* and *affordance* in accounting for common tendencies in how we navigate space. This is considered essential, as it will both establish whether *affordance* is capable of explaining navigation *and* identify practical – testable – spatial properties for use in future models of these phenomena. This is achieved in two parts by establishing the theoretical (Chapter Two) and empirical (Chapter Three) fit of local visual variables for explaining common patterns in navigation using principles of *direct perception*. The emphasis of this work is on explaining behaviour in novel, unfamiliar environments as these environments would be furthest removed from the influence of spatial memory and therefore

should be most affected by affordance. Additionally, by understanding how affordance may or may not drive navigation in unfamiliar environments, we may also gain insight into the underlying sources of bias that effect movement either fully (in the case of unfamiliar environments) or partially (as in familiar environments), essential to better models of navigation as a whole.

First, Chapter Two establishes whether locally-derived properties may exist that can explain the apparent influence of local and global measures of the complexity of space. This is necessary to establish the local properties of space that may serve as a configurational affordance in the theory of *exosomatic visual architecture* and fit the definition of an *affordance*. Without evidence for a shared relationship between measures of the complexity of space (as captured by Space Syntax analysis) and local visual features, no present theory or mechanism can account for common patterns observed during spatial navigation nor explain how we navigate successfully in unfamiliar spaces. To describe these relationships, factor analysis was used to simultaneously classify local (through factor loadings) and global spatial variables into common emergent factors and to assess the strength of the relationship between these emergent factors (through correlation amongst latent factors), particularly between those factors found to influence the complexity of a space and the size and shape of local visual space. To elaborate on the character of these emergent factors, a number of novel variables were employed to evaluate the degree of overlap between different types of descriptions of local visual space. Data were derived from both synthetic and real-world environments, varying in their spatial complexity/intelligibility. The resulting model indicated the presence of one promising latent variable – that of the local extent of surrounding space – capable of accounting for a considerable proportion of the variation in space *both* locally and globally (lying outside the present field-of-view). In addition, a number of other emergent factors were observed, consistent with previous variables influencing prospect and refuge (Appleton, 1996) and their relationship with the complexity and extent of space was described. The robustness of the findings was confirmed by examining the fit of the identified factor model with two contrasting large-scale real-world spaces, New York City (USA) and the City of London (UK). For the first time, the results establish the presence of a fit between local perceptual properties of space and spatial information lying outside the present viewpoint, sufficient to ground an account of movement through complex urban spaces in terms of the *invariants* found in local visual space.

Chapter Three builds on the finding of Chapter Two by explicitly testing whether local extent, as captured by area, perimeter, and mean surface depth, shapes movement through space in both

aggregate (Experiment 1) and individual navigators (Experiments 2 through 4). This chapter focuses specifically on establishing whether each *invariant* fits the definition of an affordance as outlined by Gibson (1979). Aggregate traffic is first examined using a number of mathematical models relating common patterns of movement to the use of invariants at a local (always maximizing the property with each 'step') and global (always steering toward locations with an ideal level of the property in an environment, regardless of local level) or a hybrid model. GPS data within the City of London were examined against each mathematical model to assess the efficacy of each model. Strong evidence is found to support the idea that traffic is actively drawn toward particular locally defined invariants, maximizing the level with each step. In particular, evidence is found for the novel parameter of mean surface depth in shaping general traffic and producing common behavioural preferences. Next, across three experiments (2 through 4), the fit for each invariant identified in Chapter Two was further established by assessing the core tenets of the theory of direct perception. That is, navigation behaviour is examined for a *critical point* (the point at which a property and navigational preference is maximized) and *singularity* (behaviour is maximized around a single, specific, level of the factor) in Experiments 2 and 3. The invariant of mean surface depth is shown to have optimal fit with the concept of an affordance (Experiment 3). This finding is notable because the affordance relationship not only was identified that can predict behaviour consistent, even in low intelligible spaces, where traditional measures have, so far, been insufficient. Finally, Experiment 4 assesses whether the affordance relationship is affected by accounting for a number of measures of spatial attention and cognitive ability. No significant relationship was observed between the affordance relationship defined by mean surface depth and navigational preference and psychometric variables, consistent with Gibson's definition of an affordance as a bottom-up process largely independent of cognitive processing. Cognitive variables were shown to influence some aspects of spatial behaviour (pausing-in-place), but not the affordance relationship. Finally, participants were shown to direct their gaze preferentially toward the critical point as defined by the invariant of mean surface depth, supporting the idea that this factor is actively perceived and explored throughout navigation.

Taken together, this body of work establishes experimentally that a single specific spatial affordance is capable of driving both individual and aggregate navigation through the world. This affordance is best informed by the invariant property of mean surface depth leading me to name this initial model of behaviour as Depth Afforded Navigation. Vitaly, the effect of this affordance relationship is found to be consistent across spatial context, suggesting a common general mechanism that is independent of context. In achieving these findings, this thesis provides evidence to support the

idea that affordance drives navigation in a manner consistent with findings attributed to both local (isovist-derived) and global (Space Syntax-derived) measures of space. In doing so, the present work may serve as a bridge to span the gap between a number of different research approaches, allowing us to understand the mechanism(s) driving human navigation in concrete and testable terms. It is through this rigorous examination of the theory of ecological perception and affordance that the precise mechanisms underlying navigation may be better understood, allowing future work to establish the role of navigation-specific spatial affordance, spatial preference, and local visual search.

In Chapter Four, the results are discussed within the context of the state-of-the-art understanding of spatial cognition within psychology. Future directions and limitations are also introduced in this chapter.

Chapter 2

Can The Local Structure of Space Explain the Efficacy of Space Syntax?

2.1 Introduction

Over the years, various approaches have been used to examine and predict where people navigate toward or what routes they may use to get between an origin and a destination. Broadly, these approaches can be broken up into two categories: (1) those describing the global complexity of the surrounding environment and (2) those describing the importance of a location on a more local scale. While each type of explanation may seem self-contained, there is an inescapable link between the two because they are both shaped by how an environment has been arranged. By placing a town square on a specific road or by constructing buildings with slightly different offsets, both the local and global parameters defining how space is arranged are modified. It is this inexorable link between the two – driven by the morphology of space as a whole – that allows for the possibility that a small number of emergent properties may be capable of explaining how spatial properties are useful for a navigating person. Accordingly, the overarching goal of this analysis was to identify whether one or more emergent properties exist that can simultaneously explain the success of measures of global spatial complexity (i.e., Space Syntax) and more local ones (i.e., isovist-derived properties).

As described in Chapter One, Space Syntax attempts to capture the complexity of an urban space, be it at the scale of an entire city or in the context of the interior of a single building, by examining the structure of the spatial system formed by the arrangement of roads and/or hallways (Hillier, 1996; Hillier & Hanson, 1984). At the core of this approach is the concept of an *axial map*, which has been defined as either the finite set of straight lines (axial lines) sufficient to explore an entire environment (Hillier, 1996) or the minimal or sufficient set of axial lines sufficient to describe the environment efficiently (Turner, Penn, & Hillier, 2005). The resulting depiction of space can be converted to graph form by quantifying how some or all of the other potential paths in the environment relate to each individual path within the environment. In this type of depiction, the complexity of space is therefore reduced to the number of available options each theorized path allows for. With this in mind, the complexity of space can be defined either locally (lying in immediate space) or globally (describing the environment as a whole or distinct neighbourhoods). Locally, complexity can be defined via *connectivity* (the number of intersections or available paths directly available from the present path).

Globally, *mean depth* can be used to capture the structure outside of the immediate area – the mean distance of one location to all other locations in an environment. Mean depth can further be decomposed into *integration* by assessing how much the mean depth varies from a symmetrically arranged environment (by dividing the mean depth of the graph by the ideal mean depth observed in a perfectly symmetrical diamond graph of identical size; for a complete description of this method, see: Park, 2005).

Prior research has shown that a strong correlation exists between pedestrian and traffic flows and the level of *connectivity* and *integration* at a specific locations in an environment (Hillier et al., 1993; Peponis, Hadjinikolaov, Livieratos, & Fatouros, 1989). This finding has been widely established across a variety of different environments (Penn, 2003) indicative of the potentially powerful role of variables capturing environmental complexity in predicting behaviour. These effects have also been observed in the paths of both experienced and inexperienced navigators (Emo, 2014; Emo et al., 2012; Hölscher et al., 2012; Haq & Zimring, 2003; Haq, 2003) and is enhanced if the complexity of the environment is assessed more locally, by only examining those axial lines within a radius of 3 turns (Haq, 2003). Together, these findings and approaches support the idea that spatial complexity can influence navigation behaviour, forming the basis of the theories of *exosomatic visual architecture* and the role of *affordance* in urban navigation. In both cases, a general drive to orient toward areas of reduced complexity is strongly suggested.

Several scholars have extended axial analysis by considering how each segment of an axial line conserves the direction of travel. Agent-based simulations (Penn & Dalton, 1994a) and behavioural experiments (Conroy Dalton, 2003; Conroy, 2001) have shown that individual navigators minimize their turning behaviour when navigating an environment. Agents specifically designed to minimize turning when navigating to a target have been shown mirror the behaviour of pedestrians and vehicular traffic (Penn & Dalton, 1994a). Individual navigators travelling to a destination have also been shown to prefer to minimize deviations in their trajectory when navigating toward a destination (Conroy Dalton, 2003). Likewise, the angle formed by adjoining axial lines has been demonstrated to be predictive of pedestrian densities (Hillier & Iida, 2005), forming the basis for a technique called *angular segment analysis*. The tendency to minimize angular deviation has also been demonstrated in the shape of planned routes (Bailenson, Shum, & Uttal, 2000) and in tasks measuring the accuracy of pointing toward an unseen landmark (Montello, 1991). One explanation for this effect is that individuals appear to encode space in inexact terms when it comes to the angle offered by individual

paths. For example, people show a tendency to straighten two paths to be more parallel than they are (Tversky, 1992; Tversky, 1981) or to believe turns consisting of acute angles are right-angled (Sadalla & Montello, 1989) when examining sketch-maps of environments. Taken together, these results suggest that space may be perceived and encoded in terms that are consistent with those derived from an axial map rather than simply and directly from local perceptual variables.

However, this concept is inconsistent with the often cited idea that *direct perception* and *affordance* are driving these findings (e.g., Emo et al., 2012; Wineman & Peponis, 2010; Maier et al., 2009; Penn, 2003; Turner et al., 2001; Hillier, 1999). To be an affordance, information must be directly perceived by an organism. Clearly, locally derived variables would have to be either partially or wholly involved in guiding the types of spatial behaviour observed to be influenced by the structure of space for an affordance to exist. Therefore, it should be expected that locally derived information – such as that of the isovist and its relation to the invariant structure of space – should influence navigation behaviour in a similar way to that of more global variables of complexity.

A variety of studies support the idea that locally-defined information is capable of systematically driving a number of different types of spatial behaviours. The *area* of an isovist and its *relative compactness* (the degree to which the shape of an isovist approaches that of a circle of identical radius as a function of area) appear to be associated with both spatial preference (Franz & Wiener, 2008; Wiener et al., 2007) and are predictive of preferred routes (Meilinger, Franz, & Bühlhoff, 2012; Franz & Wiener, 2008; Wiener et al., 2007). Isovist *area* alone has also been found to be strongly associated with how preferred a location is in virtual (Emo, 2014; Franz & Wiener, 2008) and real (Dzebic et al., 2013; Wineman & Peponis, 2010; Batty, 2001) environments. The size and shape of local visual space has also been shown to influence overall appraisal of the relative value of specific locations. For example, in architectural practice, buildings that are more open and spacious are seen as more attractive than those that are not (Handlin, 2007). In picture studies, people have been shown to prefer pictures of locations that maximize the ability to perceive information *and* are embedded in easily understood locations (Kaplan & Kaplan, 1989; Kaplan & Kaplan, 1982). Locations that offer the potential to experience new information upon moving (termed: mystery) have also been shown to be preferred both behaviourally and emotionally (Kaplan, 1988; Kaplan & Kaplan, 1982). Together, these studies strongly implicate measures of the complexity of an isovist beyond those of area alone.

Recently, building on the idea behind isovist analysis, Wiener, Hölscher, Büchner, and Konieczny (2012) showed that people are not only influenced by isovist variables but they also direct their gaze

toward specific characteristics of the environment. In their study, pictures were decomposed into isovists by tracing the lower contour formed by walls (identical to the method depicted in Figure 1.1). This approach places emphasis on the edges of surfaces as they define the change in contour, much like the vertices in a traditional two-dimensional isovist polygon. The authors found that participants tended to fixate on the vertical edges of surfaces (i.e., walls and other obstructions) when making wayfinding decisions. In contrast, when participants were asked to make a decision about which way to move, they chose the direction that afforded the maximum travel distance available within the visible spatial contour. These results show considerable similarity to those of traditional isovist analysis, but they better elaborate the mechanism through which the variables may be perceived by an individual as they navigate space. Moreover, the consideration of space as a set of edges formed by surrounding surfaces is consistent with the optic array of ambient visual information presented by Gibson as part of the process of perceiving an *invariant* spatial property.

Here, I examine whether a core set of globally defined space syntax measures can be decomposed into a set of locally defined variables, suitable as configurational affordances in *exosomatic visual architecture* and *affordances*, in general. This is plausible because the placement of boundaries and walls that define an environment as a whole fundamentally shape both local and global space (Hillier & Vaughan, 2007; Hillier & Hanson, 1984). Despite the definitional overlap between such local and global variables, this pattern has not been shown previously, making it difficult to discern the role of affordance in driving patterns of movement during spatial navigation. As was stated in Chapter One, the assumption of such a relationship has often been stated as the mechanism behind both *exosomatic visual architecture* (e.g., Penn, 2003), which proposes that we perceive *configurational* affordances from the environment, and *direction perception*, as a purely local mechanism driving movement through complex spaces. A description of the relationship between the role of local properties – those *invariants* that may inform behaviour – and more global descriptions of configuration are necessitated by a lack of evidence that we can perceive or represent configurational information without prior exposure. Considerable evidence both in my own work (Barton et al., 2014) and the work of others (Conroy, 2001) shows that the efficacy of Space Syntax extends to unfamiliar spaces – spaces where foreknowledge about the structure could not or should not exist.

To place the relationship between the global structure and complexity of space and locally perceived space, the relative importance of a location in traversing the environment was assessed. The approach used here was to define how traversable or important a position is in space as a function of

how easily it supports movement to nearby space. I termed this graph an *accessibility graph* as it described how accessible each location is in an environment with respect to adjacent locations. To quantify the importance of each location in the graph, similar measures to that of space syntax were employed, assessing how central or important each location an environment is when distance rather than pure topology (as in space syntax analysis) is evaluated. By analyzing this graph using the same types of measures of the importance of axial lines in traversing space, the importance metric distance in shaping the complexity of an environment can better be understood. While this form of analysis is considered new within this context, the general approach of treating adjacent locations as conjoined nodes in a graph has been well-established in the fields of robotics and computer science (for a general review: Murphy, 2000).

Finally, building on the findings of Wiener, Hölscher, Büchner, and Konieczny (2012), two novel measures were investigated: the number of discrete surfaces present in the local space and the average depth to those surrounding surfaces (termed mean surface depth). Here, surfaces were considered to be any vertical obstructions, such as a wall or side of a building, that restricts movement. These two measures were considered critical as they may better represent the idea of an invariant property as outlined by Gibson. More specifically, the idea of the ambient optic array from which invariant properties are computed is considered to be made up of information describing shape (Gibson, 1966; Gibson, 1950) or edges and texture (Gibson, 1979), both of which are captured by considering discrete surfaces in nearby space.

Therefore, the relationship between the complexity of space (Space Syntax's *axial analysis*) was assessed in the context of *accessibility*, *angular* preservation, and local visual (isovists and surface measures) information, simultaneously. To do this, exploratory factor analysis (EFA) was used. EFA has been used extensively in psychological research to identify common patterns of variation amongst various types of measures (Fabrigar, Wegener, MacCallum, & Strahan, 1999). EFA can be contrasted with (and is often inappropriately confused for) principal component analysis (PCA), which instead attempts to identify clusters of variables that are redundant with each other. PCA has been used previously to examine a wide variety of different isovist measures with some success at demonstrating redundancy in the factors that they capture (Stamps III, 2005). However, the goal of this chapter was specifically to identify the presence of latent factors that shape local visual space and overall global spatial complexity rather than identify redundant measures, so PCA was considered inappropriate. Secondly, the strength of the relationship between latent variables can be assessed by

rotating the resulting factor model in EFA analysis. Factor rotation, while often used in PCA, has been argued to be inappropriate as it asymmetrically distorts the model, producing an artificial or distorted solution that no longer relates to the original variables nor has any tangible meaning (Jolliffe, 2002). As I specifically wanted to describe the properties of space as they relate to each other in meaningful terms, particularly with respect to the correlation between latent factors, EFA was considered an ideal technique for both classifying and describing how the variables of interest relate to each other.

The analysis was run on a large number of variables taken from different classes (space syntax, isovists, and others) because this approach would allow any relationship between local *invariant* properties and global spatial complexity to be understood in the context of other the overall configuration in which these properties are embedded. If the analysis only included isovists and space syntax (axial) measures, potentially interesting patterns could be missed and the degree of shared variation attributed to each factor may be conflated. Accordingly, the inclusion of the five families of measures (axial measures, angular segment analysis, accessibility-graph derived measures, and isovist-derived measures) should – both theoretically and practically – increase the accuracy and reliability of the resulting models. Theoretical latent factors are identified in Study 1 and Study 2. The identified theoretical structure is examined in Study 3 using Confirmatory Factor Analysis (CFA) to determine the explicit relationship between variables.

2.2 Study 1 Identifying Whether Local Variables Can Predict Global Ones

In this initial study, the data were determined for two synthetic environments often used to depict highly intelligible and less intelligible environments. These environments are shown in Figure 2.1 (upper panels) and were originally proposed by Hillier (1996) to represent the prototypical case wherein a high intelligible space is transformed into a considerably less intelligible by simply shifting the position of the buildings that composed the environment. The two environments consist of an identical set of buildings, arranged in different positions between the two spaces. By shifting each building, the overall complexity of the environment increases by increasing the number of paths and turns necessary to traverse the environment, reducing intelligibility.

Together, these environments were considered optimal for a first glimpse into how each spatial variable may relate to the others. Cumulatively, the set of both environments describes a wide range of views of space that may be experienced in real-world environments. Additionally, as the buildings

are identical between the two environments, they describe how each variable may be influenced by the overall complexity with which an environment is arranged while controlling unrelated differences in spatial geometry (such as in the shape of buildings).

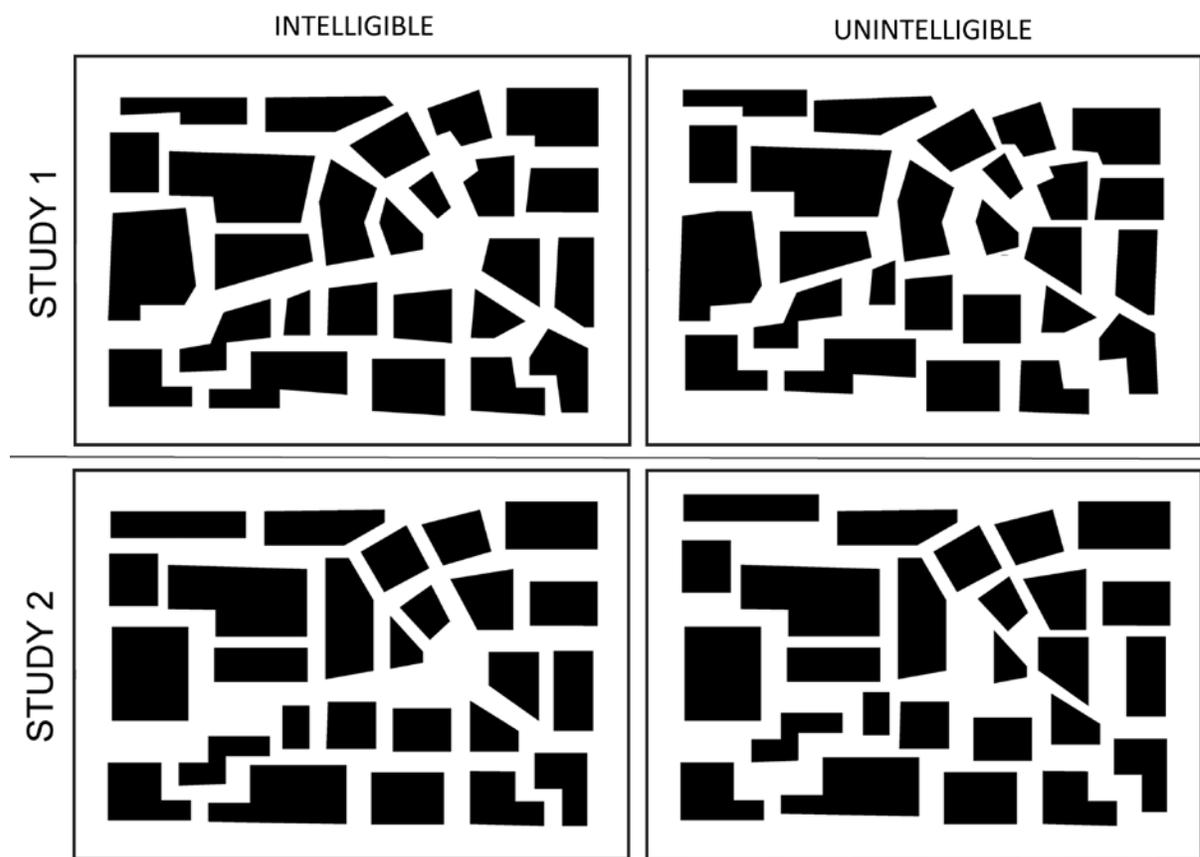


Figure 2.1 Plan views of the simulated environments used in Study 1 (upper panel) and Study 2 (lower panel). Environments in the left panes represent highly intelligible spaces while environments in the right panes represent low intelligibility cases.

2.2.1 Methods

2.2.1.1 Factor Extraction

A total of 22 variables were examined to identify any common latent factors capable of explaining the similarities between axial, angular, accessibility, and isovist-derived measures. All variables were standardized to eliminate any effect of scale across variables. The unweighted least squares (ULS) extraction method was used as it has been shown to be a robust to potential violations of normality and outliers (Zygmunt & Smith, 2014). The resulting model was rotated using an oblique Promax rotation method ($\kappa=2$) to assess the strength of association between latent factors because a non-zero correlation between any identified emergent properties is both unrealistic in most real data (Fabrigar et al., 1999; Gorsuch, 1997; Cattell, 1952; Thurstone, 1947) and is, in fact, how variables of space should function (changing properties in local space have a corresponding influence on more global properties by mere fact that the two are controlled by structure). Should latent factors actually be independent of each other, only small correlations would be expected to be found amongst latent factors and an orthogonal rotation scheme (one which assumes no relationship between factors) would instead be indicated.

The number of factors retained in the final model was determined by comparing the results of the traditional Scree test (Cattell, 1952), and the more modern techniques of the Hull method (Lorenzo-Seva, Timmerman, & Kiers, 2011) and Comparison Data (Ruscio & Roche, 2012). For the Hull method, 500 permutations were employed. For the Comparison Data method, 10000 samples of comparison data were generated with 500 samples drawn from each factor population. By using a variety of methods the resulting model is much more likely to be reproducible and an accurate depiction of the true pattern of variation amongst the factors and variables.

2.2.1.2 Data Collection

Each environment was created to be 248 meters by 176 meters. An axial map was generated for each of the two environments using the UCL Depthmap (version 10) software package. A 1 meter square grid was imposed on each environment. From this grid, the axial map, angular properties of the axial map, accessibility graph, and isovist-derived measures were determined using the PyPy programming language for each of the 52365 positions lying in open space. Once the data were computed, the initial pool of data was trimmed to include only locations spanned by *at least one axial*

line and *lying inside the border-region* of the environment (deemed to be within 10% of the outer boundary for the environment). The exclusion of data outside of axial lines was chosen as the absence of an axial line was not considered the product of a true spatial relationship but is instead the product of how an axial map is determined. To avoid this issue, only points lying along axial lines were used in the present analysis. Bordering points were excluded due to their artificial character and biasing nature (Conroy, 2001). This resulted in 22428 data points being retained for analysis.

Sampling spatial information on a consistent square grid, such as the one used here, is commonly used in spatial data analysis to assess the relationship between various types of spatial variables as they exist continuously in space. This type of analysis is termed *raster factor analysis* (see Demšar, Harris, Brunsdon, Fotheringham, & McLoone, 2013 for a review of the topic of factor analysis on spatial data). Raster analysis describes the pattern of variation across an entire space (or set of spaces), allowing the resulting model to describe a realistic range of variation across all variables, highlighting only those relationships with sufficiently large covariation (Thurstone, 1947). This is considered advantageous as it increases the likelihood of producing a robust factor model. One potential complicating factor is the situation in which a raster analysis can result in a biased model. This case arises when data points (locations) that are near each other are more related than those further away, spatial autocorrelation. The presence of spatial autocorrelation reduces overall variation across a data set, producing inflated factor loading estimates (though, this is far more pronounced in PCA than factor analysis). Two common measures of spatial autocorrelation, Moran's I (Moran, 1950) and Geary's c (Geary, 1954), describe spatial autocorrelation as a function of distance. No evidence was found for the presence of statistically significant spatial autocorrelation in the present data set, both when considering linear distance ($I=-0.025$, $c=1.30$, $p=0.99$) and when considering inverse distance ($I=0.13$, $c=1.05$, $p=0.92$). As a result, the data were considered well suited to factor analysis.

2.2.1.3 Data Aggregation

The data sets were collapsed across each other to make one large set. This approach is known as *heterogeneous* or *maximum variation* sampling (Kline, 1993). Heterogeneous sampling, much like the raster analysis approach on spatially distributed points, is intended to better describe the range of variation experienced within variables across a wider range of spaces than are available in a single environment. By examining data from the intelligible and unintelligible environments together rather than separately, the sample better reflects the variation seen in real in urban space(s). While the

alternative approach of random sampling from a large number of interior or exterior urban spaces can provide a potentially more robust factor model under some circumstances, a true random sampling approach was considered impractical for the present purpose¹. This is because the scale, particularly with respect to variables assessing the global properties of a space, varies arbitrarily with the size of the space from which the data are taken. The corresponding set of data would therefore risk describing scale rather than urban form. In addition, data sets sufficient to produce an adequately large randomly derived sample from a wide range of spaces either do not exist or would be too computationally intensive to analyze. Given these issues, the present heterogeneous sampling approach is considered a compromise between adequately describing urban spaces as a whole and meeting availability/computational demands. To further support this position, convergence across a variety of synthetic and real spaces is sought throughout this chapter, more rigorously testing the likelihood that the resulting latent factor models are a description of real-world variation brought on by architectural design and urban planning alone and not some idiosyncrasy of a specific environment or data set.

2.2.1.4 Spatial Properties of Interest

The physical basis for the measures in a hypothetical environment is presented in Figure 2.2. As described above, the data were computed on a 1-meter uniform grid across all open space in each environment.

Axial Map Measures. For the present analysis, the axial map was algorithmically determined by connecting the vertices formed by each building with all other vertices that can be reached without being obstructed by a building surface (Turner et al., 2005). A depiction of the resulting axial map for each environment can be found in Figure 2.3. The measures of *connectivity*, *mean depth*, *integration*, *mean depth (to a radius of 3 nodes)* and *integration (to a radius of 3 nodes)* were computed. To better capture the relationship between other forms of spatial analysis and the axial map, the axial map was not reduced to fewest lines sufficient to describe the environment. This is because the all-line axial map is more independent of idiosyncrasies in drawing technique or line placement. The axial map was collapsed on to convex space through the use of an anti-aliasing algorithm (Wu, 1991). The anti-aliasing algorithm allowed the value of each axial measure at each discrete location to be determined,

¹ Performing a factor analysis on the present data with a random set of locations (20% of the sample) within the present data was found to produce a near-identical factor model to that of heterogeneous/raster sampling. Consequently, no improvement in model specification appears to be gained by random sampling in this context and suggests that the heterogeneously sampled data should generalize to other data sets.

particularly for those locations lying on angled axial lines where an axial line may only partially intersect with a grid cell. In this case, the alpha value (depicted in Figure 2.2, center panel, as a range between black and white) was used as a scaling factor. Alpha therefore accounts for the influence of the resolution of the grid when determining the values of axial properties in convex space, where points that directly intersect with a grid cell are valued at 1.0 and points that grazed a grid cell were valued between 0.99 and 0.01, weighted by the relative distance from full intersection. For points in space that were spanned by more than one axial line, the values were averaged across all intersecting axial lines.

Angular Segment Analysis. Prior work presenting angular segment analysis (Turner, 2007) further examines an axial map as the product of the individual segments between each intersection point. From these line segments, the angle necessary to move from one axial line to the next can be determined. Next, the average angular cost (the propensity for a line to require more sizable turns, on average) can be determined by weighting the mean angular deviation by the relative importance of the line in traversing the spatial system (most often through the property of betweenness centrality, described below). The resulting description yields a value for each angular segment that describes the interplay between the size of turn (captured by angular deviation) and likelihood that the turn will be made (via betweenness centrality). This approach was adapted to work with an all-line axial map by reweighting the angular cost of an axial line by the number of immediately overlapping segments within a radius of 3 units. This approach was used as it would weigh the relative importance of each line segment in a way that is more consistent with that of the other axial measures, also calculated to a radius of 3. The *mean angular cost* and *mean angular variance* were calculated for each line segment.

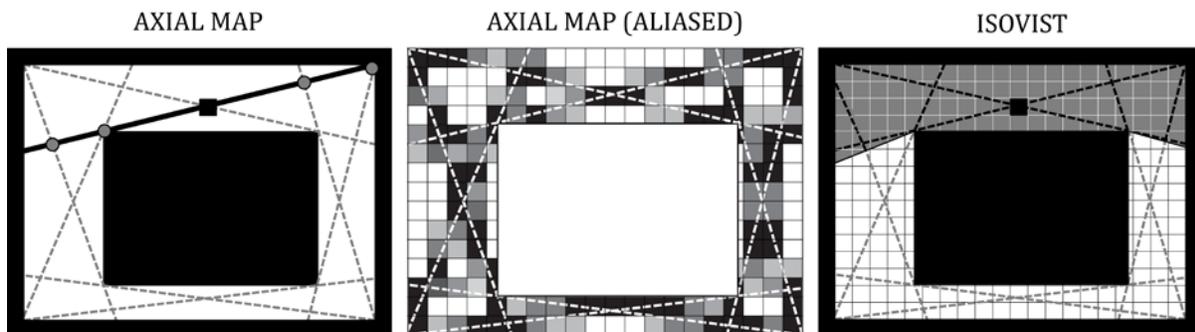


Figure 2.2 The basis for combining axial-map derived data with local, isovist-derived, space is described here. A hypothetical axial map is presented left with a line bolded. Right, an isovist computed at the center point of the bolded axial line is presented. Across all points on the axial line, isovists are determined and quantified. The axial line is subject to anti-aliasing to weight how much each line intersects with each distinct point in space, depicted as shades ranging from black (1.0; full weight) to white (0.0; no weight), allowing the properties of the axial line to be mapped on to discrete points in space.

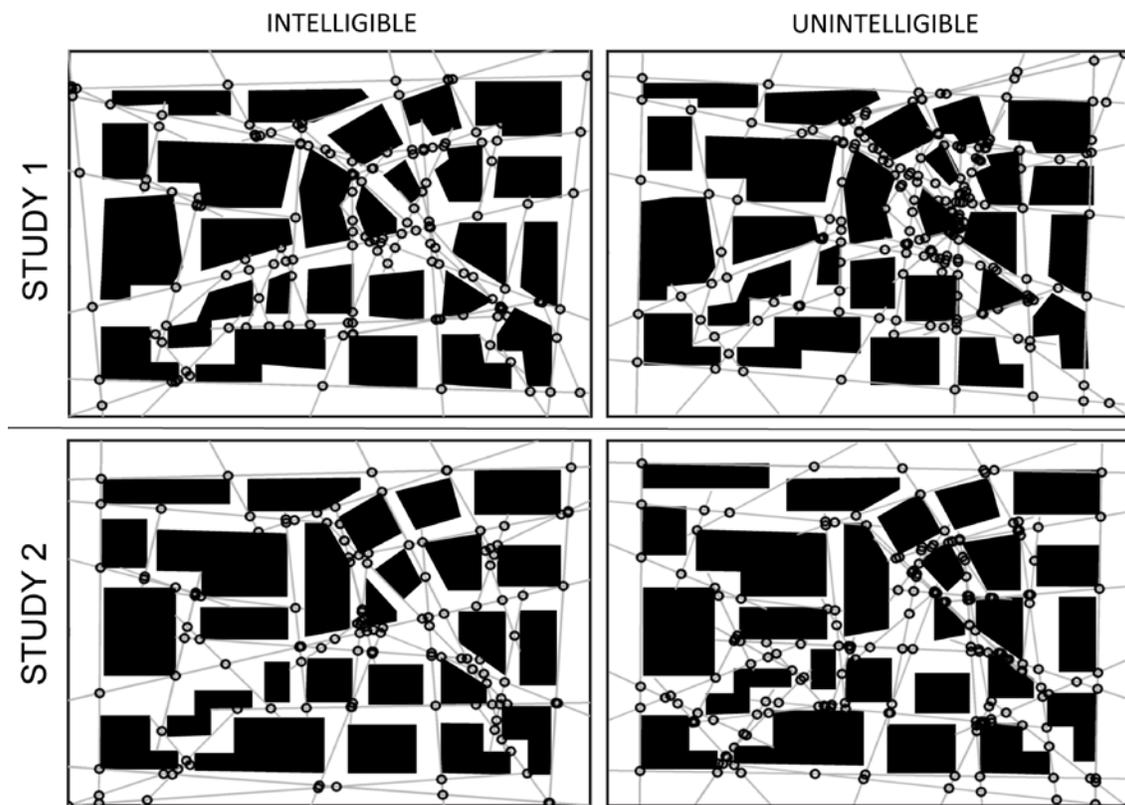


Figure 2.3 Axial maps depicted for Study 1 (upper panes) and Study 2 (lower panes). Intersections of the axial lines highlighted using circles.

Accessibility Analysis. To bridge the gap between an axial depiction of space – where importance of an element in space is determined by how it relates topologically to all other lines in a space – to that of a view of space informed purely by considering local, metric, properties, an *accessibility graph* was used. The graph consisted of all positions in open space and described whether movement could occur in each cardinal or intercardinal directions (sometimes termed a King's case in spatial analysis, after the corresponding movement rule in chess). Using this graph, the relative importance of the node in supporting or constraining locomotion throughout the environment was determined using identical measures to that of an axial map, particularly those weighting shortest distance between nodes (Turner et al., 2001; Penn & Dalton, 1994a) and immediate connectedness (Jiang & Tao, 2011). Four measures were selected for analysis due to their importance in the analysis of axial maps: *degree centrality* (e.g., connectivity of an axial map), *closeness centrality* (e.g., mean depth of an axial map), *eigenvector centrality* (local weighting of the importance of the node), and *betweenness centrality* (global weighting of the importance of a node). This set of four variables describes how well each position in space allows for movement through the environment (Borgatti & Everett, 2006; Borgatti, 2005) as a function of the presence of occluding buildings and surfaces. All measures were normalized by a factor of $n-1$, where n is the total number of positions in the graph, to allow comparisons across environments. The accessibility measures were computed using traditional measures of nodal importance in graphs, many of which are also considered in axial analysis:

Degree centrality. Degree centrality is the most basic measure of importance in the graph and forms the basis of many of the other measures of centrality used herein. This measure is simply the sum of the number of paths possible from each position to all immediately adjacent positions (Havel, 1955). Locations that are immediately accessible will display a higher degree centrality than those that are not.

Closeness centrality. Closeness centrality is a globally-derived measure of accessibility (Sabidussi, 1978). The level of closeness centrality is determined as the mean length of the shortest paths from each position to all other positions in the graph. As a result, positions that have a low mean distance to all other nodes are considered more globally accessible than those that have a high mean distance to all other nodes. Closeness centrality is therefore the analogue to mean depth in axial map analysis.

Eigenvector centrality. An alternate measure of the importance of a position is how well it connects with other highly connected positions in a graph (Bonacich, 1987). This is defined

as the sum of the centrality of the positions that each node connects to, to a radius proportional to the originating node's centrality, and is termed eigenvector centrality. Nodes that often connect with other locally connected nodes demonstrate high eigenvector centrality while those that are isolated demonstrate low eigenvector centrality.

Betweenness centrality. Betweenness centrality is the relative importance of a position can be determined by the extent to which that position is necessary to be traversed when reaching all other positions in the graph (Freeman, 1977). For the sake of computational efficiency, this can be approximated by determining the number of traversals necessary from a smaller number of positions in the graph, drawn from a uniform distribution, to a distance drawn from a uniform distribution (Alahakoon, Tripathi, Kourtellis, Simha, & Iamnitchi, 2011). In this method, k is the maximum distance to traverse, defined here as $k = 5 \ln(n + m)$, where n is the total number of positions in the graph and m is the total number of paths in the graph. The number of positions to calculate from was specified by $2k^2 n^{0.6}$. The resulting value is highest when a position must always be used to reach all other locations in the accessibility graph and lowest when the position is never used to move through the accessibility graph.

Isovist-Derived Measures. The isovist polygon was computed for each position in space lying on an axial line. The original four measures proposed by Benedikt (1979) as fitting the ideas of edge and texturally derived perception (Gibson, 1950) were examined: *area*, *perimeter*, *occlusivity* (defined by the total perimeter lying on an surface), and *circularity* (how much the shape of a circle approximates that of a perfect circle with matching perimeter, a formulation that is functionally similar to that of *compactness* which instead considers area). Previous work has also suggested (Franz & Wiener, 2008; Wiener et al., 2007; Stamps III, 2005) that the overall shape and jaggedness of the isovist polygon is associated with spatial preference. Accordingly, the *total number of vertices*, jaggedness of the isovist polygon (defined below as *normalized entropy* and *tortuosity*), *rectangularity* (ratio of the length to width of a minimum-bounding rectangle), and *convexity* (area of the polygon divided by area of the convex hull formed by the vertices of the isovist polygon) were selected to more fully capture all relevant properties of local geometry. As indicated above, jaggedness was defined in two ways: 1) as a measure of the degree of randomness in the distance of the vertices of the polygon from the originating point, determined by normalized *entropy* (for a general description, see: Shannon, 1948; for a description of normalized entropy, see: Sinai, 1959), and 2) as a measure of *tortuosity*, or square deviation in the curvature of the points in the polygon divided by the perimeter (Patasius,

Marozas, Lukosevicius, & Jegelevicius, 2005). This was done to capture the variability in the isovist edges and vertices while remaining distinct from the ideas of compactness and circularity (Franz & Wiener, 2008; Wiener et al., 2007). Circularity, rectangularity, convexity, entropy, and tortuosity were calculated such that 0.0 described no fit and 1.0 described perfect fit.

A further two novel measures were proposed to better capture the perceptual parameters outlined by Gibson in the ambient optic array as invariant, stable elements of the structure of the environment (Gibson, 1979). Here, I propose that these measures can easily be derived from the isovist as the *number of unique surfaces* identified by the isovist and as a *mean surface depth* (area divided by number of surfaces) describing the unique arrangement of these surfaces. Mean surface depth was taken to capture both size and shape of space as the division of an isovist by the number of incident surfaces is influenced by both distance and symmetry (that is, an isovist lacking symmetry would be biased by either reducing or increasing the mean depth, accordingly).

The exact formulation of each variable, a visual example of their calculation within a simple environment, and general summary of the interpretation of each variable are presented in Appendix 1.

2.2.2 Results

2.2.2.1 Data Preparation and Screening

Prior to analysis, the data were examined for violation of normality and the presence of univariate and multivariate outliers. Univariate normality was assessed for each variable by examination of skew and kurtosis and by visual examination of Q-Q plots. While not strictly required for EFA (Tabachnick & Fidell, 2007; Amemiya & Anderson, 1990; Anderson & Amemiya, 1988), approximating the normal distribution has been demonstrated to provide more consistent model results under certain circumstances. Variables showing a skewness and kurtosis of greater than 3.0 were considered to deviate from the normal distribution (Kline, 2010). Skew and kurtosis were found to be within these limits for all variables. Data were next screened for the presence of univariate and multivariate outliers using the statistically robust methods of median absolute deviation

Table 2.1 *Descriptive statistics For Study 1*

	Mean (SD)	Minimum	Maximum	Skew	Kurtosis
Axial Maps					
Connectivity	62.897 (28.717)	10.057	167.022	0.941	0.547
Integration	4.927 (1.321)	2.412	9.868	0.852	0.458
Mean Depth	1.929 (0.774)	0.385	5.531	1.345	2.711
Integration-3	2.116 (0.29)	1.459	3.185	0.433	-0.114
Mean Depth-3	5.127 (1.195)	2.905	9.868	1.016	0.815
Angular Analysis					
Mean Deviation	0.252 (0.049)	0.088	0.460	0.441	0.021
Mean Variance	0.789 (0.312)	0.011	2.026	0.632	0.924
Accessibility Graph					
Degree	7.52 (1.064)	3.000	8.000	-1.983	2.336
Closeness	0.01 (0.001)	0.007	0.012	0.000	-1.057
Betweenness	0.065 (0.012)	0.027	0.100	-0.053	-0.166
Eigenvector	0.003 (0.003)	0.000	0.018	1.725	3.106
Isovist					
Vertices	31.287 (16.115)	6.000	93.000	0.784	-0.196
Area	1409.956 (818.837)	109.500	4852.000	1.410	2.055
Perimeter	357.01 (138.441)	72.044	975.489	0.796	0.425
Occlusivity	144.279 (105.836)	0.000	527.276	1.327	0.851
Entropy	0.588 (0.346)	0.000	2.079	0.731	0.231
Tortuosity	0.266 (0.05)	0.110	0.502	0.337	0.124
Convexity	0.411 (0.143)	0.119	0.979	0.733	0.622
Circularity	0.15 (0.06)	0.037	0.395	0.926	0.617
Rectangularity	0.273 (0.116)	0.060	0.759	0.890	0.606
Surfaces	10.191 (4.083)	1.000	28.000	0.808	0.840
Surface Depth	149.34 (110.802)	23.143	1118.000	3.788	17.973

(MAD; Rousseeuw & Croux, 1993) and minimum covariance determinant (MCD; Rousseeuw & Van Driessen, 1999; Rousseeuw, 1985). MAD and MCD are advantageous in identifying whether data points are outliers as more traditional methods, such as the z-score, are less statistically robust. Identifying outliers is important as the presence of a disproportionate number or sufficiently aberrant data points can bias the resulting factor model, making the model less generalizable to other data sets. Cases found to exceed either 1.925 median absolute deviations on one or more variables or to exceed the critical value, $\chi^2(22, 22428) = 48.26$, $p < 0.001$, on the minimum covariance determinant estimator were considered outliers and inspected visually. A total of 914 cases were identified as outliers and removed from subsequent analysis. Descriptive statistics for each variable for each of the remaining 21514 cases can be found in Table 2.1.

Next, the data were screened for multicollinearity and singularity by examining the squared multiple correlation (SMC) for each variable and corresponding condition indices and variance proportion (VP) accounted for within the problematic dimension of variables. Data that are either identical (i.e., having singularity) or very similar to each other (i.e., having multicollinearity) can bias the factor model by making the model account for more variance than is reasonably possible (that is, two multicollinear variables can account for variation in each other; this artefact conflates their role in the overall model). Two sets of variables were identified as potentially multicollinear: 1) Integration (SMC=0.997; VP=0.940), Mean Depth (SMC=0.982; VP=0.850), Integration-3 (SMC=0.997; VP=0.900), and Mean Depth-3 (SMC=0.979; VP=0.800), CI=606.66; and 2) Degree Centrality (SMC=0.634; VP=0.670) and Betweenness Centrality (SMC=0.891; VP=0.890). CI=87.981. As a result, the variables of Degree Centrality and Integration and Mean Depth were removed from analysis. Retaining those measures to a radius of 3 units was selected as those variables have been most effective in explaining individual navigation behaviour in past studies). Data were re-examined for further potential cases of multicollinearity, but no further combinations were found. The remaining 19 variables were examined for their appropriateness in a factor analysis.

The factorability of the data was assessed by examining the Pearson product-moment correlations between each set of variables, Kaiser-Meyer-Olkin measures of sampling adequacy (KMO-MSA; Kaiser & Rice, 1974; Kaiser, 1970), and KMO sampling adequacy statistic (KMO-SAS; Kaiser & Rice, 1974; Kaiser, 1970), as presented in Table 2.2. The standard cut-off of 0.30 (Tabachnick & Fidell, 2007; Henson & Roberts, 2006; Hair, Anderson, Tatham, & Black, 1995) was used in determining the presence of important associations between variables and many acceptably large

associations were observed. The KMO-SAS and KMO-MSA describe the magnitude of common variation observed in the overall data and individual variables, respectively. It varies between 0 and 1.0, where 1.0 indicates that all variation can be described through a latent factor model (Kaiser & Rice, 1974). Typically, a value less than 0.50 is considered inappropriate for factor analysis. This is because variables showing low KMO-SAS and KMO-MSA have considerable amount of unique variation, behaving very differently than variables with higher values of each statistic. Based on these criteria, the variables of mean angular deviation, isovist occlusivity, and isovist tortuosity were excluded from the analysis under the grounds that these measures were statistically inappropriate within common factor model. Without excluding these variables – despite their demonstrated success at predicting behaviour in previous work – the model would be much more likely to produce a spurious result, poorly describing the patterns in the data. After removal of these variables, the omnibus KMO-SAS was found to be 0.812 be indicative of 'meritorious' factorability of the remaining data.

Table 2.2 Bivariate correlations For Study 1

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Connectivity	0.80	0.98	-0.92	-0.20	0.89	0.44	0.29	0.23	0.57	0.37	0.55	0.02	0.22	-0.27	-0.30	-0.45	-0.29	0.50	-0.04
2. Integration-R3		0.83	-0.92	-0.20	0.86	0.43	0.29	0.23	0.55	0.40	0.57	0.02	0.21	-0.26	-0.27	-0.45	-0.26	0.47	0.01
3. Mean Depth-R3			0.96	0.26	-0.82	-0.49	-0.26	-0.20	-0.56	-0.34	-0.53	-0.03	-0.25	0.24	0.31	0.47	0.30	-0.47	0.04
4. Ang.Deviation				0.57	0.00	-0.15	-0.15	-0.14	-0.22	-0.11	-0.13	0.00	-0.16	0.07	0.08	0.11	0.08	-0.13	-0.01
5. Ang.Variance					0.86	0.37	0.18	0.17	0.48	0.27	0.48	0.02	0.18	-0.28	-0.32	-0.46	-0.30	0.43	-0.09
6. Closeness						0.92	0.08	0.07	0.56	0.08	0.25	0.02	0.41	-0.23	-0.32	-0.31	-0.30	0.37	-0.20
7. Betweenness							0.84	0.82	0.43	0.69	0.57	0.02	0.23	0.06	-0.04	-0.12	-0.06	0.48	0.36
8. Eigenvector								0.82	0.40	0.64	0.53	0.01	0.20	0.02	-0.04	-0.11	-0.06	0.48	0.29
9. Vertices									0.82	0.41	0.61	0.03	0.68	-0.23	-0.42	-0.49	-0.40	0.81	-0.16
10. Area										0.70	0.83	0.01	0.10	-0.05	0.09	-0.25	0.06	0.44	0.70
11. Perimeter											0.80	0.01	0.18	-0.15	-0.38	-0.67	-0.38	0.61	0.37
12. Occlusivity												0.52	0.03	0.01	-0.01	0.00	-0.01	0.01	0.00
13. Entropy													0.67	0.10	-0.21	-0.20	-0.20	0.45	-0.17
14. Tortuosity														0.58	0.12	0.15	0.09	-0.10	0.09
15. Convexity															0.75	0.72	0.95	-0.44	0.47
16. Circularity																0.84	0.72	-0.45	0.10
17. Rectangularity																	0.77	-0.40	0.40
18. Surfaces																		0.81	-0.25
19. Surf. Depth																			0.63

Note. All correlations were significant at $p < 0.001$. Correlations of potential theoretical importance according to standard cut-offs are highlighted in grey. The Kaiser-Meyer-Olkin measure of sampling adequacy for each variable is displayed on the diagonal of the matrix.

2.2.3 Exploratory Factor Analysis

Of the original 22 spatial variables examined, a total of 16 were considered appropriate for the technique of EFA. The remaining 16 variables consisted of axial (Connectivity, Integration-3, Mean Depth-3), angular (Mean Angular Variance), accessibility (Closeness Centrality, Betweenness Centrality, Eigenvector Centrality), and isovist-derived (Vertices, Area, Perimeter, Entropy, Convexity, Circularity, Rectangularity, Surface Count, and Mean Surface Depth) measures. The number of factors sufficient to adequately encapsulate the latent factor structure of the data was found to be between 4 (Scree test; Hull method) and 5 (Comparison Data). As a result, 5 factors were retained for analysis as Comparison Data has been demonstrated in simulations to show reduced bias (Ruscio & Roche, 2012) and factor over-extraction is considered preferable to under-extraction (Wood, Tataryn, & Gorsuch, 1996) in producing reproducible factor models.

The resulting 5-factor model is presented in Table 2.3 (the unabridged factor model is presented in Appendix 2) and accounted for 88.08% of the variance in the overall data. The eigenvalue of the last unretained factor was 0.548, accounting for 3.42% of the variance in the data. Factor 1 was described by Connectivity, Integration (*radius=3*), mean-depth (*radius=3*) and mean angular variance. Factor 2 was found to be described by rectangularity, circularity, convexity and perimeter, and showed weak indirect effects on many of the experimental variables. Factor 3 was found to relate to betweenness centrality, eigenvector centrality, and the number of surfaces and showed strong indirect effects on accessibility measures. Factor 4 was associated with closeness centrality, number of vertices, entropy, and the number of surfaces, and showed moderate-to-strong indirect effect on virtually all other measures of interest. Finally, Factor 5 was associated with area, perimeter, circularity, and the mean surface depth, showing relatively weak indirect effects on the axial and accessibility family of measures.

Table 2.3 Exploratory Factor Analysis Models for Studies 1 and 2

Factor:	Study 1						Study 2					
	SC	ENC	IMP	ACC	LE	h ²	SC	ENC	ACC	IMP	LE	h ²
Connectivity	0.91					0.98	0.99					0.97
Integration-3	0.92					0.97	0.96					0.96
Mean Depth-3	-0.92					0.87	-0.89					0.87
Ang. Variance	0.93					0.79	0.88					0.74
Closeness				0.55		0.39			0.57			0.42
Betweenness			0.87			0.82				0.94		0.97
Eigenvector			0.90			0.79				0.73		0.73
Vertices				0.99		0.98			0.99			0.96
Area					0.81	0.97					0.86	0.95
Perimeter		-0.41			0.68	0.96		-0.35			0.68	0.98
Entropy				0.88		0.50			0.91		-0.33	0.50
Convexity		0.95				0.97		0.98				0.97
Circularity		0.79			-0.31	0.77		0.70				0.74
Rectangularity		0.92				0.90		0.98				0.90
Surfaces			0.35	0.49		0.70			0.71			0.80
Surface Depth					0.90	0.80			-0.57		0.88	0.60
Λ	6.90	3.05	1.87	1.43	0.80		7.47	2.26	2.03	1.63	0.68	
% Variance	43.3	62.4	74.1	83.1	88.1		46.7	60.1	73.4	83.6	87.9	

Correlation Matrix

Factors:	SC	ENC	IMP	ACC	LE
SC	-	-0.48	0.31	0.58	0.36
ENC		-	-0.23	-0.57	-0.15
IMP			-	-0.50	0.56
ACC				-	0.26

Correlation Matrix

Factors:	SC	ENC	ACC	IMP	LE
SC	-	-0.41	0.53	0.11	0.54
ENC		-	-0.58	-0.16	-0.53
IMP			-	0.32	0.58
ACC				-	0.52

Note. Factor matrix presented is the pattern matrix. All factor loadings below 0.30 have been suppressed. Factor labels have been shortened to: SC (Spatial Complexity); ENC (enclosure); IMP (importance); ACC (Access); LE (Local Extent).

Factor 1 was labeled as “Spatial Complexity” as it captured the degree to which a location was embedded in an area with increased connectivity and integration, reduced mean depth (the inverse of integration, generally), and increased angular variance. That is, locations with high spatial complexity would be embedded in spaces that are easier to linearly navigate, such as at or nearby main roads. Factor 2 was labeled "Enclosure" as it described the tendency for increased fit with convexity, rectangularity, and roundness, as well as reduced perimeter. Together, these measures strongly indicate locations that are isolated from surrounding space and more fully enclosed by the surrounding walls. Factor 3 was labeled as "Importance" as it showed a tendency toward describing spaces that were more locally connected (i.e., eigenvector centrality) more likely to be traversed when fully exploring the environment (i.e., betweenness centrality), and surrounded by more unique surfaces, such as would be typical of locations serving to transport high volumes of traffic at intersections or junctions. Factor 4 was labeled as "Access" as it defined higher number of vertices, entropy, closeness centrality, and surfaces. The isovist measures of vertex count, entropy, and surface count together are descriptive of the overall jaggedness of local visual space, while closeness centrality identifies the most accessible location in the spatial system. Mutually, these characteristics should define highly accessible points like the central square of a city. Finally, Factor 5 was labeled as "Local Extent" as it captured changes in spatial extent (area and perimeter) and relative complexity (deviation from circularity and increased mean surface depth) of a viewpoint simultaneously.

A number of moderate correlations were observed (found in Table 2.3). Spatial Complexity and the latent factors of Access and Local Extent were found to be moderately correlated. Enclosure was found to be moderately correlated with Access. Finally, Access was also found to be moderately correlated with the Importance of a location.

2.2.4 Discussion

EFA was used to explore the spatial properties of two prototypical environments, one consisting of a relatively consistently organized structure (typical of high intelligibility) and one that consisted of a much less organized structure (typical of a disordered, unintelligible, environment). Together, both environments were intended to capture a considerable variety of locations, both in terms of local geometry (i.e., a specific viewpoint) and in their role and position in the overall surrounding space. When space was examined in this way, a number of potentially meaningful and novel emergent properties were observed in the form of latent factors. Specifically, Spatial Complexity (primarily axially defined), Enclosure (isovist-defined), Importance (globally defined as how the shape of local

space interacts with the configuration of the environment), Access (degree to which the location approximates a central square), and Local Extent (degree to which the local space is systematically arranged) were identified as emergent properties of the design or urban space.

The first and most notable finding is that no evidence was found to support the idea that a single common emergent property can explain how measures that describe the global structure of surrounding space can be predicted by properties that can immediately be perceived in local space. However, the complexity of the global structure, as defined by Spatial Complexity, was shown to be associated with corresponding changes in the locally derived factors of Enclosure and Local Extent. Therefore, general descriptions of local space can provide some degree of information about the distant and global visual space by some level of shared variation. This is a promising finding as it represents initial support for the theory that local visual information could be a driving force behind how we behave in and navigate through space, as posited within the theory of *exosomatic visual architecture* (Turner, 2006; Penn, 2003) and inferred by the body of scholarly work invoking affordances. This is also consistent with the efficacy of visual graph analysis, which shows an association between the *integration* of a visibility graph (one in which mutually visible locations are connected to each other) and the preferred paths of navigators (Turner, 2006; Turner et al., 2001). Specifically, people have been shown to prefer locations that are not only large themselves but also connect with other large, integrated spaces. Similar support can also be found in the relationship between the integration of axial maps, which have been argued to represent idealized lines-of-sight (Hillier, 1996), and the number of people moving through a space. While speculative at this time, should the relationship between Spatial Complexity, Enclosure, and Local Extent be shown to be consistent in other types of spaces, it would provide further grounding for the idea that the size and shape of the local space can predict environmental features outside of the immediate field of view, a key component of any affordance-based model.

A second notable finding is that Enclosure and Access were found to be relatively independent of the Local Extent at a given point in space. Generally, Enclosure can be said to capture the relative symmetry of the shape of surrounding space via variables such as circularity and convexity. Access, on the other hand, was primarily defined by the complexity of the shape of local space (where vertices and entropy approximate the jaggedness of an isovist). Intuitively, this can be understood as the apparent link between the shape of a space and its overall size, insofar as the configuration of an overall environment allows. This finding also helps explain why when people seek out locations that

provide visual access to an environment but obstruct actual movement, such as behind a window overlooking some space (termed either *visual permeability* or *prospect*), the strongest single predictor is the horizontal span of an isovist (Stamps, 2010; Stamps III, 2005; Appleton, 1996). In the context of visual permeability theory, the size of a hiding space is irrelevant because the shape and general structure are the determining factors of whether a location is a good hiding place, an idea that is supported here. This pattern of results also provides additional support for the idea a small set of variables can be useful in summarizing and predicting behaviour in meaningful ways.

Surprisingly, occlusivity, which has formerly been demonstrated to be a promising predictor of movement through an environment (Turner, 2006; Turner et al., 2001) and predictive of spatial preference in studies using picture stimuli (Kaplan, 1988), was not found to be strongly related to any systematic property of space measured or detected herein. This most likely explanation for the lack of the involvement of occlusivity in the present model is that occlusivity, simply, describes the world in a way that is very different from all the other included variables. This is because the degree of overlap offered between different viewpoints may be associated with the size of space but is also influenced by a number of other variables simultaneously, so occlusivity would not be expected to be related to any axial, metric, or isovist measure, in a consistent way when all other factors are held constant (as is the case here). This does not mean, however, that occlusivity and how it relates to these variables is not of interest in future work. Using a similar approach to the one used here, but instead focusing on explaining how this unique variable behaves in the presence of other metrics of the structure of space, would help us understand if occlusivity itself is useful in predicting behaviour or if it is instead the relationship that occlusivity may hold with other, perceivable, variables. But this question extends well beyond the present analysis which was intended to relate and categorize local and global spatial metrics to identify common patterns in variation in a broader way.

As a whole, the initial EFA provides ample support for the idea that specific emergent properties are capable of explaining and summarizing space in potentially useful ways, both when navigating and in determining spatial preference. Additionally, Local Extent was shown to meaningfully predict the level of Spatial Complexity, albeit moderately so, supporting the idea that properties perceived in local space can be useful in determining the structure of the environment outside the field of view. This association allows stable predictions to be made about global space from the local environment alone. This also provides support for the idea that local spatial variables alone may be useful in

predicting patterns previously attributed to the variables influenced by the factor of Spatial Complexity.

However, as was previously noted, the environments used in the present experiment may have limited the relationship between the observed variables and their latent factor structure. Central to this is the idea that an algorithmically defined axial map is derived from the location of the vertices in an environment, something that is inextricably linked with the number of surfaces and walls in a space. Additionally, the number and size of surfaces in the data set was shown to be influenced by Enclosure, Access, and Importance, suggesting that the surface geometry is influential in shaping the way space is configured as a whole, at least partially. To address this issue and further evaluate the relationship between variation in the properties defined by space and the configuration of space as a whole, surface geometry must be more rigorously controlled for. Should surface geometry (as opposed to the overall configuration of an environment) be playing a critical role in one or more of the factors, it might obscure the relationship between isovist and axial measures. If, however, surface geometry is not implicated in the shared variation between Spatial Complexity and Local Extent, no difference would be expected to be observed in the corresponding model.

2.3 Study 2: The Influence of Occluding Surfaces

Study 2 was designed to assess the role of occluding surfaces in influencing the local and global structure of space. In this case, only the walls composing each building were manipulated as no other occluding surfaces were present. Each of the prototypical environments used in Study 1 were manipulated to reduce the amount of variation in surface geometry while holding the general structure of the environment relatively constant. A significant reduction in the number of surfaces, $t(25)=3.718$, $p<0.001$, 95% CI [0.326, 1.146], was achieved by enforcing two rules: (1) each face of a building should be as straight as possible; (2) the corners of the buildings should approximate right-angles. In doing so, the same relative volume and position of each building was maintained. Figure 2.1 depicts the shift in the geometry of the buildings. The mean number of surfaces per building was reduced from 5.345 ($SD=1.325$) in Study 1 to 4.615 ($SD=1.06$) in Study 2. Due to the interrelated nature of the intelligibility analysis with the overall spatial configuration, this manipulation had an incidental effect on the intelligibility of the two environments. A general reduction in the complexity of the axial map, as depicted in Figure 2.3., was observed, with a reduction in the number of axial lines necessary to describe the structure of the overall space(s). This resulted in reduced intelligibility in the Intelligible environment and increased the intelligibility of the Unintelligible environment from those used in

Study 1

Study 2

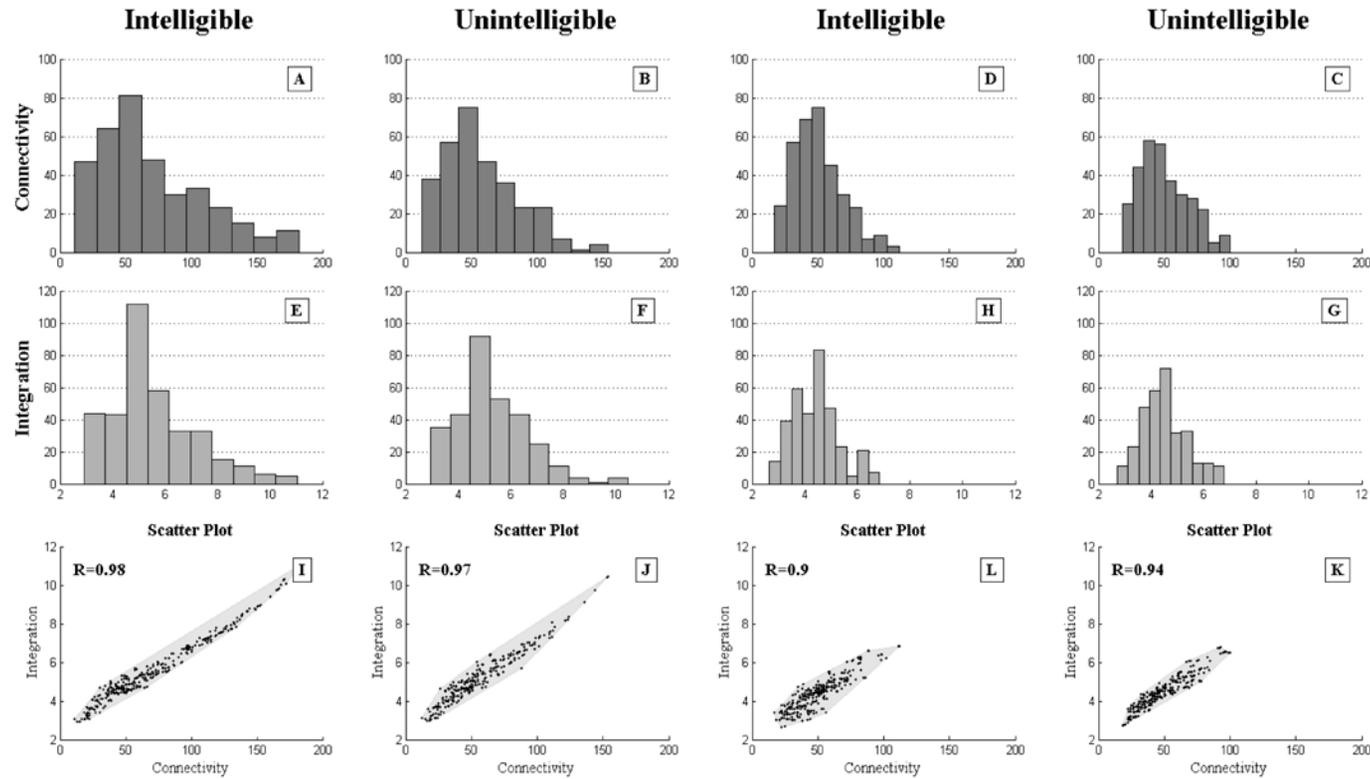


Figure 2.4 Panel A through D show histograms of the connectivity of the all-line axial map from the environments used in Study 1 (Intelligible and Unintelligible) and those constructed for Study 2 (Intelligible and Unintelligible, altered). Panels E through H present histograms of the integration of the all-line axial maps composing each environment. Panels I through L display scatter plots of the relationship between connectivity and integration for each environment. A convex hull defining the dispersion of data is presented in light grey. Pearson-product moment correlations are presented in the upper left corner of each scatter plot.

Study 1. The corresponding changes in connectivity, integration, and the correlation between the two (intelligibility) can be found in Figure 2.4. Cumulatively, the reduction in the complexity of the component buildings while maintaining relative isovist size and shape should represent a more stringent test of the relationship between local perceptual information and more global variables describing the surrounding environment. This is because a smaller set of potential isovist shapes should be available to describe the space, placing emphasis on only the key latent relationships among variables describing the surrounding environment.

2.3.1 Methods

2.3.1.1 Analysis Approach

Each of the 22 variables considered in Study 1 were again examined for common latent factors in Study 2, broadly being drawn from the axial, angular, accessibility, and isovist-derived domains, and identical methods were used to assess the relationships amongst the variables (described fully in section 2.2.1 through to section 2.3). Factors were extracted using the Unweighted Least Squares (ULS) method and subjected to a Promax rotation ($\kappa=2$). The number of factors was determined by Scree test, Hull method of parallel analysis ($n=500$), and Comparison data techniques ($n=1000$, $m=500$).

Likewise, data preparation and screening was achieved by assessing Q-Q plots to assess normality, and mean absolute deviation and minimum covariance determinant to examine the data for outliers. Multicollinearity was assessed by examining the squared multiple correlations (SMC), condition index, and variance inflation proportion (VIP). The overall suitability of each variable and the overall sample for a common factor model were assessed by KMO-MSA and KMO-SAS , respectively.

2.3.1.2 Data Sample

Each of the two modified environments was generated to be 248 meters by 176 meters. The spatial properties of each environment were determined for each of the 22 variables on a 1m square grid. Of the original 51618 samples lying in open space, the initial pool was trimmed to include only those locations bisected by at least one axial line and only those positions lying interior to the border of the environment (the outer 10% data points). A total of 22128 data points were retained for subsequent factor analysis after collapsing the data set across the two environments to maximize variation by developing a heterogeneous sample.

Table 2.4 *Descriptive statistics for Study 2*

	Mean (SD)	Minimum	Maximum	Skew	Kurtosis
Axial Maps					
Connectivity	55.767 (22.37)	10.800	145.011	0.484	-0.150
Integration	4.821 (1.132)	2.450	9.840	0.545	0.264
Mean Depth	2.093 (0.272)	1.404	3.108	0.648	0.224
Integration (R3)	4.957 (1.043)	2.940	9.840	0.654	0.508
Mean Depth (R3)	2.032 (0.208)	1.404	2.651	0.226	-0.389
Angular Analysis					
Mean Deviation	0.272 (0.047)	0.116	0.500	0.229	0.329
Mean Variance	0.719 (0.286)	0.017	1.855	0.682	0.437
Accessibility Graph					
Degree	7.548 (1.044)	3.000	8.000	-2.034	2.433
Closeness	0.01 (0.001)	0.007	0.011	-0.009	-1.170
Betweenness	0.068 (0.013)	0.025	0.100	-0.197	-0.353
Eigenvector	0.004 (0.004)	0.000	0.019	1.408	1.337
Isovist					
Vertices	26.172 (14.165)	5.000	87.000	1.247	1.255
Area	1493.751 (740.593)	151.500	4173.000	0.944	0.627
Perimeter	364.053 (141.41)	89.987	949.853	0.893	0.824
Occlusivity	160.541 (100.879)	3.000	583.071	1.233	0.768
Tortuosity	0.486 (0.307)	0.000	1.991	0.912	0.837
Entropy	0.287 (0.052)	0.121	0.484	-0.040	-0.300
Convexity	0.415 (0.133)	0.092	0.892	0.299	-0.488
Circularity	0.156 (0.062)	0.036	0.426	0.834	0.583
Rectangularity	0.281 (0.115)	0.047	0.785	0.772	0.251
Surfaces	10.016 (4.094)	3.000	30.000	1.053	1.401
Surface Depth	151.459 (53.132)	23.222	432.938	0.935	1.658

2.3.2 Results

2.3.2.1 Data Preparation and Screening

No notable departures from normality were observed in the data. A total of 409 potential outliers were removed from analysis, each of which showed significant departure from both the univariate and multivariate distributions of the variables. The descriptive statistics for the remaining 21719 data points retained for analysis can be found in Table 2.4.

Potential multicollinearity was observed for two sets of variables: (1) Condition index, 709.930: Integration (SMC=0.997;VP=0.920), Mean Depth (SMC=0.987;VP=0.820), Integration-Radius=3 (SMC=0.997;VP=0.910) and Mean Depth-Radius=3 (SMC=0.985;VP=0.800); (2) Condition index, 101.330: Degree Centrality (SMC=0.654VP=0.420) and Betweenness Centrality (SMC=0.883;VP=0.580). Integration, Mean Depth, and Degree Centrality were removed from the analysis and the data were re-examined for further cases of multicollinearity. No further cases are identified, rendering 19 variables for further examination.

The data showed sufficient intercorrelation and KMO statistics amongst the individual variables, as is portrayed in Table 2.5. As in Study 1, mean angular deviation, occlusivity, and tortuosity were excluded from the analysis due to relatively poor fit with the common factor model. The omnibus KMO sampling adequacy statistic was also found to be 0.812, indicative of meritorious factorability of the remaining data. Accordingly, 16 variables were retained for the EFA.

The data were examined for the presence of spatial autocorrelation by examining Moran's I and Geary's c statistics. No evidence was found for the presence of statistically significant autocorrelation between each location and neighbouring locations, both when considering the distance between locations linearly, $I=0.15$, $c=1.08$, $p=0.91$, and when using inverse distance, $I=0.04$, $c=1.05$, $p=0.98$. Locations that were nearer to each other were not shown to be more related to each other than those further away.

Due to agreement across each family of statistics, the data were considered well suited for examination using factor analysis.

Table 2.5 Bivariate correlations for Study 2

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	
1. Connectivity	0.83	0.97	-0.92	-0.27	0.87	0.48	0.27	0.23	0.53	0.52	0.57	0.04	0.24	-0.16	-0.31	-0.46	-0.29	0.51	0.16	
2. Integration-R3		0.86	-0.92	-0.25	0.83	0.47	0.23	0.19	0.52	0.52	0.58	0.05	0.22	-0.19	-0.29	-0.47	-0.28	0.50	0.16	
3. Mean Depth-R3			0.95	0.33	-0.78	-0.50	-0.20	-0.16	-0.51	-0.47	-0.54	-0.05	-0.25	0.19	0.30	0.48	0.29	-0.48	-0.13	
4. Ang.Deviation				0.70	-0.04	-0.17	-0.15	-0.12	-0.26	-0.16	-0.14	0.01	-0.21	0.05	0.08	0.08	0.10	-0.17	-0.06	
5. Ang.Variance					0.88	0.38	0.21	0.19	0.35	0.46	0.52	0.04	0.13	-0.08	-0.26	-0.42	-0.25	0.40	0.18	
6. Closeness						0.94	0.10	0.10	0.56	0.33	0.38	0.06	0.42	-0.24	-0.24	-0.37	-0.21	0.45	-0.06	
7. Betweenness							0.82	0.84	0.44	0.69	0.52	0.00	0.17	0.12	-0.24	-0.11	-0.23	0.51	0.40	
8. Eigenvector								0.79	0.42	0.65	0.48	-0.02	0.20	0.13	-0.18	-0.11	-0.16	0.46	0.38	
9. Vertices									0.84	0.66	0.70	-0.01	0.66	-0.29	-0.44	-0.49	-0.39	0.84	-0.03	
10. Area										0.77	0.88	-0.01	0.19	-0.07	-0.38	-0.43	-0.37	0.75	0.54	
11. Perimeter											0.84	0.01	0.21	-0.11	-0.66	-0.74	-0.62	0.77	0.35	
12. Oclusivity												0.53	-0.02	-0.05	-0.02	-0.02	-0.01	0.00	-0.01	
13. Entropy													0.74	-0.12	-0.12	-0.19	-0.11	0.43	-0.21	
14. Tortuosity														0.53	0.03	0.11	-0.01	-0.07	-0.02	
15. Convexity															0.74	0.76	0.95	-0.50	0.04	
16. Circularity																0.83	0.75	-0.51	-0.01	
17. Rectangularity																	0.74	-0.45	0.00	
18. Surfaces																			0.76	-0.11
19. Surface Depth																				0.41

Note. All correlations were significant at $p < 0.001$. Correlations of sufficient magnitude for factor analysis are highlighted in grey. The KMO-MSA for each variable is displayed on the diagonal of the matrix.

2.3.2.2 Exploratory Factor Analysis

A total of 16 measures were considered appropriate for the common factor model, consisting of the same axial, angular, accessibility, and isovist-derived measures as were assessed in Study 1. Parallel analysis and the Scree test again suggested the presence of 4 factors in the resulting factor solution while Comparison Data again suggested the present of 5. Consequently, 5 factors were retained in the final factor model to ensure model robustness.

The resulting 5 factors identified by the ULS extraction and Promax rotation accounted for 87.90% of the variance in the data. The eigenvalue of the last, unretained, factor was 0.517 and accounted for 3.23% of the variance in the data. The pattern matrix and factor intercorrelations are presented in Table 2.3 (the unabridged factor model can be found in Appendix 2). Factor 1 described Spatial Complexity (connectivity, integration, mean depth, and mean angular variance). Factor 2 described Enclosure (perimeter, convexity, circularity, and rectangularity). Factor 3 described degree of Access (closeness centrality, number of vertices, entropy, number of surfaces, and mean surface depth). Factor 4 defined nodal Importance (betweenness centrality and eigenvector centrality). Finally, Factor 5 was found to define Local Extent (perimeter, entropy, mean surface depth).

A number of potentially important correlations were found between the latent factors, as presented in Table 2.3. Spatial complexity was found to be moderately positively correlated with Local Extent and negatively correlated with Enclosure. Enclosure was also found to be moderately negatively correlated with Access and Importance. Finally, Local Extent was observed to be strongly associated with all other latent variables.

2.3.3 Discussion

Exploratory Factor Analysis of the two modified environments, controlling more for variation induced by the shape of buildings while holding the global complexity of space relatively constant, revealed a number of important results.

A nearly identical structure of latent factors was identified, shaping the how space can be described. That is, evidence was again shown for the emergent properties of Spatial Complexity, Enclosure, Access, Importance, and Local Extent with a few minor differences in how the shape of space can be accounted for (particularly in the variables of circularity and surface count). These exceptions noted, a nearly identical pattern of relationships was observed between the latent factors and their component variables, providing stronger evidence for generalizability of the relationships in different environments. Particularly interesting is that the properties of Local Extent and Enclosure

were not shown to be influenced by a reduction in surfaces, despite both variables being explicitly by local geometry alone. This is evocative of the idea that the positioning of nearby buildings rather than their explicit geometry is highly influential in variables of both local and global space.

Critically, Local Extent again was again found to be associated with measures of Spatial Complexity. Further, Local Extent was now found to have strong associations with all other latent factors, ranging from those of potential practical importance (i.e., Access; identifying the central square of an environment) to those that may offer a specific function (i.e., Enclosure; hiding and concealment). This pattern of results is strongly supportive of the idea that certain elements of Local Extent may serve as proxies for globally-derived measures such as those of axial maps and accessibility graphs. That is, *affording* variables of Local Extent such as mean surface depth (the best single predictor of spatial extent) may allow a person to make a variety of predictions about the structure of space around them. This is consistent with a previous investigation of navigation performance that showed that when participants were exposed to distinct vistas prior to navigating a path toward a goal landmark, performance was enhanced when the vistas were along the most direct, unambiguous, paths to the goal landmarks (Heft, 1996). As indicated here, in spaces outside of these direct paths, Local Extent, Enclosure, and Access would be expected to be more similar to each other, reducing their overall usefulness and potential for affordance, an idea that is consistent with this finding.

This study also demonstrated a weak relationship between Enclosure and Access. This finding is consistent with the dichotomous relationship between the two factors and bears considerable overlap with visual permeability theory (Stamps III, 2005). In both cases, the placement of buildings rather than the explicit local geometry alone is important in identifying potential locations offering visual access or identifying locations that may serve as ideal hiding spots. This is also consistent with studies of the influence of isovist shape at intersections on spatial memory, where poorer spatial memory is observed at intersections of ambiguous shape, even when other types of visual cues (each building appearing visually distinct and unique) are present in the local environment (Meilinger et al., 2012). Together, these studies provide further support for the idea that the interplay between the local isovist and overall configuration of the environment is sufficient to account for how we behave in space, not just when we are navigating space.

These findings highlight the critical influence of the configuration of an environment above and beyond that of the influence of local geometry defined by the individual structures therein. By

controlling for variation in surface geometry, a stronger relationship between Spatial Complexity and Local Extent was observed, suggesting that local surface geometry (and by extension, potentially, the algorithmically-defined axial maps) is more heavily influenced by global rather than local features. This is because a reduction in the local complexity of space should also reduce the relationship between Local Extent and Spatial Complexity if local complexity or geometry was driving the effect alone. Instead, the opposite pattern was observed. Likewise, should local geometry be driving the effect of Access and Enclosure, a stronger effect should be observed between these two factors. Instead, the effect is weakened, suggesting dependence between Access and Enclosure on more than just the local space, particularly in the case of Access. While local surface geometry does influence how varied the isovist is on a local level, the overall pattern of variation appears much more related to global spatial variables, strengthening the argument that a stable, functional, relationship exists between the configuration of local space and global space.

While the results of Study 2 provide a clearer picture of the interactions between spatial properties and their controlling latent factors, the modeled relationship between local and global properties is still only theoretical as the environments were both synthetic spaces and relatively small in size. To establish the consistency of the model described in Study 1 and 2, a *much larger, real-world* sample was evaluated using Confirmatory Factor Analysis (CFA), allowing both the strength and the fit of the model to be stringently assessed.

2.4 Study 3: Confirming the Presence of Latent Factors

Study 3 sought to test the hypothetical relationships established in Studies 1 and 2 through the use of Confirmatory Factor Analysis (CFA). That is, the adequacy of the 5 latent variables of Spatial Complexity, Enclosure, Access, Importance, and Local Extent at explaining how variables of local (i.e., isovists) and global (i.e., axial) scope may vary was explicitly tested here.

Of particular interest in Study 3 was establishing the precise relationship between local perceptual characteristics (such as Local Extent) and those characteristics of a space that define its function, but which may lie outside present perception (namely, the properties of Access, Importance, and Spatial Complexity). Should local perceptual properties demonstrate inconsistent or poor fit with such more global variables, an affordance relationship as suggested by previous authors, such as in exosomatic visual architecture, would not be supported. Unless factors defined by isovists are predictive of other properties of space, particularly those lying outside the directly perceivable viewpoint, the argument

that the perception of invariant structure (Gibson, 1979) and its proposed role in spatial navigation would be considered weak at best.

For the confirmatory factor analysis, two large-scale real-world spaces were examined. The first, defined by the City of London (UK), a distinct city and county within the city of London that was the product of planning and a variety of historical and growth forces. The resulting city structure shows the influence of both short-term and long-term planning influences. Additionally, this area and areas like it are prototypical of real-world spaces that demonstrate low intelligibility (Bafna, 2003). To validate the model tested in London, a second environment was selected from a portion of Manhattan Island in New York City (USA). The area of Manhattan was chosen due to a much more stringent adherence to planned grid-like road networks – longterm planning alone, largely – enhancing the intelligibility of the overall space. New York City is also considered a classic example of a high intelligibility space (Bafna, 2003). By separately examining fit of the factor model in these two spaces – largely existing on opposite ends of the intelligibility spectrum – the generalizability of the model to other real world spaces is enhanced. This is because a successful model that fits both types of environments would be demonstrative of types of variation seen in space as a whole, independent of the influence of more generalizable influences on the planning and structure of space². As such, this approach was considered ideal, as the finding of a consistent fit of the hypothetical model in two large, real-world and opposing spaces, would be a strong test of the robustness and fit of the latent factor model and its underlying patterns of association.

2.4.1 Methods

2.4.1.1 Data Collection

The data for the two real-world urban environments was extracted from two sources. Plan views of both environments, those of the City of London and of New York City, can be found in Figure 2.6.

The urban space for the City of London was adapted from the OpenStreetMap database (OpenStreetMap users, 2013), made available under the Creative Commons Attribution-ShareAlike 2.0 license, using the Maperitive (Brejc, 2013) software package. An 1800-meter by 720-meter segment of the City of London region, centered on St. Paul’s Cathedral, was selected. This area was

² It is worthwhile to note that a general factor of *planning* could potentially be extracted in a more hierarchical analysis, where any general factors are examined separate from more dynamic relationships. This was largely considered a different question than the relationship of local and global properties, though.

selected as it is one of the oldest counties in London, influenced largely by local, organic forces as it developed across time. This was considered ideal, as it would place emphasis on the reduction in intelligibility across the majority of the space. Of the area within this county, a total of 605137 data points were found to lie in open space when examined with a 1 meter square grid and included in the analysis.

The urban space for New York City (NYC) was determined from the a LIDAR-based building footprint database retrieved as part of the NYC Open Data program (City of New York, 2013) and was adapted for analysis using arcGIS 9.3.2. The NYC data set consisted of a 1950m by 955m area centered on Washington Square Park on Manhattan Island. This region was selected due to the considerable influence of an adherence to a grid in development, while still retaining some individual variation among city blocks. From this region, a total of 882479 data points were found in open space and retained for analysis.

Data were analyzed in parallel using the PyPy programming language and Stanford Network Analysis Platform (Leskovec, 2009). The axial map was generated and analyzed in Depthmap (UCL, version 10). Each of the sixteen variables identified in the previous EFAs were computed: axial map-based (connectivity, integration, and mean depth), angular segment analysis (mean angular variance), accessibility (closeness, betweenness, and eigenvector centrality), and isovist-derived (vertices, area, perimeter, entropy, convexity, circularity, rectangularity, number of surfaces, and mean surface depth).

2.4.1.2 Data Composition and Screening

As the previous two experiments demonstrated a fairly consistent theoretical structure between the different types of measures, the CFA focused only on those measures found to be considerably impacted by the purported latent factors (Spatial Complexity, Enclosure, Access, Importance, and Local Extent). Descriptive statistics are presented for each of the two environments in Table 2.6.

Univariate and multivariate outliers were identified by MAD and MCD, respectively. Cases found to exceed 1.1925 MAD on one or more variables or exceeded the critical value, χ^2 (15, 1447412) =39.25, $p < 0.001$, were flagged as potential outliers and examined by visual inspection. None of the identified cases was considered sufficiently aberrant from the data to be considered a meaningful outlier, all data points were retained for analysis.

City of London



New York City:



Figure 2.5 A plan view of the sections of real-world locations, City of London (UK) and the New York City (USA), used in Study 3.

Table 2.6 *Descriptive statistics for Study 3*

	Model Evaluation - London			Cross-Validation - NYC		
	Mean (SD)	Skew	Kurtosis		Skew	Kurtosis
Axial Maps						
Connectivity	625.030 (522.453)	1.382	2.193	1071.532 (700.418)	0.854	0.542
Integration	6.210 (0.881)	-0.405	0.004	6.987 (0.844)	-0.574	1.314
Mean Depth	2.530 (0.111)	-0.302	1.326	2.471 (0.125)	-0.084	1.098
Angular Analysis						
Mean Variance	1.520 (0.789)	0.835	0.729	2.684 (1.36)	0.556	-0.037
Accessibility Graph						
Closeness	0.002 (0.005)	48.680	2910.0	0.002 (0.007)	58.359	4017.390
Betweenness	0.002 (0.001)	-0.251	-0.463	0.001 (0.001)	-0.254	0.242
Eigenvector	0.001 (0.001)	0.334	-1.282	0.001 (0.001)	0.242	-1.239
Isovist						
Vertices	73.060 (42.213)	0.819	0.617	96.304 (44.526)	0.686	0.155
Area	8104.118 (6691.101)	0.864	-0.022	18089.753 (13291.654)	1.140	1.266
Perimeter	923.512 (619.450)	1.091	1.375	1798.639 (968.166)	0.497	0.282
Entropy	0.820 (0.384)	0.659	0.865	0.829 (0.306)	0.363	0.301
Convexity	0.447 (0.175)	0.304	-0.355	0.451 (0.216)	0.039	-0.954
Circularity	0.147 (0.100)	1.634	3.464	0.091 (0.071)	2.652	9.970
Rectangularity	0.297 (0.146)	0.729	0.284	0.295 (0.167)	0.467	-0.579
Surfaces	18.400 (9.433)	0.610	-0.107	18.839 (7.425)	0.507	0.127
Surface Depth	420.674 (316.7)	4.678	2.118	976.557 (693.733)	2.034	2.703

Table 2.7 *Bivariate correlations for Study 3(London)*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Connectivity	0.83	0.88	-0.73	0.72	-0.02	0.04	0.22	0.47	0.58	0.68	0.04	-0.24	-0.51	-0.26	0.26	0.52
2. Integration (R=3)		0.86	-0.65	0.70	-0.05	0.05	0.25	0.51	0.61	0.72	0.00	-0.29	-0.64	-0.31	0.32	0.57
3. Mean Depth (R=3)			0.93	-0.56	0.01	-0.06	-0.18	-0.35	-0.45	-0.54	-0.03	0.19	0.40	0.20	-0.22	-0.42
4. Angular Variance				0.95	-0.03	-0.12	0.11	0.33	0.46	0.57	-0.01	-0.15	-0.45	-0.16	0.17	0.44
5. Closeness					0.64	-0.04	-0.03	-0.03	-0.02	-0.03	0.00	0.04	0.07	0.03	-0.04	-0.03
6. Betweenness						0.71	0.76	0.43	0.19	0.06	0.32	-0.32	0.04	-0.29	0.58	-0.04
7. Eigenvector							0.84	0.69	0.50	0.37	0.44	-0.38	-0.12	-0.35	0.72	0.20
8. Vertices								0.83	0.76	0.63	0.54	-0.46	-0.32	-0.43	0.79	0.39
9. Area									0.79	0.86	0.13	-0.40	-0.43	-0.39	0.46	0.79
10. Perimeter										0.90	0.03	-0.49	-0.66	-0.48	0.37	0.73
11. Entropy											0.65	-0.14	0.14	-0.12	0.51	-0.14
12. Convexity												0.72	0.47	0.96	-0.41	-0.19
13. Circularity													0.84	0.50	-0.21	-0.42
14. Rectangularity														0.72	-0.38	-0.20
15. Surfaces															0.82	0.00
16. Surface Depth																0.78

However, as depicted in Table 2.7, the suitability of several variables was found to be lacking. Namely, Closeness Centrality was not found to demonstrate pairs of intercorrelation sufficient for fit with the common factor model outlined by the EFAs. This was further confirmed by poor KMO-MSA for the variables of Entropy and Closeness Centrality. Due to both the violation of normality and poor empirical fit, the purported latent factor of Access was removed from the analysis as the prior hypothesized relationships were poorly substantiated here in the City of London data set. Following removal of this factor, the remaining data showed good fit with a common factor model (KMO-MSA=0.820). A nearly identical pattern of correlation was observed in the New York City data set, supporting the removal of Access from the factor model.

2.4.1.3 Confirmatory Factor Analysis

The CFA was performed in AMOS (Arbuckle, 2013) using the maximum likelihood estimation (MLE) with the covariance matrix providing initial estimates for the remaining four latent factor model defined by Spatial Complexity, Enclosure, Importance, and Local Extent. The fit of the factor model was evaluated by assessing convergence across the Goodness of Fit (GFI), Tucker-Lewis Index (TLI), Comparative Fit Index (CFI), Root Mean Squared Error (RMSEA) and Root Mean Squared Residual (RMSR) statistics. GFI, TLI, and CFI statistics greater than 0.90, RMSEA less than 0.10, and RMSR approaching 0.0 were taken to indicate good model fit.

2.4.2 Results

2.4.2.1 Confirmatory Factor Analysis of the Naive EFA Model in the City of London

After excluding the Access factor for the reasons described above, the four remaining factors that were extracted from the spaces studied in the EFA's from Studies 1 and 2 – Spatial Complexity, Enclosure, Importance, and Perceptual Complexity were included in the initial factor model. Spatial Complexity was defined by connectivity, integration (*radius=3*), mean depth (*radius=3*), and mean angular variance (*radius=3k*). Enclosure defined convexity, circularity, rectangularity, and perimeter. Importance was defined by betweenness and eigenvector centrality. Perceptual importance characterized isovist area, perimeter, and mean surface depth. All latent factor intercorrelations were included in the model. The model was over-identified with 49 degrees of freedom.

The initial, naive, model suggested by Study 1 and 2 was evaluated with the City of London data set. The model was considered naive as any pattern of variation that was unique to each variable could not be identified by the EFA and thus were left unconstrained. The resulting CFA showed

marginally poor fit, $GFI=0.845$, $TLI=0.860$, $CFI=0.896$, $RMSEA=0.162$, $RMSR=0.043$, for the naive factor model. Standard indices of good fit should either be greater than 0.90 (GFI , TLI , and CFI) or below 0.10 ($RMSEA$ and $RMSR$). So the naive model proposed by the factor analyses was considered an inappropriate depiction of the true patterns in the data.

To move beyond the naïve model, two modifications were made to the factor model. First, variance derived from similar data or calculation methods were allowed to covary, reflecting the shared variation between measures, which can be explained by calculation method (as opposed to latent factors) alone. Eigenvector centrality and betweenness centrality, area and mean surface depth, and integration and mean depth were each allowed to covary with each other, reflecting these underlying, previously uncaptured, relationships. Second, modification indices were evaluated to determine if any potentially important associations existed in the real data that were not adequately described in the smaller, synthetic data sets. One potentially important and previously unenclosed cross-loading was detected, $\chi^2(1)=148866.891$, $p=0.119$, between the factor of area and Importance. That is, perimeter was shown to be influenced by both Importance and Local Extent, rather than simply by Local Extent alone. This was considered reasonable as the absence of cross-loadings, enforced in the original factor model, is rare in real models (Widaman, 1993), and was both theoretically and empirically supported. This new model showed good fit across the majority of fit indices, $GFI=0.957$, $TLI=0.966$, $CFI=0.978$, $RMSEA=0.083$, $RMSR=0.015$. The corresponding model was retained and is depicted in Figure 2.7.

Spatial Complexity was revealed to influence connectivity, integration, mean depth, and mean angular variance. In contrast, the more local factor of Local Extent was found to influence perimeter, area, and mean surface depth. Enclosure was found to influence convexity and rectangularity. The Importance of a location in supporting traffic was defined by betweenness centrality, eigenvector centrality, and isovist area.

Critically, Local Extent and Spatial Complexity were found to be highly positively correlated with each other. Strong positive correlations were also observed between Importance and Local Extent and Importance and Spatial Complexity. Moderate negative correlations were found between Enclosure and Importance, Spatial Complexity and Enclosure, and Enclosure and Local Extent.

2.4.2.2 Cross-Validation of the CFA Model with data derived from NYC

To evaluate the consistency and robustness of the model tested in the the City of London, a comparatively low intelligibility space, the factor model was cross-validated with the novel data derived from NYC, a comparatively high intelligibility space (Bafna, 2003). This was considered ideal as the overall structure defining NYC is the opposite case to that of the City of London, is therefore a strong test of the sufficiency of the model. The CFA model was overidentified, having 45 degrees of freedom. Good model fit was observed between the CFA model derived using the City of London dataset and the New York City dataset, $GFI=0.956$, $TLI=0.966$, $CFI=0.978$, $RMSEA=0.086$, $RMSR=0.022$. The result is presented in Figure 2.7

A near identical pattern of factor loadings was revealed in the NYC data set. However, the pattern of association amongst latent variables was found to differ in two ways. First, the strength of the relationship amongst the Importance of a location and Spatial Complexity was now found to be weakly correlated instead of highly correlated. Second, the correlation between Spatial Complexity and Enclosure was now observed to be weakly correlated instead of moderately correlated. Otherwise, the results were consistent between the two datasets.

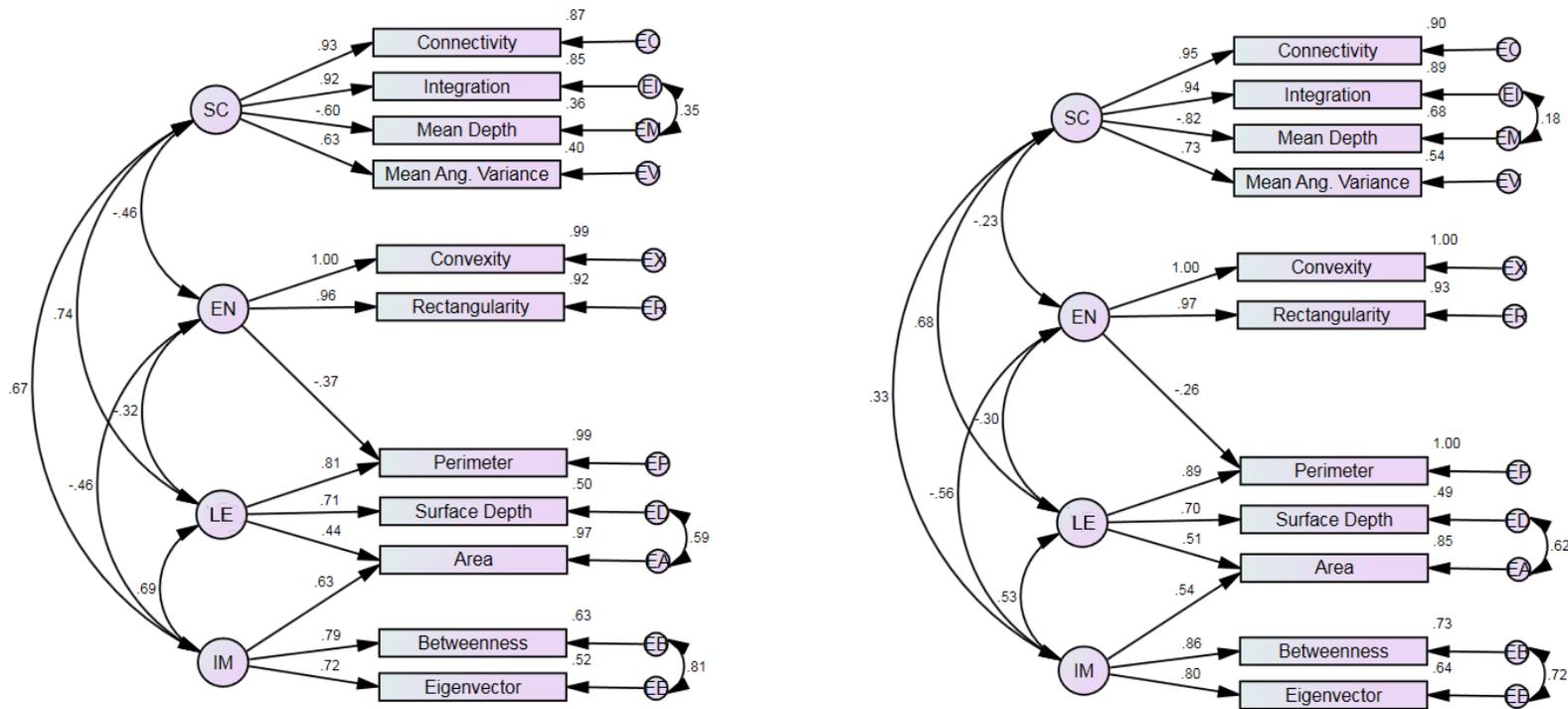


Figure 2.6. The standardized solution of the accepted factor model representing the factors of Spatial Complexity (SC), Enclosure (EN), Local Extent (LE), and Importance (IM). Squared multiple correlations can be found to the right of each experimental variable. Correlations between factors are presented for each double-headed arrow. Relative involvement in each factor is depicted between each factor and its member variables. The amount of variance explained by the model is depicted in the top-right of each variable.

2.4.3 Discussion

Through CFA and cross-validation, four latent causal variables were identified to account for variation in how space can be described. This account was further strengthened by examining two large-scale urban spaces that stand as counterpoints to each other: New York City, an organized city following a primarily grid-like structure and the City of London, an organic urban space. By assessing the fit of the factors in each environment separately, a strong case develops for the resulting description of their behaviour to extend to urban spaces as a whole. This inference is strengthened by the number of distinct locations that were examined (spanning 1447412 square meters in total), describing a sizable number of different shaped spaces, both within the field-of-view and in the surrounding configuration of the environment.

In contrast to the previous models, Access was not found to be supported in the real spaces that were examined. A likely explanation for this effect is that these environments simply do not contain any locations that could be described by Access. Another possibility is that the algorithmic application of axial lines may not have spanned these open spaces as thoroughly as in the previous models. Likewise, the consideration of more varied street architecture revealed less effect on the variable of circularity, suggesting that the influence of street architecture is more prominent than that of a variable that largely described the enclosure of a space – opposing concepts. Smaller scale simulations would be helpful in establishing whether these proposals are the case but were considered beyond the scope of the present thesis.

Prominently, the emergent properties defining the environment's construction were found to be highly associated with each other. Particularly strong was the relationship between Local Extent and Spatial Complexity in both the City of London and New York City datasets. A consistent but moderate association was also observed between Enclosure and Importance, as well as Spatial Complexity and Importance, strongly supporting the idea that the shape of an overall environment is core in determining the potential function of its component parts. At the same time, local geometry can be informative about the configuration of a city as a whole. While Local Extent was observed to be highly associated with Spatial Complexity, it was not, however, associated sufficiently to consider them the product of a single unitary factor. This is most easily explained by the construction of the measures themselves, as their statistical behaviour is considerably different, yet their variation is systematically and informationally related.

The association between Local Extent and Spatial Complexity is consistent with the idea that people move in directions that conserve linearity in their paths (Conroy Dalton, 2003; Conroy, 2001; Penn & Dalton, 1994a). It is through the interplay between the size of local visual space and the embedded spatial configuration that this sort of linearity could optimally be conserved. Without such an association between these two latent factors, linearity could only be conserved across short distances as following a path that is linear within the local view may incidentally lead to a location that obstructs linearity.

The latent factors of Importance and Enclosure were found to be negatively associated with each other, supporting of their dichotomous nature in both permeability (Stamps III, 2005) and prospect-refuge theory (Appleton, 1996). But, in this large-scale data set, a much weaker pattern of association was observed between factors reflective of spatial preference and that between more explicit movement-related factors of Local Extent and Spatial Complexity.

The CFA models reveal a consistent and relatively simplistic picture of how the properties of local visual space may relate to and predict other types of descriptions. The precise character of the relationships amongst factors was better elucidated through the use of CFA and examination of fit across two distinct data sets.

2.5 General Discussion

Across three factor analyses derived from both synthetic (Studies 1 and 2) and real-world (Study 3) environments, a consistent picture of the behaviour of spatial variables emerges. These patterns cast light on properties that may serve as a potential underlying mechanism of how we navigate through space.

At the core of this chapter is the goal of identifying how space may function in terms that are *exosomatic* to an individual person. That is, to identify properties that may drive behaviour simply by virtue of describing space in practical or useful terms. It is this idea that forms the basis for the theory of *exosomatic visual architecture* (e.g., Turner, 2006; Penn, 2003), which posits that we perceive configurational affordances from the world around us in determining how we choose to move through space. The existence of a relationship between configuration and local perception would also allow testing of the hypothesis that the perception of *invariant structure* may generally be behind how we navigate space. To both understand and test these ideas, it is fundamental that we understand whether the structure of built spaces is systematic enough to fit these proposed mechanisms. Additionally, in

taking this approach, we are able to identify likely local perceivable properties of space that may be driving spatial behaviour, allowing these ideas to explicitly be tested in the experiments of the next chapter.

Prior work, primarily in the form of agent-based analysis (Turner, 2006; Turner et al., 2001) has attempted to link traffic and pedestrian count data to the concept of a visibility graph, an approach that bears conceptual similarity to that of the measure of occlusivity proposed by (Benedikt, 1979). Both scholars have proposed that the fit between extant behaviour and the variable of occlusivity helps to explain our navigational tendencies. Yet, the present results show that occlusivity has very little in common with how space is structured as a whole. This does not, however, mean that occlusivity may not be useful for a person to navigate space successfully, as seeking out locations that offer more visual access is useful in certain contexts. But, it does suggest *general* navigation behaviour may be less driven by occlusivity and more driven by variables, such as those of local extent. By this, I mean that the strategy and goals of the participant may lead to two very different patterns of movement. This is something that a more advanced hierarchical analysis would be ideally suited to assess but is considered outside the scope of the present topic of the role of affordance in accounting for how we commonly navigate through space.

Local Extent appears to be a promising factor in the affordance of movement. Across all three studies, each with progressively larger samples, the variation in the properties of area, perimeter, and mean surface depth were found to be moderately-to-strongly associated with information about the configuration of space lying outside directly perceivable space. In addition, as this association was enhanced when considering these larger samples, the relationship between the properties of the size and shape of space defined by Local Extent are considered to be very promising. This is because for the invariant structure of space to be useful in the affordance of movement, it must provide information about the world that is of practical importance to a person. If the size of space were not systematically related to anything outside the present viewpoint, it would be much harder to navigate the world consistently and effectively. Yet a large number of studies demonstrate that the opposite is seen, people seem to navigate space in similar ways to each other, even when they have no knowledge about the environment that they are navigating in. This gives strength to the idea that affordance of movement is informed by local variables, particularly those of extent.

Some support for the view that we may perceive space in the way defined by Local Extent was recently described by Wiener, Hölscher, Büchner, and Konieczny (2012). The authors calculated a

depth profile using the pattern of distances from a viewer's position to occluding surfaces (i.e., walls). Effectively, the shape of the space was defined by the contour created by the junction between visible walls and the floor, an idea that is similar to that of an isovist but more explicitly specified in direct perceptual terms. The authors showed that people appear to make movement decisions in a way that is consistent with metrics derived from this depth profile. This type of data has the advantage of being formed by the local geometry of space, and therefore approximates the isovist method used herein. Their measure also has considerable overlap with the factor of Local Extent that helps to describe the configuration of space as a whole.

Evidence for the use of Local Extent-type cues has also been found in other experiments on spatial behaviour. For example, people have been shown to be able to accurately reconstruct distance and orientation from static views of an environment (e.g., Shelton & McNamara, 1997), a finding that suggests that space can be encoded using purely depth-based information. These findings have shown to be dependent on the degree of variation in the surrounding surfaces (Kelly et al., 2008). Participants showed task performance that varied as a function of the homogeneity of the surrounding views of the environment. These results suggest that purely depth information is behaviourally relevant to spatial behaviour, further supporting their promising role in explaining navigational tendencies.

The importance of local extent has also been shown in studies requiring self-motion through an environment. Several classic studies of the encoding of heading and displacement have indicated that static depth cues are informative in integrating the route of travel through an environment (e.g., Best, Crassini, & Day, 2002; Wang & Cutting, 1999; Vishton & Cutting, 1995). One example of this is the relative invariants formed by the walls on either side of an observer. The presence of this type of self-motion cue has been found to constrain judgments about position and to encourage the use of a fixed heading. This sort of pattern would help to account for movement along relatively fixed and linear paths (Conroy Dalton, 2003; Conroy, 2001; Penn & Dalton, 1994b), such as axial lines, as a function of depth and self-motion cues, as long as invariants are available to observer.

Cumulatively, these findings provide ample evidence for the potential role of area, perimeter, and mean surface depth in guiding navigation behaviour. Building on this understanding, Chapter Three will test whether people use these properties in such a way that an affordance exists. In doing so, the sufficiency of *direct perception* and *exosomatic visual architecture* as the underlying mechanism behind navigation will be established.

Chapter 3

Behavioural Evidence for the Affordance of Movement

Chapter Two successfully identified a shared relationship between those properties describing the local shape of space (area, perimeter, and mean surface depth, to be specific) and those describing the overall configuration of the environment (namely, connectivity, integration, and mean angular deviation). Given this, the perception of the invariant structure of space can now be evaluated in more detail for their fit with the hypothetical affordance of movement. This type of mechanism has been hypothesized to be integral in guiding navigation through complex environments, both directly through affordances (e.g., Emo et al., 2012; Wineman & Peponis, 2010; Maier et al., 2009; Penn, 2003; Turner et al., 2001; Hillier, 1999) and through other means based largely around similar concepts, such as Turner's *exosomatic visual architecture* (Turner, 2006; Turner et al., 2001). In both cases, authors contend that we navigate space in systematic ways because invariant information (such as that of the perceived shape of the environment around us) in the environment informs our movement decisions.

Affordances have been well studied outside of the field of navigation. Classically, affordances have been understood in terms of the interaction between people and some relatively simple property of their environment. For example, people have been shown to modify how they move through a doorway based on the interplay between their shoulder width and the diameter of the aperture being traversed (Warren Jr & Whang, 1987). Likewise, the length of our legs has been shown to influence what riser height we consider climbable when attempting to climb stairs (Warren Jr., 1984). In both cases, the affordance was understood by exploring the relationship between a person and their surrounding environment – an idea known as the *theory of constraints*. The theory of constraints specifies that *optimal points* should exist whereby a behaviour shifts from being practical to being impractical. In the case of the stair climbing study, the point at which a stair was judged as climbable was defined by the riser height (the local perceived property derived from *invariance*) and the individual's capability (i.e., leg length), distributed around a central point. That central point described the optimal point at which climbing was energetically useful to the person – around the optimal point, the frequency of climbability judgments declined steadily. A similar approach has been proposed by other authors in the form of *critical points* or *affordance thresholds* (Franchak & Adolph, 2013). This type of approach describes an affordance by the probabilistic (rather than discrete) relationship

between a behaviour and an invariant. Fundamental to both *optimal* and *critical* points is that the ratio in the amount of observed behaviour to the physical properties of the environment or an object must be defined by a single, ideal, level between the two. These are consistent with Gibson's concept of an affordance as the presence of multiple ideal fits between the capacity of an organism and invariant would be difficult to rectify without interceding processing or cognition.

This type of approach has been used extensively to explore a wide variety of behaviours, such as describing how we determine comfortable sitting positions (Mark & Vogeleson, 1987), whether a barrier can be traversed (Wagman & Malek, 2009), deciding whether we need to duck to pass an object successfully (Stefanucci & Geuss, 2010), and determining if a ball can be caught (Oudejans, Michaels, Bakker, & Dolné, 1996). In each case, a consistent relationship was observed between a specific perceived property of an object or environment and the capability for action by an individual within that environment.

To establish the case that an affordance explains common patterns in navigation, I tested the fit between preferred route choice and the spatial properties of *area*, *perimeter*, and *mean surface depth* identified in the previous chapter as being potentially promising elements of the *invariant structure* for explaining navigation in both familiar and unfamiliar spaces alike. These properties were also demonstrated to show considerable overlap with measures of Spatial Complexity, representing ideal candidates for explaining patterns of navigation in the context of intelligible and unintelligible spaces *and* in explaining how people may navigate space when they have no existing experience or knowledge about the specific environment. As an initial approach into this topic, Experiment 1 sought to determine if aggregate traffic behaviour is determined by any of these spatial properties, or is instead simply associated with them. To achieve this, a number of mathematical models were developed to see if groups of navigators, varying in their goals and experiences, actively appeared to seek out optimal levels of measures of these spatial properties. This experiment not only determined initial suitability for affordance in describing human navigation but also helped to establish how these properties behave in a real world environment with a large, varied sample, typical of more traditional analyses used within the field. Next, across three experiments, individual behaviour was assessed for the presence of *critical points* (Experiments 2 and 3) and the independence of the use of affordance from general measures of spatial ability and attention (Experiment 4). As a whole, the results give a clearer picture of how a specific affordance, outlined by mean surface depth, may be responsible for shaping navigation behaviour.

3.1 Experiment 1 Evidence for Affordance in Aggregate Traffic

Chapter One introduced a considerable volume of evidence to support the relationship between specific types of spatial information and how pedestrian and vehicular traffic appears to move through cities, neighbourhoods, and buildings of varying scale. Most commonly, the global variables of connectivity and integration have long been found to be correlated with both vehicular (Penn et al., 1998a; Penn et al., 1998b) and pedestrian traffic (Hillier et al., 1987; Hillier et al., 1993; Hillier et al., 1987). Prior work by myself (Barton et al., 2014) and others (Penn, 2003) has suggested that the correlation between these axial measures and traffic counts ranges from moderate to substantial, depending on the sample the data was drawn from. This is consistent with studies of individual navigation and exploration behaviour, which have established a probabilistic relationship between axially derived descriptions of space and preferred routes (Hillier & Iida, 2005; Haq & Zimring, 2003; Haq, 2003; Conroy Dalton, 2003; Conroy, 2001; Peponis et al., 1990). In both the aggregate and individual studies of navigation, the results suggest that people prefer to follow specific paths, consisting of maximal levels of connectivity and/or integration.

I begin by establishing whether the key affordance-related variables proposed in Chapter Two can predict how we move through real-world spaces. This will both establish the suitability of the local spatial properties for driving behaviour in a real-world space but will also establish how well *direct perception* can account for these patterns of movement. This will be achieved by comparing two critical models (and a third intermediate to those models) designed to assess the degree to which traffic is drawn toward these spatial properties at both a local and a global scale. Should affordance be the primary motivator, little or no influence of the global level of variables should be observed.

Additionally, this approach will represent a stronger test of whether the local extent of a space is related to the global structure of space, as the two factors will be simultaneously evaluated. For the present experiment, a real-world environment was selected, as it would best evaluate the influence of spatial variables on a variety of navigators, independent of individual differences. Specifically, the City of London environment described in Study 3 was employed due to its substantial variation in the variables of Local Extent (area, perimeter, and mean depth) and embedded Spatial Complexity (connectivity, integration, and mean angular deviation). To determine the relationship between spatial variables and the magnitude of traffic accounted for by each variable, the association between the two will be assessed while controlling for the potential influence of each other variable. The resulting data

therefore describes how each individual variable can independently predict the amount of traffic passing through a location.

Should traffic be best captured by a direct relation between a local visual property of space and movement, across the large real-world space of the City of London, evidence would first exist for an affordance-based explanation of navigation in a complex, built space³. If, on the other hand, the affordance hypothesis is spurious, considerable deviation would be expected between the variables of local extent and the dependent variable of traffic count.

To assess the fit of the affordance model in accounting for common patterns in how people, regardless of their goals, navigate space, several mathematical models were employed. Each model was designed to assess whether traffic tended toward the spatial variables either locally (at each step, maximizing the value at the next step), globally (always steering toward the optimal level of the variable within the space as a whole), or a hybrid of the two, termed the: (1) Global Attractor, (2), Local Attractor, (3) and Simultaneous Attractor models, respectively.

The Global Attractor model assumes that traffic is guided toward an optimal level of any potential factor regardless of what the level of the variable is within the local, visible environment. Accordingly, the Global Attractor model assesses whether groups of individuals tend toward high or low levels of the spatial properties with some level of fore knowledge or intuition about the layout of the space. The Simultaneous Attractor model, in contrast, assumes that traffic can best be accounted by assuming that the amount of observed traffic is the product of both the tendency toward steering toward the optimal level of the variable in the surrounding environment and some degree of random variation (such as that induced by different origins or destinations, individual differences in spatial knowledge, etc.). Hence, where the Global Attractor model is deterministic, the Simultaneous Model is probabilistic. Finally, the Local Attractor model is used to assess the degree to which purely locally visible levels of properties drive the magnitude of traffic. At each point in the environment traffic steers itself toward the next-best location without reversing trajectory. In this case, traffic is assumed to be driven only by locally defined invariants, rather than depending on knowledge outside the present field-of-view.

³ It is important to note that the majority of the samples used in this study were of vehicular traffic, which is fundamentally constrained by traffic regulations, the presence of other traffic, and other factors. This could, feasibly, reduce the amount of variation observed in the data. However, given the results, the effect of these limiting factors is considered negligible.

Should an effect of either the Global Attractor or Simultaneous Attractor models, poor support for the idea that affordance drives *general* patterns of navigation and spatial preference would be found. If, in contrast, the Local Attractor model is found to have efficacy in predicting traffic counts, a much stronger case for affordance in driving navigation behaviour would be revealed.

Some initial support for these models was introduced at the beginning of this thesis. Crowds having a tendency to flow like water (Matheson, 1909) through a space can be thought of as being the product of either (or both) local or global influences of the structure of space. More recent models have used fluid dynamics equations to show that the tendency to flow through space is substantiated empirically (Helbing et al., 2001; Helbing, 1993; Helbing, 1992; Helbing, 1992). However, for the present analysis, this form of model is considered unnecessarily complex as it describes something more than just the attractiveness of a location. For example, Helbing's (beginning in Helbing, 1992) research postulates that the force driving navigation is the product of an interplay between the individual and all other individuals in a space. Accordingly, to estimate the influence of local, simultaneous, and global effects, a much more simplified, but conceptually related, diffusion model is employed.

3.1.1 Methods

3.1.1.1 Data Sample

Publicly available GPS traces (OpenStreetMap users, 2013) for the area of the City of London (identical to that used in Experiment 3 and depicted in Figure 2.6) were used to produce an aggregate traffic map of area. Each GPS trace was submitted by users voluntarily for a variety of purposes, including pedestrian (i.e., joggers, mappers, etc.) and vehicular traffic, as documented in the XML files. In both cases, origins and destinations varied widely across the data set. A total of 232 GPS traces were found to be suitable for inclusion in the data set, having no missing points or extremely aberrant tracking errors. The mean GPS trace covered a displacement of 745 meters ($SD=974$ meters) as determined by the Haversine method and ranged between 10.433 km/h to 71.99 km/h.

To account for potential errors in tracking accuracy, which are commonly between 10 and 15 meters in urban centers, the data was convolved with a 15m linear filter. Instead of assuming perfect precision in tracking, any tracking points within 15 meters were summed to produce the estimate of the true volume of traffic at a location. In doing so, error should be minimized and locations of convergence should be emphasized.

3.1.1.2 Models of Movement

Three distinct models were examined to assess what properties in the environment are likely attracting traffic and pedestrians. Each hypothesized attractor was derived identical to those variables used in Studies 1 through 3. The variables defined by the latent constructs of Spatial Complexity (connectivity, integration, and angular deviation) and Local Extent (area, perimeter, and mean surface depth) were subject to different modifications to evaluate whether traffic was directed toward the highest level of the purported attractor at all times (Global Attractor Model), steered toward the Global Attractor by seemingly random chance (Simultaneous Attractor Model), or were always steered toward the best level of the attractor within local space alone (Local Attractor Model). A graphical depiction of the different predictions of the models is presented in Figure 3.1.

3.1.1.2.1 Global Attractor

The traditional model of the success of Space Syntax holds that traffic generally tends toward optimal levels of axially-defined spatial variables, such as connectivity and integration (Hillier, 1996). It is considered important to evaluate whether this model is observed to fit the present data. This is most often demonstrated by showing a strong correlation between connectivity, integration, and traffic count.

To achieve an estimate of how attractive each location is to a potential navigator, the Global Attractor model posits that a person has a reasonably accurate understanding of where to go in an environment to make optimal use of an attractor. That is, for example in the case of integration, traffic will always steer itself toward the highest level of integration available, environment-wide. A group of participants would therefore tend to show a linear relationship between the measure of the variable and the amount of traffic. This sort of model is implicit in traditional accounts of Space Syntax and places emphasis on understanding and representing the structure of an environment rapidly upon entering an environment (Hillier et al., 1993) an idea that is, to some degree, at odds with the affordance model proposed in this thesis and in that of exosomatic visual architecture.

3.1.1.2.2 Simultaneous Attractor Model

The Simultaneous Attractor model represents a modification on the Global Attractor model to account for individual differences in goals and degree to which a person may tend towards the ideal level of an attractor variable. In this model, traffic would be expected to steer itself toward an

attractor only part of the time (the amount of which can be manipulated directly). The remaining time, trajectories would be inherently unpredictable, showing up as random variation.

This sort of tendency in can be estimated by diffusing the data in two-dimensions using a Gaussian function. In effect, the Simultaneous Attractor model is a blurry Global Attractor model to induce random, unpredictable, variations in individual trajectories. By making the Gaussian have a larger or smaller radius, the distance at which traffic steers toward the optimal level of an attractor can be manipulated. If traffic were to tend toward the optimal level of an attractor within the nearest 100 meters (the approximate size of the average city block), and otherwise randomly vary, a Gaussian of 100 meter width would be employed. In more explicit terms, the level of attraction (A) is the product of the Global Attractiveness (defined by g at each position, x and y in space), convolved with a two-dimensional Gaussian (G) of width d with the slope of the function determined by ∂_x and ∂_y :

$$A(x, y) = g(x, y) * G(x, y)$$

$$G(x, y) = \frac{1}{\sqrt{4\pi d}} e^{-\frac{\partial_x^2 + \partial_y^2}{4d}}$$

To account for the inability for traffic to disperse through buildings toward optimal levels, the Gaussian is bounded to extend only into nearby open space, stopping when it hits a building. This modification allows traffic to reduce near to buildings and move away from obstructions.

This type of model would be expected to perform well under general conditions where a navigator's goals, knowledge and experience, and degree to which they seek out an attractor may differ amongst individuals. For the present analysis, people were expected to tend toward those locations within 100 meters of their present location – the approximate length of an average road within the dataset.

3.1.1.2.3 Local Attractor

The Local Attractor model posits that traffic will always tend toward the most attractive point within eyesight. As a result, this model places no demands on the individual to know about the global level of properties outside the local visual space and instead purely considers the values offered by immediately adjacent locations. Consequently, it is the opposite case of that of the Global Attractor model, where navigation is not biased in a specific direction (at least locally).

Accordingly, the local attractor model is fundamentally a model of directed flow. This can be represented numerically is as the product of anisotropic diffusion (where the Simultaneous Attractor

model is isotropic). In an anisotropic model, the attractiveness of a local attractor is the product of all other values within the local view and can vary with respect to each direction. This is because traffic will have a tendency to flow toward or along progressively increasing values until it reaches the optimal level within the local space. Intuitively, this can be understood as water flowing along a slope where the steepness or gradient of the slope is determined by the level of the spatial variable(s) while preventing movement across boundaries (such as buildings or walls). It can be contrasted with Simultaneous Attraction, where flow is equal in all directions due to random variation, outside of the case of occlusions.

To approximate this model, Weickert diffusion (Weickert, 1998) was employed. To determine how much traffic should be driven in each direction – whether a higher level can be reached by traveling forward, turning, or moving diagonal – the amount of force (\mathbf{F}) is determined at each point in space in each potential direction (the x , y , or x - y directions) using the structure tensor:

$$\mathbf{F} = \begin{pmatrix} \partial_{xx} & \partial_{xy} \\ \partial_{xy} & \partial_{yy} \end{pmatrix}$$

The force is determined purely as the product of immediately adjacent locations. This can be represented by the partial derivative, ∂ , in the x , y , and diagonal (xy) directions. To determine the average attractiveness of a location – how attractive that location is with respect to all incoming traffic – the eigenvalues, λ_1 and λ_2 , of the structure tensor are computed such that:

$$\lambda_{1,2} = \frac{1}{2} \left((\partial_{xx} + \partial_{yy}) \pm \sqrt{(\partial_{xx} - \partial_{yy})^2 + 4\partial_{xy}^2} \right), \quad \lambda_1 \geq \lambda_2$$

The corresponding λ are the sum of a movement in the x or y -direction, reweighted with the amount of movement diagonally. Hence, the eigenvalues describe the amount of movement expected in two dimensions, decoupled from the somewhat arbitrary x and y planes (here they approximate typical compass bearings of North-South and East-West). The eigenvalues therefore describe force or attractiveness in general, rather than force with respect to a specific direction. The difference between the two eigenvalues is termed α , representing the general attractiveness of an individual location.

Having established how attractive each location is as a function of the values of the property in nearby space, we can now determine how much traffic would be expected to move toward each location, depending on how long a person would be expected to follow the level with no deviation. To achieve this, α is adjusted as a function of distance:

$$\kappa_1 = \alpha$$

$$\kappa_2 = \begin{cases} \alpha, & \text{if } \lambda_1 = \lambda_2 \\ \alpha + (1 + \alpha) e^{\left(\frac{-C}{(\lambda_1 - \lambda_2)^2}\right)} & \end{cases}$$

where α is the aforementioned relative amount of traffic expected to be attracted to a location (set to be 0.001; equal to 99.9% of traffic moving toward the most promising local level of the attractor) and C represents the locations at which random movement would be expected (such as at peaks/optimal levels of the variables; set to be 1e-10). In a sense, then, anisotropic diffusion is like the Gaussian diffusion scheme used above, but where the shape of the G varies at each location in the environment rather than being constant and symmetrical at all times. This is captured by the tensor \mathbf{D} (representing the amount of change expected in each direction, κ , with respect to the amount of adherence that traffic is expected to have with this model, α , and willingness to accept random movement, C):

$$\mathbf{D} = \begin{bmatrix} \kappa_1 & 0 \\ 0 & \kappa_2 \end{bmatrix}$$

This tensor is the product of the original expected amount of force or attraction in each direction, \mathbf{F} , summarized in general terms (via each λ) and subject to specific assumptions guiding how well people follow the model (captured by κ).

As before, data is convolved with the tensor \mathbf{D} to determine how attractive each location is as a product of distance. In this case, data was diffused to a distance of 100 meters, the length of an average road within the environment and identical to that of the Simultaneous Attractor (isotropic) model. This resulted in the Local Attractor data describing how attractive each location is should a person choose the ideal amount of the attractor at each step for 100 meters before re-evaluating where to go next. In this formulation, individual differences in navigation are accounted for in rough terms, but people are expected to move toward the local level most of the time.

3.1.2 Results

3.1.2.1 Analysis Approach

A set of linear multiple regression analyses were performed to assess the relationship between the aggregate traffic flow produced from crowd-sourced GPS traces and each of the three potential traffic models (Globally, Simultaneously, and Locally driven) for each of the hypothetically influential variables of interest: Spatial Complexity (connectivity, integration, and mean angular deviation) and Local Extent (area, perimeter, and mean surface depth). The result of these models therefore assessed

the degree of fit between traffic count at a given location and the level of attractiveness of each variable while controlling for the attractiveness of other types. Fundamentally, the regression models identify the degree of fit between traffic and each attractor, independent of each other.

The data were assessed for their suitability to regression analysis. The variables were assessed for univariate normality and multivariate normality. The attractiveness of the variables of mean surface depth (*skew*=3.903, *kurtosis*=148.076) in the Global model, connectivity (*skew*=3.186, *kurtosis*=10.791) in the Local model, and raw traffic data (*skew*=3.448, *kurtosis*=13.259) were to be approximately non-normal. Each of the three variables was subject to a square root transform, which successfully ameliorated the non-normality. The corresponding descriptive statistics are provided in Table 3.1.

Next, the data were assessed for multicollinearity. As in the factor analyses, mean depth (radius=3) was found to be highly related to that of integration (radius=3), showing a mean Variance Inflation Factor of 0.88. Accordingly, the variable of mean depth was removed from subsequent analysis.

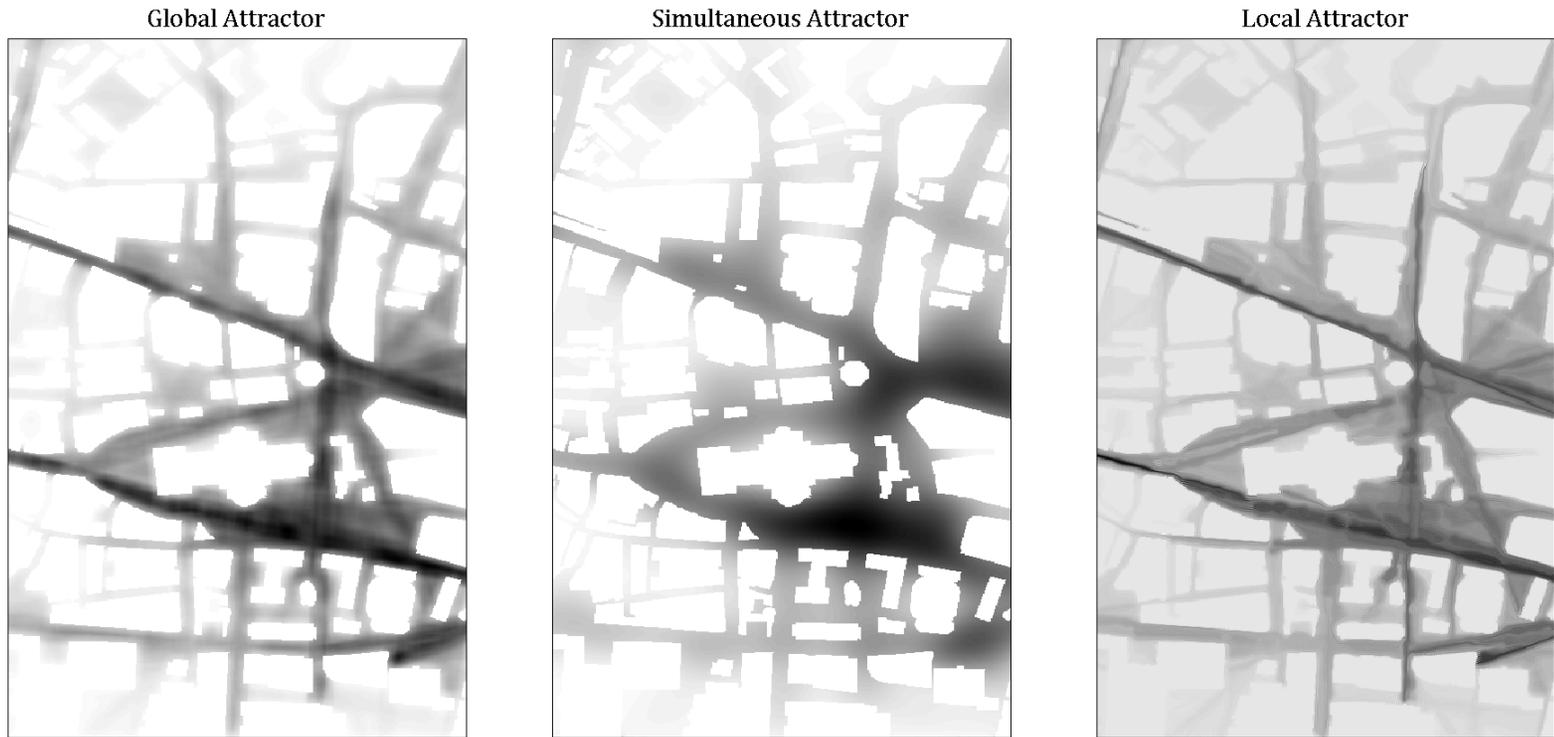


Figure 3.1 Models of the expected traffic distribution as a function of Globally, Simultaneously, and Locally directed movement. Data presented here are a 400m by 750m subset of the data used in the overall analysis, surrounding St. Paul's Cathedral. Areas of confluence or attractiveness are depicted ranging from black (high) to white (no attraction).

Table 3.1 *Descriptive statistics for Experiment 4*

Movement Data	Mean (<i>SD</i>)	Skewness	Kurtosis
Traffic Count (sqrt)	2.463 (5.539)	2.198	3.810
Global Attractor Model			
Connectivity	286.068 (473.876)	2.152	5.210
Integration	1.71 (1.943)	0.388	-1.607
Mean Depth	1.928 (2.169)	0.351	-1.624
Mean Ang. Dev.	0.691 (0.926)	1.228	0.811
Area	3742.493 (6091.894)	1.795	2.520
Perimeter	429.893 (629.512)	1.675	2.749
Mean Surf. Depth (sqrt)	9.024 (10.872)	0.768	-0.504
Simultaneous Attractor Model			
Connectivity	0.086 (0.139)	1.844	2.764
Integration	0.236 (0.294)	0.706	-1.080
Mean Depth	0.299 (0.355)	0.475	-1.577
Mean Ang. Dev.	0.134 (0.186)	1.122	0.067
Area	0.059 (0.1)	1.927	3.080
Perimeter	0.073 (0.111)	1.672	2.381
Mean Surf. Depth	0.005 (0.007)	1.798	4.523
Local Attractor Model			
Connectivity (sqrt)	0.079 (0.179)	2.177	3.539
Integration	0.24 (0.283)	0.485	-1.503
Mean Depth	0.259 (0.294)	0.295	-1.854
Mean Ang. Dev.	0.133 (0.179)	1.110	0.195
Area	0.076 (0.124)	1.803	2.537
Perimeter	0.085 (0.122)	1.604	2.205
Mean Surf. Depth	0.007 (0.01)	1.888	6.119

3.1.2.2 Global Attractor Model

A multiple linear regression analysis was used to test the model of aggregate traffic count data (square root transformed) as being predicted by connectivity, integration, mean angular deviation, area, perimeter, and mean surface depth, under a strictly globally defined model. Should traffic primarily be directed toward locations of maximum amplitude, environment-wide, good fit would be expected to be observed with this model.

Pearson product-moment correlations were computed for each variable and can be found in Table 3.2, along with the computed regression model. Each of the predictor variables significantly correlated with the aggregate traffic counts, but the correlations were found to be small in magnitude (ranging from 0.025 to 0.043). Together, the predictors accounted a small proportion of the variation in traffic counts, $F(6,1129593)=593.406$, $p<0.001$, $R^2=0.003$. The residual plot was examined and was found to be well behaved, showing no clear bias or violation of homoscedasticity.

One possible reason for the poor predictive performance of the model is due to the granularity of the data. Both diffusion models intrinsically compensate for granularity over time, but the basic Global Attractor model did not. Accordingly, each predictor value was summated by convolution with a 15m x 15m linear filter to produce identical resolution to that of the GPS traces, greatly reducing the granularity of the data. The adjusted variables were again tested using multiple regression, but only showed marginal improvement, $F(6,1129594)=693.370$, $p<0.001$, $R^2=0.004$. The model showed significant predictive power of each predictor: Connectivity ($\beta = -0.072$), Integration ($\beta = -0.131$), Mean Angular Deviation ($\beta = 0.086$), Area ($\beta = -0.01$), Perimeter ($\beta = 0.116$), and Mean Surface Depth ($\beta = 0.051$); a pattern closely matching that found in the original regression model, but an R^2 that strongly suggested the pattern was not meaningful.

3.1.2.3 Simultaneous Attractor Model

The Simultaneous Attractor Model was tested to evaluate the possibility that individuals tend toward preferred spatial variables at pseudo-random intervals across the entire sample of navigators. As such, areas of higher attractiveness would be formed by the confluence across between the closest global

Table 3.2 Zero order and multiple regression results under a Global Attractor model

Variable	Zero Order Correlation							Regression Model		
	1	2	3	4	5	6	7	β	r^2	t
1. Connectivity		.797	.786	.837	.847	.764	.025	-0.023	.001	-10.887
2. Integration			.866	.757	.817	.903	.026	-0.084	.001	-30.394
3. Mean Ang. Dev.				.752	.774	.815	.033	0.033	.001	16.493
4. Area					.920	.843	.039	-0.008	.001	-3.079
5. Perimeter						.874	.040	0.034	.002	11.918
6. Mean Surface Depth (sqrt)							.043	0.087	.002	30.650
7. Traffic Count (sqrt)										$R^2 = 0.003$

Note. All correlations and regression weights were significant at $p < 0.01$.

Table 3.3 Zero order and multiple regression results under an Simultaneous Attractor model

Variable	Zero Order Correlation							Regression Model		
	1	2	3	4	5	6	7	β	r^2	t
1. Connectivity		.849	.849	.918	.931	.820	.520	-0.023	.270	-10.059
2. Integration			.933	.818	.863	.812	.530	0.075	.281	33.237
3. Mean Ang. Dev.				.835	.851	.785	.492	-0.079	.242	-36.557
4. Area					.945	.886	.531	-0.404	.282	-157.56
5. Perimeter						.896	.587	0.494	.345	171.31
6. Mean Surface Depth (sqrt)							.621	0.556	.386	311.83
7. Traffic Count (sqrt)										$R^2 = 0.410$

Note. All correlations and regression weights were significant at $p < 0.01$.

attractor and random chance (which can be introduced by either individual differences in behaviour or cognition).

A multiple regression analysis predicting traffic count (square root transformed) from each of the aforementioned six spatial variables was performed and Pearson product-moment correlations were computed. The results of the model are presented in Table 3.3. The model was significant, $F(6,1129594) = 130940.230$, $p < 0.001$, $R^2 = 0.410$. Each predictor was significantly associated with the aggregate traffic count, but across the whole model, mean surface depth, perimeter, and area were found to contribute more than the other spatial variables, presented in order of descending magnitude.

3.1.2.4 Local Attractor Model

Local Attractor Model was formulated such that the attractiveness of each location would be formed by movement along the gradient with preference toward locations of least difference. Therefore, a location that is optimally attractive would be located nearby to other attractive locations (as determined by the local spatial properties assessed herein). Should a person *always* seek out the highest *local* level of the spatial property in their journey, at each step, it would be expected that they would show very close fit with this model.

The resulting Pearson product-moment correlations and multiple regression model predicting aggregate traffic count from diffused connectivity, integration, mean angular deviation, area, perimeter, and mean surface depth, are presented in Table 3.4. The result indicated a considerable proportion of traffic variation was accounted for by these six spatial variables, $F(6,1129594) = 853010.124$, $p < 0.001$, $R^2 = 0.820$. The variables of connectivity and mean surface depth were found most strongly to predict aggregate traffic count. These two variables alone were capable of accounting for 80.9% of the variation in traffic count suggesting a strong tendency for traffic to seek out optimal levels of connectivity and integration, but also to a lesser degree that of area, on a local scale. To assess the degree of overlap between Globally determined traffic and Locally determined traffic, a step-wise regression was performed between aggregate traffic count and the predictors of connectivity and mean surface depth under both forms of diffusion simultaneously. The combined model accounted for a further 40% (in total, 71%) of variation in the data, $F(4,1129595) = 1581554.671$, $p < 0.001$, $R^2 = 0.848$. Specifically, Local Attractor connectivity ($\beta = 0.891$, $t = 1856.49$, $p < 0.001$) and Local Attractor mean surface depth ($\beta = 0.236$, $t = 162.409$, $p < 0.001$) were found to predict traffic the most, with Simultaneous Attractor connectivity ($\beta = -0.346$, $t = 513.017$, $p < 0.001$) and Simultaneous Attractor mean surface depth ($\beta = 0.599$, $t = 375.373$, $p < 0.001$) accounting for marginally

Table 3.4 Zero order and multiple regression results under the Local Attractor model

Variable	Zero Order Correlation							Regression Model		
	1	2	3	4	5	6	7	β	r^2	t
1. Connectivity		.546	.523	.594	.638	.588	.895	0.864	.801	-1654.0
2. Integration			.890	.748	.810	.754	.504	0.013	.254	13.085
3. Mean Ang. Dev.				.761	.792	.716	.465	0.060	.216	-64.848
4. Area					.935	.861	.541	-0.131	.293	-108.91
5. Perimeter						.870	.586	-0.045	.343	-33.461
6. Mean Surface Depth (sqrt)							.599	0.276	.358	319.48
7. Traffic Count (sqrt)										$R^2 = 0.820$

Note. All correlations and regression weights were significant at $p < 0.01$.

less variation. Accordingly, it appears, that under general conditions there is a tendency to seek out specific spatial properties, with the most promising local variable being that of mean surface depth.

3.1.3 Discussion

Several interesting results emerged from the mathematical modeling of behaviour. First, despite using several different forms of aggregation, the Global Attractor model was not found to be a good explanation of aggregate traffic data. This result was not anticipated, as prior investigations have long established a link between many of the specific spatial variables using in the study and emergent traffic counts of both vehicular and pedestrian movement (e.g., Penn et al., 1998a; Penn et al., 1998b; Hillier et al., 1993; Hillier et al., 1987). Several possibilities exist for the lack of effect. First, the Global model depends on the data being relatively noiseless. Sources of noise could include the resolution of the GPS traces; however, the smoothing employed to reduce this effect should have at least partially eliminated this noise. Second, it remains possible that more discrete methods of traffic count or use of a larger data source could improve performance, but this is considered unlikely due to the rather sizable number and displacement of the observed tracks. While it bears further investigation, no strong influence of the level of the axial and spatial properties of local visual space is assumed to exist based purely on the present data.

In contrast, a significant effect was observed for the Simultaneous Attractor model. That is, traffic was well predicted by the local extent when the constraint for traffic to *always* seek out maximum values was relaxed. Under this model, traffic was inherently constrained by nearby geometry to some degree (as it defined both start and end points arbitrarily). Since the origin and destination of each navigator varied with respect to time and across space, many additional influences would be expected to contribute to the traffic data, not captured by the Global model. However, this does not fully account for success or failure of the Simultaneous Attractor model. This is because the much more stringent Local Attractor model showed significantly higher efficacy in accounting for traffic. Specifically, the Local Attractor model accounted for ~67% of the overall variation of the data. This finding is both consistent with classical (Matheson, 1909) and modern (Helbing et al., 2001; Helbing, 1993; Helbing, 1992; Helbing, 1992) fluid-dynamic approaches that suggest the critical influence of local geometry in predicting common patterns in how groups of people will navigate space.

As was originally suggested in Chapter Two in theoretical terms, Local Extent showed substantial success in predicting overall traffic counts. Recent work investigating the relationship between global spatial variables, such as integration, and view-dependent properties lends further support to this finding. Specifically fixation patterns while selecting potential paths have been shown to be biased

toward areas of increased floor volume (Emo, 2014) and the edge of surfaces (Wiener et al., 2012). Together, these variables are conceptually related to connectivity (further supported by the incidental effects observed in Study 2 when controlling for surface), and adequately explain the finding that connectivity and mean surface depth are influential in predicting where people will navigate.

More generally, some evidence was shown for the variables of Spatial Complexity and Local Extent to capture behaviourally relevant spatial preferences in explaining *common* patterns in traffic, an idea that has been implicitly part of *exosomatic visual architecture* and affordance proposals but not previously explicitly tested. These data also demonstrate that the tendency for movement is to be driven by the level of the variable in view at any given point in time, something that is consistent with affordances as *directly* perceived and employed. Having demonstrated this fit, the argument that affordance or exosomatic visual architecture is driving common tendencies in how we move through space is considered reasonable.

These strengths noted, it is important to note that the data sample was derived from crowd-sourced data, which varied with respect to purpose and function. It is possible that individuals contributing data to OpenStreetMaps may differ from normal navigators in a number of ways. This possibility noted, crowd-sourced GPS data has been shown to be useful in consensus-based mapping. For example, the presence and *timing* of road impediments, such as stop lights and stop signs, has been shown to be reliably detected using a relatively small number of crowd sourced GPS traces (Carisi, Giordano, Pau, & Gerla, 2011). Additionally, as the data converged on a range of common locations, not simply optimal locations (which would have purely been captured by the Global Attractor model), the presence of strange patterns in route behaviour is considered less likely. That said, the results would need to be replicated in an independent and more controlled sample to ensure that the findings are consistent with real behaviour.

3.2 Experiment 2 Does Local Extent Predict Individual Movement?

Experiment 2 sought to further investigate the finding that the properties of Local Extent may represent the relevant stimuli sufficient to guide navigation, characteristic of an affordance. In doing so, we continue to develop an understanding of manner in which the apparent contributions of global spatial variables to navigation may come about as a consequence of concomitant local spatial invariant properties, such as area, perimeter, and mean surface depth.

To assess whether the local spatial properties of *area*, *perimeter*, and *mean surface depth* describe an affordance, the consistency of behaviour of each proposed property was assessed for the presence of a *critical point* around which movement toward the location diminishes rapidly (e.g., Warren Jr & Whang, 1987). To achieve this goal, participants were asked to perform two different tasks, first navigating into a virtual environment followed by effortful wayfinding out of the environment. This was meant to assess whether experience with an environment influences the observed affordance. Additionally, participants navigated in one of two environments (the same environments assessed in Study 1) representing prototypical levels of intelligibility and unintelligibility of space (Hillier, 1996). The intelligible environment consisted of buildings arranged to preserve sight lines and maximize the correlation between connectivity and integration. The unintelligible environment consisted of the same general composition as the intelligible environment but the position of the buildings was shifted to reduce the correlation between connectivity and integration. The use of two environments allowed the influence of spatial context to be examined.

Two different levels of intelligibility were examined because the strongest case of an affordance would be to show a pattern of behaviour that is consistent, regardless of the overall global organization of the space. Prior work has shown that route preference varied systematically with respect to the intelligibility of these two environments. Individuals were shown to follow more idiosyncratic routes in the less intelligible environment than in the more intelligible environment (Conroy, 2001). Similar findings have also been demonstrated across a wide variety of real and virtual environments (Barton et al., 2014; Hölscher et al., 2012; Haq & Zimring, 2003; Haq, 2003; Penn, 2003; Conroy, 2001). But, to date, no convergence has been demonstrated in predicting where an individual will move in both types of configured environments.

One further stipulation was made to further examine behaviour in the face of *direct perception*. Recently, I demonstrated that navigation is largely achieved through the use of visual cues lying in local space within the central visual field rather than peripheral vision (Barton et al., 2014). When the availability of distant visual information was controlled for, a significant influence of syntactic variables (i.e., connectivity and integration) was observed on the preferred route of the participants. This suggests that the local visual space is useful in determining an effective route between familiar and unfamiliar locations and is, to some degree associated with intelligibility and Spatial Complexity. This paradigm of constraining the visual field can be useful in determining the precise source of the spatial information being used to drive navigation. Importantly, this manipulation also gives a

navigator-centric scale that can be used to assess the consistency of affordance. That is, the distance with which a person can perceive information clearly or usefully can be used to scale the variables of Local Extent, allowing comparisons to be made across a variety of spaces. In normal space, this would be controlled by the presence of walls, detection of edges, and ability to differentiate the textures defining nearby structures. Here, as many of these properties were controlled for to ensure precision, the manipulation of visibility (constrained or unconstrained) was meant to approximate this capacity to perceive nearby space clearly.

Using such an approach, should the perception of the *invariant structure* be achieved in local space, as suggested by the mathematical and factor models, a reduction of visual range to that only of local space should have a consistent influence on the affordance relationship that is observed between variables of local extent and preference for movement. Such a finding would suggest that the driving mechanism behind the affordance is one of maximizing the perception of the local spatial property at all times, much like that of the Local Attractor model in the previous experiment. Here, this is manipulated by either allowing the navigator normal, unconstrained, vision or limiting the Visible Range of the central field by degrading it with virtually rendered fog. It was predicted that the navigator's perceptual capacity (as measured by the mean distance that a person can see without being obscured by fog) would scale but not drastically change the shape of the affordance relationship, showing that not only is the relationship between action and behaviour an affordance, but that it is also scaled by the extent to which a person can perceive the environment around them. As such, the following hypotheses were put forward:

- (1) For an action-behaviour relationship to be considered an affordance, the action-behavioural relationship must be described by a *single* inflection point (the *critical point* at which the action loses efficacy). Further, movement about this inflection point should be unimodal. That is, individuals should only move toward a specific optimal level of the perceptual stimulus, decreasing steadily away from this optimal point.
- (2) The affordance of movement through the perception of Local Extent will be scaled by the Visible Range of the navigator (as captured by maximum distance with which perfect visual distance is available at each location that the navigator moves), consistent with the idea that there is a relationship between the perceptual limits of the navigator and the physical constraints of the surrounding environment.

- (3) The relationship should be consistent across environments, supporting the idea that the proposed affordance relationship is not dependent on more general context or spatial memory about the surrounding environment. This would indicate a common mechanism of the type purported to exist by other authors.

3.2.1 Methods

3.2.1.1 Participants

45 participants (26 female) attending the University of Waterloo participated in the experiment in exchange for course credit. The mean age of the sample was 18.82 years ($SD=1.56$). All participants were fluent English speakers and had normal or corrected-to-normal vision.

3.2.1.2 Apparatus

Virtual Environments. Two virtual environments (high intelligibility and low intelligibility) were constructed using Sketchup Pro 6.0 (Google Inc., Mountain View, California), a 3D modeling and graphics package, matching two environments proposed to be prototypical examples in intelligibility analysis (Hillier, 1996; depicted in Figure 3.1). Each building was between 8 and 16 meters in height and textured identically, using a traditional apartment façade.

Both models were designed to be 248 meters by 176 meters and to consist of 26 buildings. The low intelligibility environment was identical to that of the high intelligibility environment, but buildings were shifted to reduce the intelligibility of the space. A target monument was placed in the central plaza of both environments and an identical copy was placed at the participant's start location, located along the edge of the environment. The border of the environment consisted of an 8 meter tall wall with a distinctive brick texture. In the Vision condition, vision was either natural or constrained to the local environment by rendering fog with geometrically increasing density beginning at 22 meters and reaching maximal density at 35 meters.

Visual Displays. The navigation task was scripted using Vizard (Worldviz Inc., Santa Barbara, California), a Python-based virtual reality toolbox. The environment was stereoscopically rendered on an nVisor SX head-mounted display (nVis Inc., Reston, Virginia) which offered a 60-degree diagonal field-of-view and was rendered at 1280 x 1024 pixels per eye. A thick fabric shroud prevented participants from seeing the room around them, allowing them to focus exclusively on the virtual scene presented to them by the head-mounted display (HMD). Example views of the environment can

be found in Figure 3.2. The HMD was fitted with an InertiaCube2 (InterSense Inc., Billerica, Massachusetts) tracking device and was calibrated to update changes in viewpoint in real time. This allowed the participant's true head orientation to be represented accurately in the virtual environment and allowed the participant to visually explore their environment without necessarily moving through space.

Movement Control. Participants were asked to navigate through the virtual environments using a combination of wireless mouse control and changes in head direction. Movement was controlled by the wireless mouse, with depressing the left mouse resulting in forward movement at a typical walking pace, 1.2 meters per second (approximately 5 km/hr). Direction changes were made by the participant turning his or her head in the preferred direction of movement. The participant could also scan the local environment by ceasing forward movement and using head turns. The participant's location within the virtual environment and their heading were recorded at a sampling rate of 50 Hz throughout the navigation task.

3.2.1.3 Procedure

The experiment consisted of four experimental conditions (Intelligibility: High or Low; Vision: Constrained or Unconstrained) administered as a between-participants design. Each participant was randomly assigned to one of the four experimental conditions. Prior to commencement of the experiment, each participant was provided with a detailed explanation of the experiment and procedures. The participant was then assisted in donning the HMD and provided adequate time to become familiarized with the controls necessary to complete the experiment. After the participant indicated comfort with the apparatus, the appropriate environment and visual condition was presented to the participant. Each participant started on the west edge of the environment (depicted in Figure 3.1 with an (S)) next to an identifiable landmark. The participant was instructed to face the landmark and then was informed that an identical landmark could be found somewhere in the nearby city. The participant was informed that their task would be to navigate through the city to find an identical landmark and, upon finding the target landmark, to find their way back to the starting position. After the participant indicated that the instructions were understood, the experiment began, and the participant's heading and location were digitally recorded. Each participant was allowed as much time as was necessary to complete the experiment.

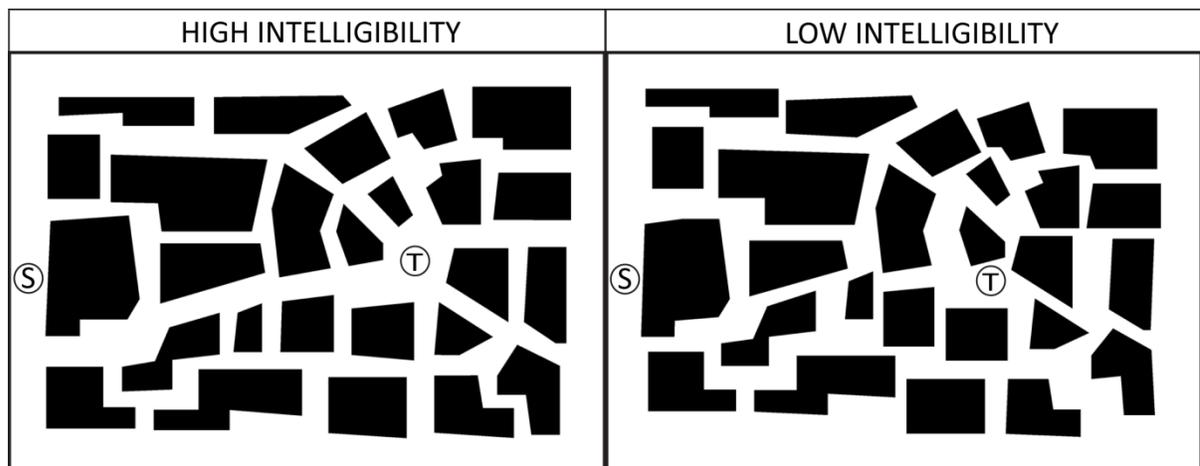


Figure 3.2 Plan views of the two virtual environments used in Experiment 4. The start position of each participant is indicated by (S) and the target landmark indicated by (T).

Unconstrained Vision



Constrained Vision



Figure 3.3 Example views provided to the participants in Experiment 1 and 2. Left depicts the target monument in the unconstrained vision condition. Right depicts a the same location under the constrained vision condition.

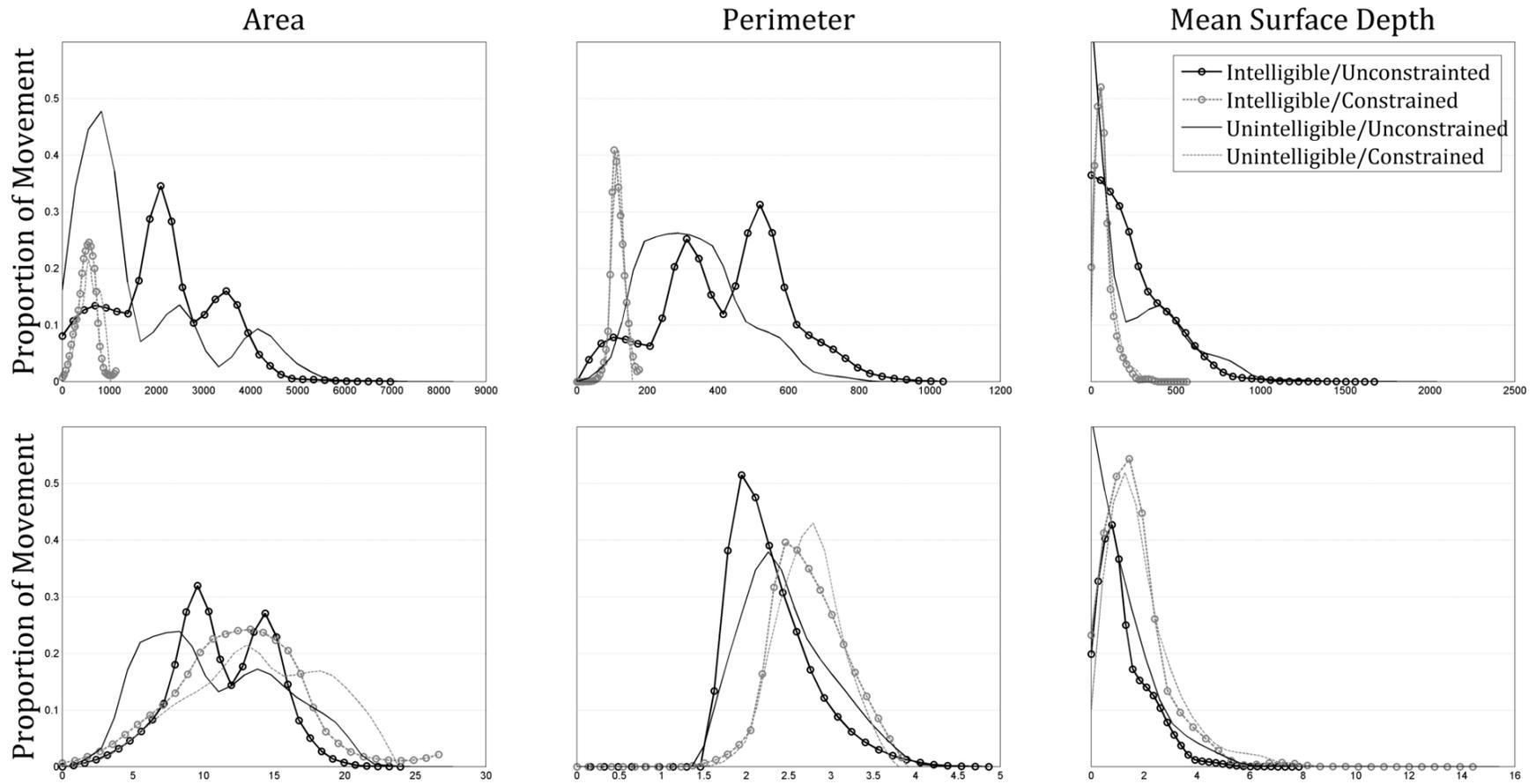


Figure 3.4 The relationship between *area* (left panes), *perimeter* (middle panes), and *mean surface depth* (right panes) as a function of environment and visual condition. The top panes present the affordance relationship as the product of raw units. The bottom panes have scaled each affordance using the maximum possible visual range.

3.2.1.4 Data Analysis

The location and heading data for each participant was aggregated to provide a number of discrete measures of performance. To assess the fit between locomotive behaviour and perception of local geometry with an affordance function, the *area*, *perimeter*, and *mean surface depth* were determined for each distinct step rather than for each unit of time. Each step was defined as moving into unique space – dwelling explicitly ignored by this analysis. The critical points for each function were identified as local maxima in the affordance relationship. Data were then examined for the influence of Vision by scaling the affordance function to the visual range available at each location in space, rendering a dimensionless, scaled affordance function in the form of a π number. These scaled affordances were then examined for similarity to ensure that the presumed affordance depends on the perceptual capacity intrinsic to the navigator. The data were also examined for dependence or independence from context by comparing navigation behaviour across both environments and across both tasks (initial exploration and wayfinding phases).

3.2.2 Results and Discussion

The data were first analyzed with respect to the general nature of the affordance relationship described by the local properties of *area*, *perimeter*, and *mean surface depth* with respect to the individual participant's observed movement. The averaged results are plotted in Figure 3.4 in both real units and intrinsically scaled units (that of the limiting of incoming visual information). Each potential affordance was approximated from the data using the Freedman-Diaconis approximation (Diaconis & Freedman, 1984) of the overall distribution of behaviour in the context of the property. This approximation reduces the number of points necessary to represent a mathematical function while preserving the shape of the function using a calculated number of bins.

Results indicated that Hypothesis 1 was not supported by the properties of *area* and *perimeter*. However, *mean surface depth* defined was shown to consist of a single peak – a single critical point – consistent with the concept of an affordance relationship.

A 2 x 2 ANOVA (Intelligibility: High vs. Low; Vision: Constrained and Unconstrained) was performed on the mean movement data. A significant main effect of intelligibility, $F(1,43)=6.193$, $\eta_p^2=0.126$, $p<0.017$, was found across the two environment conditions such that people were found to spend more time in locations offering larger area in the highly intelligible environment ($M=1516.77$, $SD=503.459$) as compared to the low intelligibility environment ($M=1272.276$, $SD=276.500$). A similar effect was also observed for the effect of perimeter on navigation movement, $F(1,43)=6.193$,

$\eta_p=0.126$, $p<0.017$, and perimeter, $F(1,43)=22.893$, $\eta_p=0.347$, $p<0.001$, with participants preferring locations offering larger mean perimeter in the high intelligibility environment ($M=301.548$, $SD=22.300$) versus the low intelligibility environment ($M=250.658$, $SD=33.085$). Critically, no significant difference was observed for mean surface depth $F(1,43)=0.525$, $p=0.473$. In both environments, participants preferred a mean surface depth distributed about 175 meters/surface. This suggests that Hypothesis 3 holds for the mean surface depth, but not area and perimeter. That is, the type of environment seemed to have negligible effect on the pattern of the mean surface depth-driven affordance of movement.

Next, the influence of Task (Exploration vs. Wayfinding) was assessed to determine if the purported affordance was subject to, or shaped by, experience with the environment. Task was examined through repeated measures ANOVA, assessing the role of Vision (constrained and unconstrained) and Task (initial exploration vs. outgoing wayfinding) on the affordance function. No significant pattern was observed for task type on the use of area, $F(1,45)=2.002$, $\eta_p=0.042$, $p=n.s.$, perimeter, $F(1,45)=2.020$, $\eta_p=0.043$, $p=n.s.$, or mean surface depth, $F(1,45)=1.954$, $\eta_p=0.042$, $p=n.s.$, nor was the interaction between Vision and Task significant, suggesting the lack of an influence of the demand on spatial memory on the preferred stimulus. Combined with the previous finding, neither the configuration of the environment nor the cognitive set of the participant appeared to shape the affordance.

The degree of perceptual scaling was then examined by considering the maximum distance the environment and Vision manipulation would allow. Should a true affordance be observed, no difference would be expected to be found, reflecting that the navigator perceives the affordance in perceptually relative terms. These perceptually relative terms are quantified by π numbers (perceived property scaled by visual range) for each visited location (Warren Jr & Whang, 1987). Each affordance function was assessed for the influence of visual range in the context of raw data and π number. Constraining visual range was found to significantly impact the use of the local visual property of mean area, $F(1,43)=249.484$, $\eta_p=0.853$, $p<0.001$, perimeter, $F(1,43)=748.851$, $\eta_p=0.946$, $p<0.001$, and mean surface depth, $F(1,43)=132.981$, $\eta_p=0.756$, $p<0.001$. As is evident in Figure 3.4, scaling the affordance relationships to represent perceptual units adjusted both the constrained and unconstrained affordance relationships overlap or represent a single, common, affordance relationship. A significant Vision x Intelligibility interaction was observed for both the factors of area, $F(1,43)=10.370$, $\eta_p=0.194$, $p<0.002$, and perimeter, $F(1,43)=22.907$, $\eta_p=0.348$, $p<0.001$, but not

for *mean surface depth*. This is reflective of the fact that, as visual range of the participant and intelligibility of the space are manipulated, the complexity of the affordance increases for the properties of *area* and *perimeter* but not *mean surface depth*. In contrast, the character of the *mean surface depth*-defined affordance was shown to be relatively insensitive to these manipulations, appearing consistent across these two manipulations. This finding, combined with the lack of significant difference across the types of environments is further supportive of the idea that the affordance function defined by mean surface depth is relatively insensitive to manipulation, consistent with Hypothesis 3, and is scaled to be biologically meaningful, consistent with Hypothesis 2.

Post hoc analysis was performed to assess statistically the presence of a critical point. Data were collapsed across environments and examined using a bootstrapped t-test with 95% confidence intervals. Significant convergence in the affordance was observed at a mean raw surface depth of 188.330 ($SD=42.560$), $t(45)=11.433$, $p<0.001$, 95% CI [140.311, 200.317], and at the Vision-scaled point about 1.017 ($SD=0.289$), $t(45)=-9.882$, $p<0.001$, 95% CI [-1.007, -0.667].

Taken as a whole, Experiment 2 provided poor fit for the visual properties of area and perimeter with the concept of affordance as outlined by Gibson. Furthermore, these properties did not appear to be used in any consistent way after accounting for visual range when navigating through space. In contrast, a strong, stable fit was observed for the property of mean surface depth, suggesting that this property may be capable of driving the affordance of movement and navigation regardless of the structure of surrounding space. Mean surface depth was shown to be insensitive to task demands, the intelligibility of the environment, and visual range. Mean surface depth also consisted of one critical point about which the affordance was maximized. These findings joins the results of Experiment 1 as suggesting that mean surface depth may be critical in determining the routes with which we navigate space and suggest that affordance theory itself may be able to predict observed patterns of navigation. Furthermore, this suggests that the previous characterization of the effect of intelligibility on navigation as a preference for longer sight lines may not be accurate because the area variable was poorly suited to the idea of an affordance.

3.3 Experiment 3 Do Surfaces Themselves Control the Affordance of Movement?

Experiment 2 identified *mean surface depth* as a potential perceptual property capturing the invariant structure of space in a practical way, consistent with both the theory of an affordance and

the theory of constraints. The findings suggested that perception of mean surface depth was employed throughout the navigation process regardless of global intelligibility or task parameters (such as the requirement that spatial memory be used). This initial evidence strongly supported the idea that the affordance of movement does meaningfully drive both exploration and wayfinding behaviour in a consistent way.

Given the relative importance of surface geometry in defining mean surface depth, the complex surface geometry was simplified by reducing the variation in angle of the walls and corners of each building (as is outlined in Study 2). The mean number of surfaces was significantly reduced from the original intelligible environment to the new environment, $t(25)=3.718$, $p<0.001$, 95% CI [0.326, 1.146], from the mean number of 5.345 ($SD=1.325$) in the high intelligibility environment used in the previous experiment to 4.615 ($SD=1.06$) in the present one. The precise effect of this manipulation on other spatial parameters was described in Study 2, so will not be elaborated on here. Generally, it was effective in restricting the range of values that many of the spatial properties could take on, simplifying the visual properties perceived when navigating each environment. Should the affordance of navigation truly be the product of the use of local structurally-defined visual properties rather than the more global properties suggested by space syntax analysis, these more controlled environments should provide a stronger test of the presence and character of the affordance relationship.

3.3.1 Methods

3.3.1.1 Participants

89 participants (51 female) attending the University of Waterloo participated in the experiment in exchange for course credit. The mean age of the participants was 20.65 ($SD=2.47$). All participants were fluent English speakers and had normal or corrected-to-normal vision.

3.3.1.2 Apparatus

Virtual Environments and the Visual Range Manipulation. Two virtual environments were adapted from the Intelligible and Unintelligible spaces used in Experiment 1 using Sketchup Pro 6.0 (Google Inc., Mountain View, California). The buildings of each environment were manipulated to reduce the mean number of surfaces present by making the remaining surfaces more orthogonal. Each environment consisted of the same number of buildings and each environment was identical in their

overall dimensions – 248 meters x 176 meters. A plan view of each environment is presented in Figure 3.5.

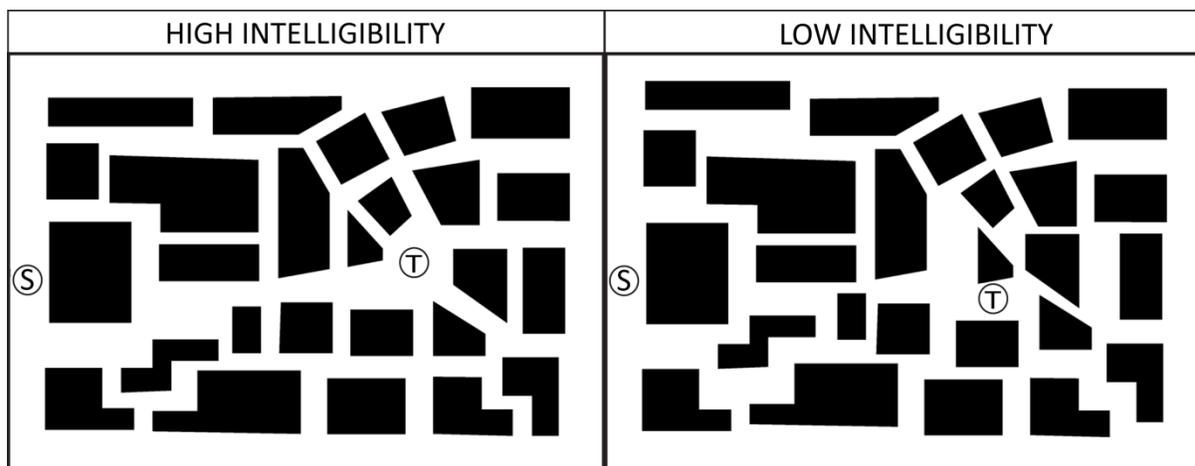


Figure 3.5 Plan views of the two virtual environments used in Experiment 5. The start position of each participant is indicated by (S) and the target landmark indicated by (T).

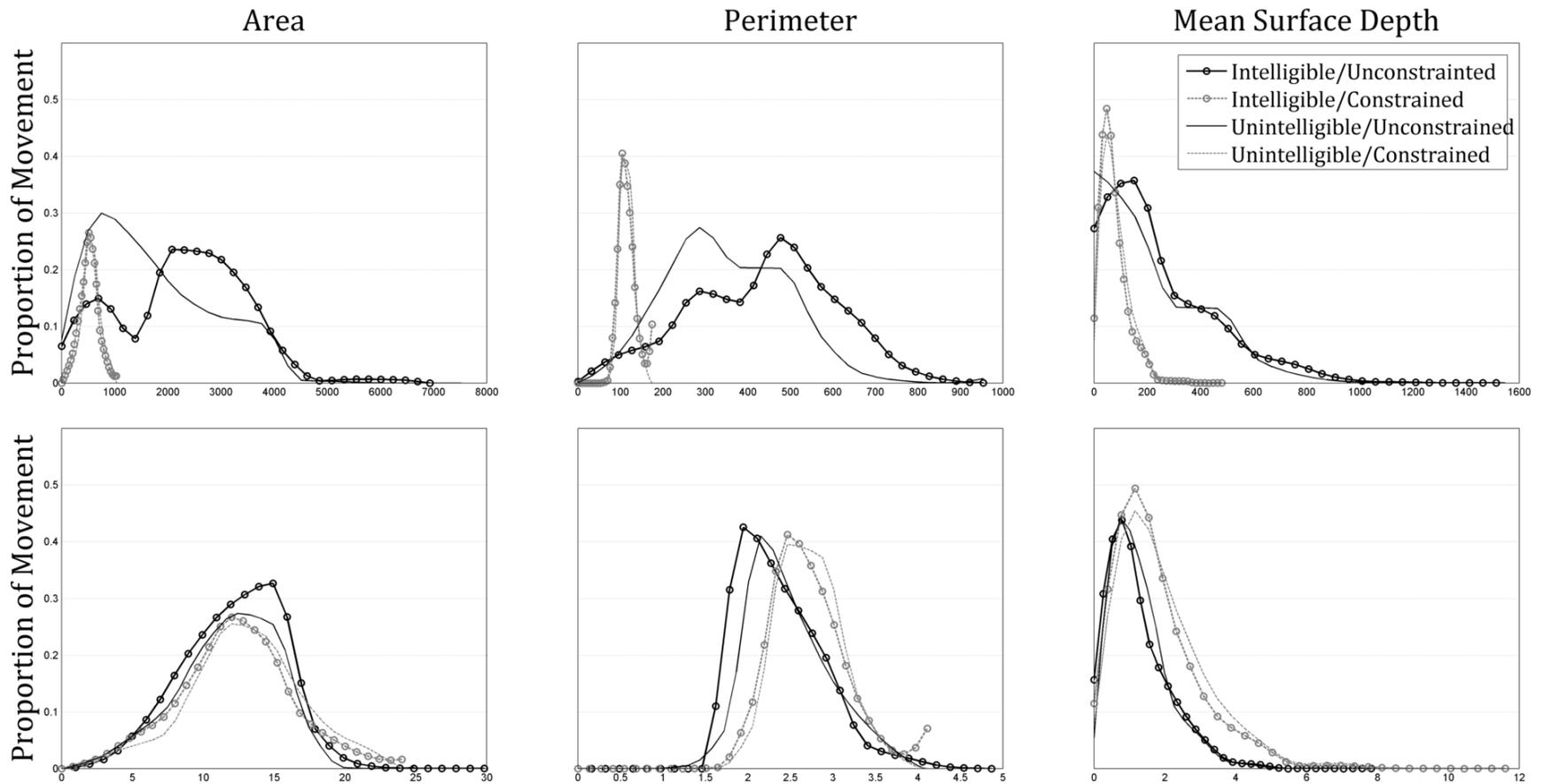


Figure 3.6 The relationship between area (left panes), perimeter (middle panes), and mean surface depth (right panes) as a function of environment and visual condition in Experiment 6. The top panes present the affordance function as the product of raw units. The bottom panes have normalized each function using the maximum possible visual range.

An identical Vision manipulation to that of Experiment 1 was imposed on half the participants.

3.3.1.3 Procedure and Analysis Strategy

The procedure and data analysis strategy were identical to those of Experiment 1, outlined in 3.2.1.3 and 3.2.1.4, respectively.

3.3.2 Results and Discussion

Data were first analyzed by characterizing the relationship between the local geometric properties of *area*, *perimeter*, and *mean surface depth* with respect to movement throughout the navigation task. Specific interest was paid to data that described common patterns of movement. The probability density function describing movement tendencies was computed under the Freedman-Diaconis rule. The affordance relationships in the presence of environment and visual range are depicted in Figure 3.6. Distinct unimodal curves appear present in all three factors of Local Extent: area, perimeter, and mean surface depth. Furthermore, sharp decay functions can be observed, indicating the potential to meet the definition of critical points – defining the transactional relationship between spatial properties and their practical use to a navigating agent.

The initial suitability of the affordance relationships was determined by 2x2 ANOVA (Intelligibility: High vs. Low; Vision: Constrained and Unconstrained). Results indicated a significant effect of the configuration of the environment on locomotion with respect to area, $F(1,83)=11.618$, $\eta_p=0.123$, $p<0.001$, and perimeter, $F(1,83)=23.399$, $\eta_p=0.227$, $p<0.001$. Specifically, locations that offered a larger area or perimeter in the high intelligibility environment were once again preferentially explored to those in the low intelligibility environment. However, similar to the results of Experiment 1, no effect was observed for mean surface depth, $F(1,83)=0.619$, $p=ns$. Across all three variables, a slight improvement of the effect size was observed, suggesting that the reduction of variation sought by the manipulation of the environments was effective and produced behaviourally relevant differences. As before, no significant effect of Task type or Task by Vision interaction was observed by mixed factors ANOVA, with area showing no main effect of Task, $F(1,85)=2.202$, $\eta_p=0.025$, $p=0.142$, or interaction with Vision, $F(1,85)=0.198$, $\eta_p=0.002$, $p=0.657$. A similar lack of effect was also observed in the other variables of perimeter, $F(1,85)=2.185$, $\eta_p=0.025$, $p=0.143$, and mean surface depth, $F(1,85)=2.326$, $\eta_p=0.027$, $p=0.131$. Combined with the lack of the influence of the overall structure of the environment, as captured by intelligibility, these data support the idea that while mean surface depth is behaviourally relevant as an affordance property, it is largely not subject to cognitive demands placed upon the navigator.

Constraining vision was found to have a sizable influence on all three variables. Mean area, $F(1,83)=565.337$, $\eta_p=0.872$, $p<0.001$, mean perimeter, $F(1,83)=1529.691$, $\eta_p=0.949$, $p<0.001$, and mean surface depth, $F(1,83)=565.337$, $\eta_p=0.872$, $p<0.001$, were found to be significantly different when comparing constrained to unconstrained vision condition. As in Experiment 2, this finding suggests a link between the perception of the invariant properties and the ability for the individual navigator to perceive more or distant visual information. A significant 2-way interaction was observed between Vision and Intelligibility, such that area, $F(1,83)=14.204$, $\eta_p=0.146$, $p<0.001$, and perimeter, $F(1,83)=26.034$, $\eta_p=0.239$, $p<0.001$, showed a tendency toward a behavioural difference for the properties of *perimeter* and *area*. However, upon converting the affordance functions to the critical ratio of visual range and expanse (as captured independently by area, perimeter, and mean surface depth), the idea that perimeter and area are reflective of patterns of behaviour rather than an explicit behaviour-action relationship is further elaborated.

The clarity with which the affordance of movement is controlled by *mean surface depth* alone speaks to both the effect of reduced complexity in the data and the corresponding effect that a simpler environment has on the observed affordance relationship. As before, post hoc analysis was performed to identify the critical point at which the two curves converged (that of raw mean surface depth and scaled mean surface depth) in the face of differing visual range. A significant difference was observed between the affordance of movement from the raw mean surface depth and scaled mean surface depth, $t(85)=13.262$, $p<0.001$, 95% CI [155.877, 210.859]. The critical point was found to be at 196.854 ($SD=43.712$). Similarly, when the affordance was scaled to perceptually relevant units, a single critical point was observed, $t(85)=-14.275$, $p<0.001$, 95% CI [-0.950, -0.718], showing an inflection point about 1.07 ($SD=0.250$). These values, particularly the scaled units, are consistent with those found in the previous experiment, further supporting their relevance for guiding navigation behaviour.

Accordingly, Hypothesis 1, 2, and 3, were each upheld for the measure of *mean surface depth*, but rejected for area and perimeter. Together, Experiments 2 and 3 are supportive of the property of *mean surface depth* as an visual property of the invariant structure that is consistent with affordance theory. However, it remains to be seen whether spatial preferences are influenced by overall spatial ability. This is important because affordances are generally expected to be independent of high-level or top-down processing. Consequently, Experiment 4 was designed to test this idea.

3.4 Experiment 4 The Influence of Cognitive Variables on the Affordance of Movement

Experiment 4 sought to investigate the contribution of cognitive variables to movement in navigation tasks in two different ways. First, the role of high-level cognitive functioning in influencing the preferred perceptual affordance was assessed directly. The perception of an affordance is purported to be the result of a *direct perception* of the relationship between an action and a perceptual characteristic (Gibson, 1966). This pattern of directly perceived affordance has been well established in a large body of work, such as when climbing stairs (Warren Jr., 1984), traversing doorways (Warren Jr & Whang, 1987), and selecting a sitting position (Mark, Balliett, Craver, Douglas, & Fox, 1990). In each case, the action is performed without substantial error, even when the stimuli do not conform to traditional expectations of the shape of an object or the environment. Should the affordance relationship described herein be influenced by high-level cognitive demands, the shape of the affordance function would be expected to change based on the individual cognitive capacities of the navigator. Traditional affordances are considered to be the product of *direct perception*, so would be expected to be relatively insensitive to cognitive demands (particularly, Gibson, 1979).

Second, the influence of cognitive processing on other forms of spatial behaviour was assessed. Previous investigations have suggested that individuals tend to pause in-place and visually explore their surrounding environment when disorientated (e.g., Conroy, 2001). Pausing in place is therefore considered linked to a difficulty in spatial learning rather than in making explicit movement decisions. In this context, cognitive ability would be expected to have a pronounced influence on pausing behaviour (Garden, Cornoldi, & Logie, 2001) but not on movement itself. To further establish whether pauses represent a breakdown of the affordance or some other process (such as that of spatial learning), the locations that were looked at were assessed for fit with the idea of an affordance. That is, despite pausing due to a breakdown in cognitive ability, the individual would still be expected to look preferentially at locations that show fit with the affordance of movement itself.

To investigate the role of cognitive processing on movement affordance, three high-level cognitive processes were assessed: the ability for Sustained Attention, the ability to maintain Mindfulness, and the possession of good General Spatial Ability in effectively navigating and in representing spaces mentally. Sustained Attention and Mindfulness have been widely understood to be important in avoiding task-related errors in cases where attention is necessary (e.g., Smallwood et al., 2004). Mindfulness has also been associated with increased cognitive flexibility, resulting in improved

performance on tasks that require attentional resources (Moore & Malinowski, 2009). Prior work specific to navigation has demonstrated that the effectiveness with which a person can navigate is directly related to their ability to maintain a good sense of direction and to monitor and update wayfinding strategies (Kato & Takeuchi, 2003) both of which demand attention. Accordingly, if the pattern of behaviour observed as part of an affordance function depends on active processing, cognitive flexibility, or maintaining a sense of direction in real-time, it would be expected that the affordance would be impacted directly by the level with which the navigator can maintain Sustained Attention and Mindfulness. General spatial ability has previously been found to be the single best predictor of navigation performance (Hegarty, Richardson, Montello, Lovelace, & Subbiah, 2002). Should the affordance of movement depend on either effortful maintenance of attention or spatial ability, the impact of general spatial ability would be expected to change the relationship between visual properties and movement.

At the same time, *intentional* perception of properties of the invariant structure like mean surface depth will be described. By examining whether people preferentially gaze toward locations offering similar levels of the properties linked to eventual movement, the capability to explicitly perceive these properties and apply them to movement can be assessed. Accordingly, gaze behaviour will be assessed, where gaze is defined by the range of head motion observed while each participant was paused in place. It is proposed that each time a person gazes to evaluate or re-evaluate the environment around him or her, the person's gaze should be biased toward the locations that afford movement if the visual property is to be understood to be directly perceived by the navigator. It is noteworthy that, while this is not an explicit requirement for an affordance, it would better elaborate affordance as a plausible mechanism of movement.

3.4.1 Methods

3.4.1.1 Participants

16 participants (8 female) attending the University of Waterloo participated in the experiment in exchange for course credit. The mean age of the participants was 18.00 ($SD=1.72$). All participants were fluent English speakers and had normal or corrected-to-normal vision.

3.4.1.2 Apparatus

Virtual Environments. The experiment consisted of identical high intelligibility and low intelligibility environments to those used in Experiment 1. Plan views for each environment are depicted in Figure 3.1.

Virtual Reality. The same head-mounted display and movement controls were used in the present experiment as outlined in 3.1.2.3 and 3.1.2.4.

3.4.1.3 Questionnaires

Santa Barbara Sense of Direction Scale (SBSDS; Hegarty et al., 2002) is a 15-item Likert scale assessing self-reported environmental spatial ability. Items range between 1 (“Strongly Agree”) and 7 (“Strongly Disagree”). A higher score indicates a greater self-perceived sense of effectiveness at maintaining direction and representing space as a whole.

Mindful Attention Awareness Scale (MAAS; Brown & Ryan, 2003) is a 15-item Likert scale developed to assess mindfulness in everyday circumstances. The scale items ranging from 1 (“Almost always”) to 6 (“Almost never”) with a higher overall score indicating a relative increase in focus within a given task.

Attention-Related Cognitive Errors Scale (ARCES; Cheyne, Carriere, & Smilek, 2006) is a 12-item Likert scale which measures the relative frequency with which a person experiences a variety of cognitive failures related to attentional lapses. Each item is indicated by a Likert item ranging from 1 (“Never”) to 5 (“Very Often”). A higher overall score on the ARCES is taken to indicate a higher frequency of attention-related cognitive errors in the participant’s day-to-day life.

3.4.1.4 Procedure

The experiment consisted of one experimental condition (Intelligibility: High or Low) administered in a between subjects design. Each participant was randomly assigned to one of the two virtual environments. The experiment consisted of two phases: 1) completion of the SBSDS, ARCES, and MAAS questionnaires, and 2) completion of a navigation task in the randomly selected environment. Half of the participants completed the questionnaires before the navigation task, while the other half of the participants completed the questionnaires following the navigation task. For the navigation task, the participant was immersed in the virtual environment in one of the four corners of the environment (counterbalanced across participants). The participant was instructed to complete all questionnaires according to the standard set of instructions included with each. Next, the participant

was instructed that the navigation task was for him or her to *learn the surrounding environment as best as he or she could within 15 minutes*. To encourage the participant to learn the environment fully, the participant was further instructed that *he or she would be required to draw an overhead view of the environment upon completion of the navigation task*. This instruction was meant to encourage the participant to be as efficient as possible in his or her exploration of the environment. The participant was monitored for simulator sickness throughout the experiment. After 15 minutes, the participant was removed from the environment.

3.4.2 Results and Discussion

As the purpose of the experiment was to investigate the sensitivity of the affordance of movement to spatial and cognitive ability, the data were pooled across both environments to render a general estimate of the relationship between ability and affordance. This is considered acceptable given the previously established lack of effect of environment as a whole on the general character of affordance observed. The general pattern of affordance is presented in Figure 3.9, scaled to the mean distance that the navigator can perceive. As with Experiments 1 and 2, the property of *area* again showed a tendency being bimodal, demonstrated two critically preferred levels of area in supporting movement. However, mean surface depth again was found to demonstrate relatively unimodal fit, consistent with the previously established pattern of affordance. It is noteworthy that the critical point was also similarly placed to that of Experiments 2 and 3.

The data were first analyzed using multiple linear regression to establish the relationship between the mean and standard deviation of mean surface depth experienced through the course of completing the navigation task. The *mean surface depth* and *standard deviation of mean surface depth* and the total score on the ARCES, MAAS, and SBSDS were evaluated for the full 15 minutes of active navigation. No significant relationship was observed between *mean surface depth* and any of the cognitive factors, $R^2=0.193$, $F(3,20)=1.592$, $p=0.223$. Similarly, no relationship was observed between the *standard deviation of mean surface depth* and the attention, mindfulness, or spatial ability scores, $R^2=0.127$, $F(3,20)=0.966$, $p=0.428$. In both cases, the amount of change in the preferred level of visual property when moving was found to be relatively minute when accounting for cognitive variables. This is supportive of the idea that the perceptual property of mean surface depth largely does not depend on general comfort with and effectiveness at navigation as measured by the SBSDS nor sustained attention and mindfulness, as measured by the ARCES and MAAS, respectively. While it is likely that a larger sample would be statistically significant, the marginally

low effect size of the regression results suggests that the affordance of movement is not *strongly* influenced by cognitive variables. This is particularly noteworthy as the task the participants were asked to engage in – that of learning the surrounding environment as well as they could – was one that should place emphasis on the use of these cognitive faculties.

To cast this result in clearer light, the effect of cognitive ability was evaluated in the context of another type of spatial behaviour – pausing. A pause was considered to occur if the participant remained stationary for two or more seconds and, during that time, the participant actively visually explored their surrounding environment. This criterion was used to ensure that pauses were meaningful in nature and not related to potential task fatigue, accidental halting by releasing the mouse button, etc., but were instead the result of a desire to re-evaluate the nearby environment toward some goal. First, data were assessed to determine if pauses were found to occur at sub-optimal levels of the local visual properties. This would be expected to occur if the capacity to remain oriented depended the specific level of the visual property. Hence, *mean surface depth recorded during locomotion* was evaluated against the *mean surface depth during pauses* to assess whether this was the case. No significant difference between the motion-oriented and pause-oriented data were observed $t(23)=-0.698$, $p=0.498$, suggesting that pauses were not the result of an inability to perceive optimal levels of the visual property to remain oriented but were instead the product of some other processing of space. Next, the *total pause time* and *total number of pauses* were examined using multiple linear regression to determine if they were instead the product of poor spatial ability, mindfulness, or ability to sustain attention. A significant relationship between the amount of time spent paused in-place and each of the cognitive variables, $R^2=0.596$, $F(3,20)=9.836$, $p<0.001$. Specifically, a significant effect of the ability to sustain attention, $B=0.542$, $t=2.973$, $p<0.008$, mindfulness, $B=-0.915$, $t=-5.099$, $p<0.001$, and spatial ability, $B=0.317$, $t=2.187$, $p<0.041$, was observed on pause time. Likewise, a significant effect of the cognitive variables was found on total number of pauses, $R^2=0.457$, $F(3,20)=5.622$, $p<0.006$, through attentional error, $B=0.702$, $t=3.323$, $p<0.003$, mindfulness, $B=-0.711$, $t=-3.418$, $p<0.003$, and spatial ability, $B=0.364$, $t=2.167$, $p<0.042$. Together, these results establish that the measures of spatial ability were effective in accounting for the approximate degree of difficulty in encoding surrounding space and not a result in a breakdown of the affordance relationship itself.

The lack of a strong cognitive influence on the affordance of movement was followed up with an examination of how people's gazes varied when they were paused, something that should be considerably more driven by bottom-up influences if the affordance is understood to be directly

perceived by the navigator. This would be consistent with the idea that processing of low-level features is relatively independent from that of cognitive ability (Neisser, 1976; Gibson, 1979) and informs the actual movement decision. To establish if participants actively sought to perceive the critical level of the visual property in the world around them, individual gaze patterns were averaged across all pauses engaged in by the participant. To establish whether gazing around the environment was influenced by whether the gaze is to guide movement locally or more globally, gaze behaviour was separated into that which was directed toward the local environment (lying within 10 meters of the participant or half the span of the average intersection) from that of distant environment (lying beyond 10 meters). Data from this analysis are presented in Figure 3.8. A 2x(2x11) nested repeated measures ANOVA (Gaze distribution: Local or Global; Intelligibility: High or Low; By visual property level) was varied with respect to the environment and the location of the evaluated features. A significant main effect of Gaze Distribution was observed both for accessible space and distant features, $F(1,22)=94.104$, $\eta_p=0.811$, $p<0.001$, and $F(1,22)=48.095$, $\eta_p=0.686$, $p<0.001$, respectively. Across both local and global space, participants spent more time gazing at locations close to a mean value of 0.98 when paused in place, approximately equal to the critical point established earlier in the analysis and similar to that identified in the previous experiments. This pattern was revealed to differ based on the overall intelligibility of the surrounding environment, $F(1,22)=72.136$, $\eta_p=0.766$, $p<0.001$. That is, gaze times were found to vary with respect to local visual property level more in the intelligible than the unintelligible environment, particularly beyond the preferred critical point. A significant interaction was also observed between Gaze Distribution and Intelligibility, $F(1,22)=4.662$, $\eta_p=0.175$, $p<0.042$. This reflected the tendency for individual navigators to visually examine less of the surrounding distant environment when the environment was intelligible than when it was unintelligible. In contrast, no significant difference was observed between gazes directed at the local environment, regardless of intelligibility. In all cases, however, gazes were found to be most directed toward locations lying between 0.79 and 1.19 scaled units of mean surface depth, evenly about the critical point, regardless of the distance at which gaze was directed.

Together, this complex pattern of results reveals that gaze behaviour, independent of movement, is directed toward a behaviourally relevant *critical point* and is not simply distributed randomly throughout space. This pattern was demonstrated both when considering space that was immediately useful for navigation and when examining distant visual space. Combined with the previous data suggesting that pauses were most likely the result of disorientation or reduced spatial ability, this

suggests that the visual properties that are relevant to movement are also relevant when attempting to regain orientation.

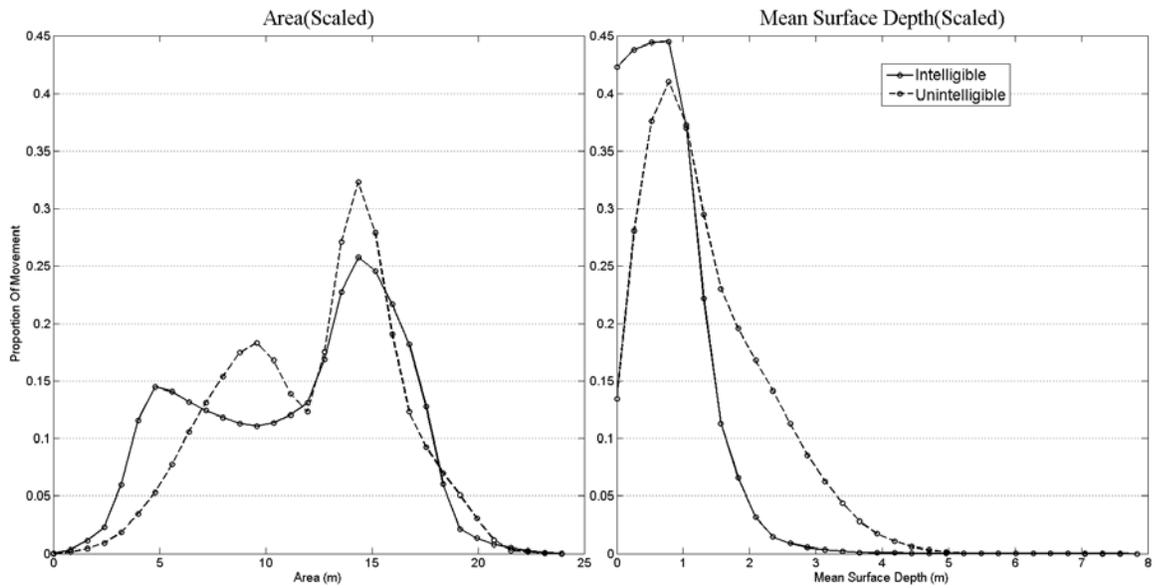


Figure 3.7 The critical ratio of area (left), and mean surface depth (right) as scaled by visual range in a free exploration task.

As in the prior experiments, Experiment 4 demonstrated a consistent affordance relationship between the local visual property of mean surface depth and an individual's movement through space in a more general spatial learning task. As before, no evidence was observed for the suitability for area alone to subserve an affordance relationship as multiple optimal points were observed. These results further confirm the general finding that a consistent affordance relationship appears to exist independent of task demands, particularly when considering the property of *mean surface depth*.

Of particular interest was the lack of effect of the variables of mindfulness, sustained attention, and sense of direction. This is consistent with the intuition that perception of such relatively simple spatial summary variables, captured by the rapidly perceived size and shape of space, is independent from more intensive types of navigation such as traditional studies of spatial learning and the acquisition of landmark knowledge. The present analysis did reveal a tendency for people to gaze toward optimal level of these properties primarily in the distant environment. Two eye-tracking studies of how isovist area (Emo, 2014) and the conceptually related idea of maximum distance-to-contour (Wiener et al., 2012) have shown that people have a tendency to direct their gaze toward locations of maximum magnitude prior to navigation. This result is consistent with the present studies but must be taken with caution as neither of the aforementioned studies presented an analysis of the continuum of preceding visual properties that were explored prior to final movement. Instead, they tended to focus on the locations that captured attention the most, making a direct comparison between the present work and this past work more difficult to achieve. This is important because affordance was still hypothesized as the underlying cause, despite a lack of the assessment of the quality or fit of the affordance relationship. Therefore, the present data may instead serve to enhance these findings by suggesting a link between area and movement through the related variable of depth-informed affordance.

This experiment also revealed an effect of the spatial cognitive variables on pause behaviour, but a marginal influence, at best, on movement itself, something that is both intuitive and may serve to reinforce the idea that the affordance driving behaviour is relatively independent of individual ability. Prior work on the encoding of routes has suggested that when a person gives directions to another person, sustained attention and sense of direction are invoked to retrieve and describe the surrounding space (Michon & Denis, 2001). Hence, when the participant sought to better encode the environment rather than simply navigate it, a pause is often engaged in to better observe the surrounding environment. This is, in fact, precisely the pattern of data observed here, as the views observed during pauses were focused on critical points as predicted from the affordance account. The current data are also consistent with previous work that demonstrates that pauses occur at visually informative locations rather than at isolated locations (Conroy, 2001).

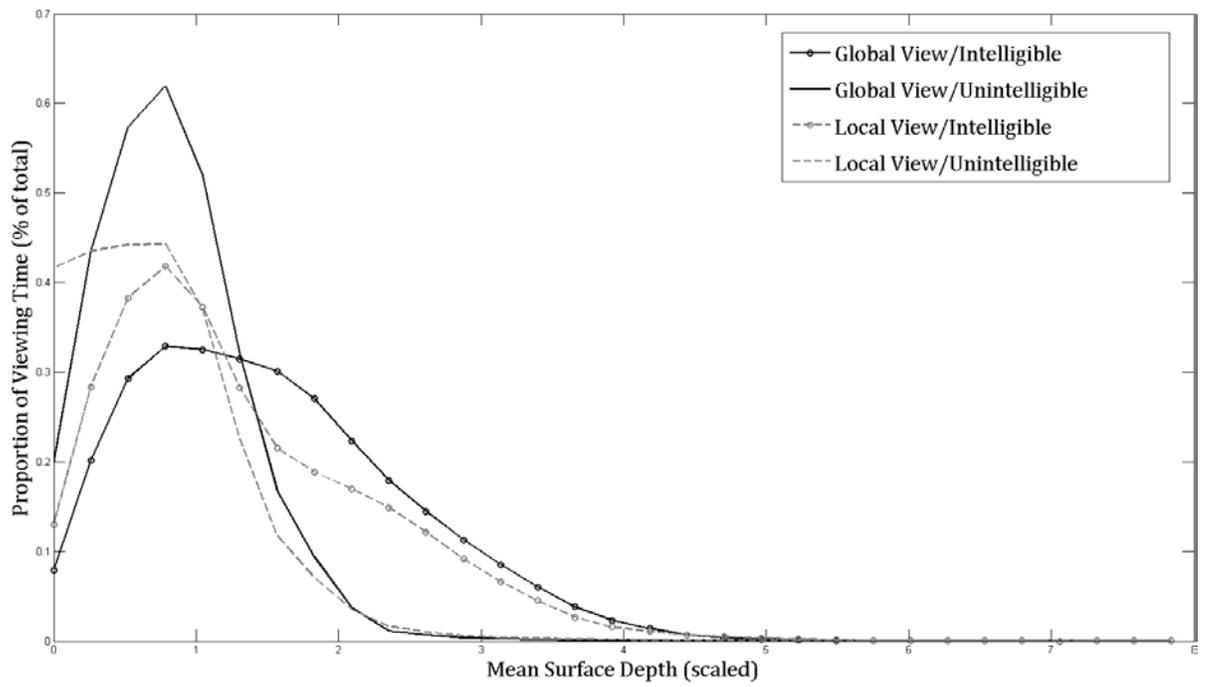


Figure 3.8 Gaze distribution across space as a function of task and proximity for Experiment 4.

Chapter 4

General Discussion

Understanding how we can navigate both familiar and unfamiliar environments is a topic that has received substantial interest within both scientific and applied fields. Of particular prominence is the subfield of Space Syntax, which attempts to predict how pedestrians and vehicles will move through an urban space by examining the spatial system formed by the environment as a whole (Hillier, 1996). The Space Syntax approach has been used successfully to predict where we will go in an environment and how we might behave in a space based simply on how it is configured (Barton et al., 2014; Penn, 2003). These effects have been demonstrated so reliably that many have proposed that we engage automatically with one or more of the spatial properties defined by space syntax in order to move adaptively. Some of the candidate possibilities suggested as the prime movers of human navigation in built spaces have been the connectivity provided by a view (Emo et al., 2012), the overall area of a space (Emo, 2014), the maximum visible distance (Wiener et al., 2012), the arrangement of attractors relative to each other (Wineman & Peponis, 2010), and the perception of more elaborative configurational cues (Turner, 2006; Penn, 2003; Turner et al., 2001), to name a few. But, despite the frequency with which affordances are invoked as the causal mechanism explaining how we move through space, particularly with respect to the overall configuration of spaces, very little direct evidence exists to account for the majority of findings. As a result, at present, we simply do not have a good model that explains how the configuration of space controls and guides behaviour.

For this reason, the three initial studies (Studies 1 through 3) were used to determine whether any common patterns might exist amongst the considerable body of previously described spatial properties in explaining how we may move through space. At the core of this body of work is a drive to identify *shared* properties that can mutually account for the role of configuration in a way that is parsimonious with the findings of the field as a whole. In this endeavour, I have shown that the global configuration of space lying outside the perceived viewpoint is related directly to the properties of local space that have been associated with navigational behaviour. In doing so, I have argued against the primacy of configurational cues (i.e., exosomatic visual architecture) and instead taken the position that local perceptual information must be primary in accounting for behaviour. This is because there is simultaneously a relative lack of direct evidence supporting the view that people perceive complex configurational data in the surrounding environment, particularly those data outside the present field of view, and to ensure parsimony with the purest definition of affordance and direct

perception found in the literature. The result of this work was the identification of a simple collection of properties that describe how space is arranged, named Spatial Complexity, Enclosure, Importance, and Local Extent. Critically, a strong relationship is shown between the variation in local extent and the variation in the overall complexity of an environment across a variety of spaces. In identifying this link, the variables that define local extent can be understood as providing potential information content about the overall global structure of a space, providing initial fit with the idea that the affordance of configuration is driven by viewing local space itself (for example: Emo, 2014).

In further testing this model, one in which the variables of local extent appear to be useful in describing space, a mechanism driving both aggregate and individual navigation is identified (Experiments 1 through 4). Throughout the experiments, I attempt to develop analytically a simple model of how the structure of space may drive behaviour based on the ideas underlying affordances alone (Gibson, 1979). In doing so, considerable evidence is found to correlate one particular variable of Local Extent, mean surface depth, and predicted patterns of movement and behaviour in various types of navigation. Accordingly, I name this model *Depth Afforded Navigation* as an account that the affordance of movement is guided by the concept of depth, independent of the role of landmarks and other potential attractors lying in space. These effects are also demonstrated to be relatively insensitive to task demands, environmental context, and general spatial cognitive ability. As the explicit fit of the variables with direct perception is assessed directly throughout, for the first time, the present work helps describe how local spatial properties may drive navigation in very specific and testable terms.

4.1 Contributions of Depth Afforded Navigation

This dissertation makes initial headway into developing a comprehensive model to account for naive tendencies in how we explore the world as a whole. The overarching principle put forward here is that Depth Afforded Navigation appears to be integral in navigation across a variety of contexts and tasks. This is shown in both the experimental evidence and the result of the aggregate traffic modeling. This is a novel account of how navigation behaviour in different types of intelligible spaces can be understood using a single mechanism. Traditionally, people were expected to steer toward ideal configurational or metric spatial cues, something that has largely only been useful in predicting behaviour in well-structured, intelligible environments (e.g., Penn, 2003). Instead, the present depth-derived model proves informative in both well-organized and poorly organized spaces, as it is purely dependent on knowledge found in the nearby local environment alone. Studies 1 through 3 also

establish the case for mean surface depth providing information about the expected spatial structure beyond the present viewpoint, something that can be useful in planning how we will move through space, but placing little-to-no demands on the spatial knowledge or experience level of the navigator.

The interplay between these two factors – the local extent of a location and the overall complexity of space, particularly between connectivity and mean surface depth – has potential to improve a number of agent-based and simulation techniques used in research and urban planning. Most notable is the approach put forward as the basis for exosomatic visual architecture – the visual graph. As the visual graph captures the relative value of a location as the sum of its potential to lead to other more connected/larger possible views, the visual graph captures a similar idea to that of Depth Afforded Navigation. However, the present work indicates that area itself is not consistently preferred by navigators, at least generally (as is shown in Experiments 1 through 4), suggesting that a consideration of depth may improve the predictive power of this type of modeling. This is because participants were shown to prefer multiple ideal levels of area and perimeter as they navigated space, something that was not revealed in Depth Afforded Navigation.

Across a variety of different tasks, participants were also shown to attempt to preserve a relative level of depth when navigating, scaled by the size of the local view. This finding provides some evidence for the idea that Depth Afforded Navigation is the product of the capacity to perceive the nearby environment and its fundamental structure, captured by visual range and mean surface depth, respectively. Should these results be found to hold, in other types of environment or navigation tasks, these results suggest that traffic may best be predicted by considering a much simpler model of spatial perception and spatial complexity than have previously been suggested.

Depth Afforded Navigation was also shown to be constrained by local viewpoint consistently across three different behavioural experiments, two of which (Experiments 2 and 3) explicitly manipulated the visual range offered locally and one of which showed a more general effect of visual range on both movement and gaze, without explicit manipulation (Experiment 4). This is reflective of the fact that the local spatial complexity, as captured by variables of local extent, is strongly influenced by both the layout of the local environment and the global environment. This can be understood as the direct product of the factor models and upon reflection on the makeup of local extent. Mean surface depth, for instance, which considers the approximate distance between a navigator and each nearby surface, is influenced both by the size of space and by its relative symmetry. This is because the mean would be biased toward lower values if compression of depth-to-surfaces occurred asymmetrically in the visual field. Consequently, when mean surface depth is

scaled into relative π units, some degree of independence from area is highlighted. Thinking about space in relative terms such as these provides a novel way of understanding the visual complexity of space in terms that are related to the visual limits of the navigator. We know from work in scene perception that humans can recognize the general character of a visual scene rapidly and with ease (Greene & Oliva, 2009; Oliva & Torralba, 2001). Additionally, gaze behaviour has been shown to be directed toward properties of floor area (Emo, 2014) and surrounding surface geometry (Wiener et al., 2012) when evaluating nearby space. Taken as a whole, these findings provide support for the view that affordance places emphasis on how space can be summarized into movement-relevant terms.

Cumulatively, the pattern of results shown here, which support the idea of Depth Afforded Navigation, provides a novel way of thinking about how we may move through space, and provides novel parameters (i.e., mean surface depth and range-scaled mean surface depth) to describe space and the complex milieu within which behaviour may occur (Spatial Complexity as it relates to Local Extent). Therefore, at present, Depth Afforded Navigation is meant to augment rather than supplant existing theories.

4.2 Why Associate Local Extent with Spatial Complexity?

One question that arises from both the behavioural work and the factor analysis, suggesting a link between the properties of local spatial extent and the complexity outside the local viewpoint, is, what does the relationship capture? There is no simple answer to this question, but I will attempt to address it using a simple set of models. In doing so, I will demonstrate not only where the relationship between local extent and spatial complexity is strongest but also demonstrate where the relationship is no longer of practical use. Each model is depicted in Figure 4.1.

We may begin to investigate this question by starting with an environment that attempts to eliminate the amount of information about the structure of space by controlling for the amount of variation across an environment. This is achieved by using an environment proposed by Conroy Dalton (2001), which consisted of a uniform arrangement of streets, controlling for the relative length of each road (depicted in Figure 4.1, top left). In this model a demonstrably low correlation is observed between local extent and spatial configuration, $R=0.35$. This is to be expected as the uniform arrangement of streets leaves very little variation that can be accounted for by local extent.

This correlation can be enhanced by modifying the environment very slightly by including one or more spanning arterial road(s) (made to collect and transport traffic between distinct areas of an

environment), while otherwise preserving the road length and symmetry of the environment. When this is done, the association is found to be enhanced, $R=0.45$ and $R=0.58$, respectively. This suggests that at least part of the association may be driven the presence of *functional* roads designed to increase the efficiency at which a person can traverse the space.

Having demonstrated the effect of arterials, two possibilities arise: (1) the relationship is a result of arterial roads spanning distinct sections of space, or (2) the relationship is instead a more pure measure of how to identify arterials in nearby space. The first position can be investigated by progressively rotating each distinct block (lying in the northeast, northwest, southeast, and southwest, quadrants) to manipulate how unique each adjacent neighbourhood to the arterial roads. When this is done, no change in correlation is observed, reflecting that the type of spaces to which the arterials connect is not captured by the shared relationship. Next, the second position was assessed by testing progressively larger models, otherwise preserving symmetry and consisting of a single arterial across the center of the environment. In this case, the correlation between local extent and spatial complexity was found to reduce as a function of the distance from the arterial road or roads. In the original environment, the arterial roads were found within 50 meters and showed a moderate correlation of 0.58. When this distance is doubled to 100 meters, the observed association is found to be halved, $R=0.30$. When this distance is quadrupled to 200 meters, the correlation again is found to be reduced, $R=0.25$. This suggests that the relationship identified between extent and spatial configuration is not useful in identifying whether a road or path will take you to a different neighbourhood but instead is simply the product of how arterial roads function in space: spanning environments and allowing movement to be more efficient than would otherwise be possible.

Therefore, this simple example strongly suggests that the variables of local extent can serve to guide a navigator toward arterial roads found nearby (but outside the scope of the present field). In a space lacking any arterial roads, this relationship simply cannot exist. This was observed most strongly in the environments of NYC and the City of London because each environment consisted of numerous arterial roads and paths spanning distinct regions of the spaces. In contrast, a weaker relationship was observed in small-scale space because less space was available to span. Based on these findings, the relationship is not a product of the function of all space but is instead a product of *functional* or *designed* space.

Implicit in Space Syntax is the idea that people understand the function of space in some way (Hillier, 1996), and indeed the present findings are consistent with this view. However, the Depth

Afforded Navigation model differs from the configurational view of space by showing that individuals appear to be strongly guided by the extent of space itself rather than as a direct result of perceiving configurational affordances. Though the interplay between both factors is necessary to effectively describe and understand the layout of space, the perception of variables of local extent clearly provides some information about nearby spatial complexity within a reasonable distance. Elaborating on how this spatial information is perceived and acquired will need to be explored in future research. That said, the present data provides a convincing case for Depth Afforded Navigation to be a useful explanation for how we navigate familiar and unfamiliar spaces by recognizing the link between Depth and finding *useful* roads and pathways.

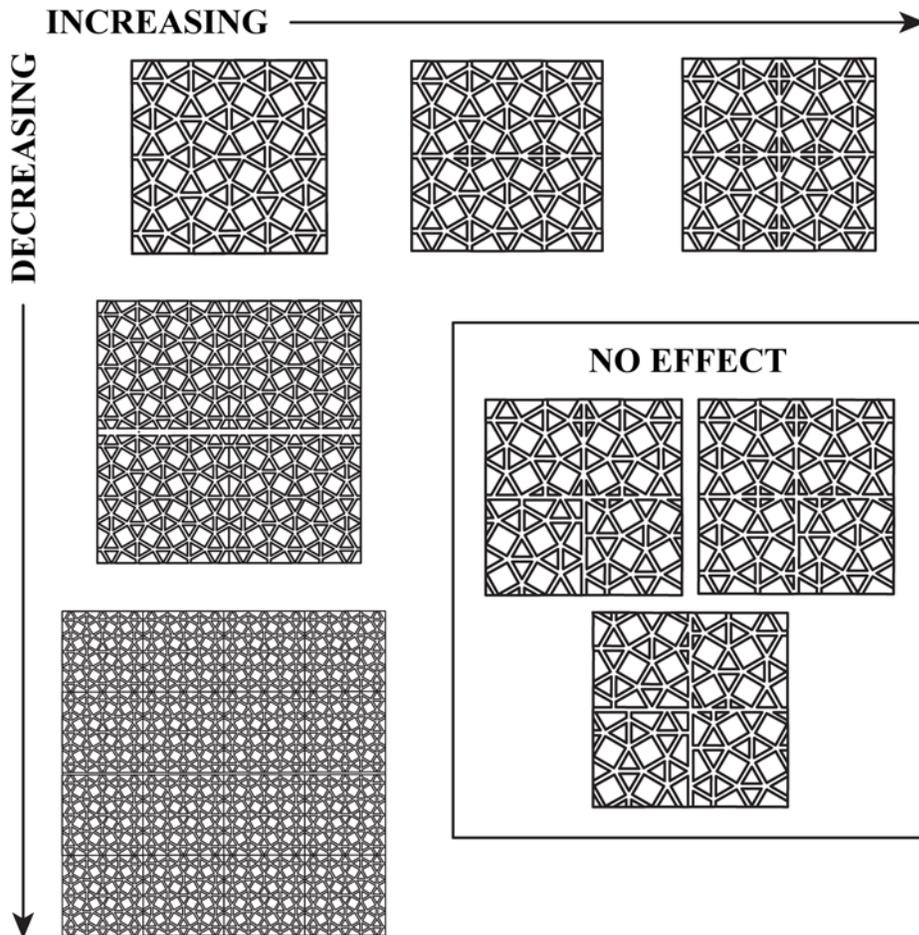


Figure 4.1 How systematic changes in the structure of a simple model alter the association between the latent factors of local extent and spatial configuration. Generally, an increase in association is observed when adding one or more arterial roads. In contrast, increasing the distance between arterial roads by expanding the size of the space 2x and 4x results in a decrease in association. There is no effect of varying the degree of local complexity or symmetry of each city block.

4.3 Relationship of the Results to Other Fields of Research

The results of the present work are relevant to a number of other complementary fields of research interested in accounting for how people may move through the world around them. While a number of areas could profit from the present work, I will highlight two: that of travel choices and that of desire lines.

One key area on which the Depth Afforded Navigation proposal could shed light is in the area of transportation research. Within transportation research, travel choices are often considered the product of *inertia*. When a person is making a choice during any type of travel, habit is expected to play some role, particularly when determining the utility of a mode of transport. Previous work has shown that the addition of a term that accounts for the influence of habit – inertia – into a utility function resulted in more accurate predictions in the mode of transport selected (Mackie, Fowkes, Wardman, Whelan, & Bates, 2001). Others have argued that the effect of inertia on travel decision making is the product of risk aversion (Chorus & Dellaert, 2012). These effects can be contrasted with influences produced by more immediate demands on a traveler. The present work provides a way to consider transportation decisions, at least when physically moving through the world, as a product of inertia as well as risk aversion. In this case, the affordance of movement through mean surface depth could be considered an *inertial* influence on travel behaviour. That is, a person enters unfamiliar and familiar environments with the affordance as a default, guiding factor, driving them to navigate to distinct locations. The degree of adherence and resistance to change (as introduced by more immediate demands or expectations of the environment) are important variables to consider when describing how transportation decisions are made in the presence of inertia. Here, no data exists yet to adequately describe how the affordance changes, though the choice of task showed no effect on the observed affordance relationships, suggesting some degree of resistance to change. Should this be found to be consistent, models of discrete travel behaviour could be better understood by considering Depth Afforded Navigation as an inertial factor. This would allow further precision to be developed within these models and better establish how travel decisions and affordance can interact to produce the behaviours that we see in the world around us.

A second area that could potentially profit from the present work is the study of *desire lines* in architecture and urban planning. Desire lines or desire paths created by foot travel, often deviating away from physical walkways, frequently increase the ease in navigating between an origin and a destination. These sorts of paths are commonly seen in a variety of areas, ranging from wilderness parks to university campuses. Only a few passages over a desire path are necessary to produce a distinct trail and attract further use from other travelers (Hampton & Cole, 1988). In the context of the present work, particularly in urban spaces, it is possible that desire paths are partially formed by a desire to maximize the Depth

Afforded Movement phenomenon described in this thesis. This would be particularly true in cases where the built walkways are either sparse or rigid in their placement. It is possible that desire paths are, in some way, steered toward mean surface depth and other properties of Local Extent when connecting an origin to a destination. Should this be the case, an even stronger understanding of the source of psychological drives like affordances and their influence on the creation of desire paths could be established potentially to improve design choices during the planning of urban spaces.

4.4 Limitations of the Current Research and Proposed Future Directions

The research presented in this thesis attempts to establish an understanding of how spatial navigation may be accounted for by affordance alone, from the ground up. As this work is an initial step into explaining the complex patterns of behaviours observed across space and attributed to its structure, a number of important limitations must be noted on the present findings.

Gibsonian affordances are typically used to capture behaviourally relevant relationships with specific stimulus qualities, such as stair riser height, door width, degree of graspability, etc., that occur regardless of the ability for the individual to perceive the actual level of the property. To achieve this, the affordance-invariant relationship must initially be learned (e.g., Montesano & Lopes, 2009) in order to see a person engage in the appropriately scaled behaviour. For example, an infant learns that the diameter and make-up of their hands is what allows them to grasp objects such as rocks across a relatively short time span. By generalizing affordance into a more complex domain than that of simple motor behaviour – that of navigation – we have assumed that the same basic learning must occur *at some point in life* in order for Depth Afforded Navigation to be realized. While the present work supports the concept of the use of affordances in navigation, it remains possible that a better account of behaviour can be established by accounting for spatial learning and experience in some way. One way this could be achieved is by investigating whether prior expectations about the make-up of the environment accord with those predicted by the relationship between local extent and spatial complexity.

Agent-based analyses could also establish the relationship between invariants and movements while controlling for or manipulating experience (and other factors) in specific terms to establish whether tendencies in how we navigate space are indeed the product of affordance. Studying the perception of specific visual properties more explicitly using visual search paradigms might shed light on how and when we pay attention to perceptual invariants in more explicit terms. In doing so, the fit between direct perception and navigation could be assessed even more concretely than was presented here, particularly with respect to the apparent relationship between Local Extent and Spatial Complexity.

Alternately, the perception of space could be studied *ex situ* to evaluate whether we intrinsically understand and engage the affordance of movement through depth or instead automatically engage in this process organically as we navigate physical space. One way this could be achieved is through picture studies prompting the participant to indicate preferred direction of movement without explicitly engaging in that movement. This would allow a more constrained test of the fit between the perceptual qualities of the environment and spatial preferences. This sort of decoupling has previously been used to establish whether aperture size alone could influence ratings of potential for movement without experiencing self-motion cues (Warren Jr & Whang, 1987). A similar approach could be employed here to evaluate whether self-motion cues are in any way required to observe Depth Afforded Navigation. One reason to think that self-motion cues may play a role is because locomotion through space has previously been shown to be heavily influenced by optic flow (Warren Jr., Kay, Zosh, Duchon, & Sahuc, 2001). As a person walks through space, the way that surfaces around him or her appear to translate provides meaningful information about the environment, such as which direction the person should head to maintain his or her heading (Wang & Cutting, 1999). While it is noteworthy that the demonstration of a tendency toward visually exploring depth when stationary was observed independent of movement, limiting the potential influence of gross self-motion cues, it remains possible that change in gaze alone could still provide adequate information to guide movement. Consequently, as a counterpoint to the study of affordance in more controlled and static cases, the evaluation of the influence of movement and optic flow must still be established.

It also remains possible that the latent factors underlying the model developed in Chapter Two, such as that of local extent and spatial complexity, may better predict individual and aggregate behaviour than that of the individual variables. In this case, rather than Depth Afforded Navigation driving behaviour, Local Extent Afforded Navigation may be more useful, particularly in simulation studies. The present analysis did not investigate this possibility, as the goal of this thesis was to identify *tangible* properties of space and establish whether they are employed when navigating. A latent factor does not fit this goal as it represents a composite of all the measures that it predicts, thus is less likely to be directly inferred from the local environment alone. This stipulation noted, the use of factor scores could help to establish fit with the present theory in more general terms, allowing a potentially more robust model to be established.

A stronger case for the lack of the effect of cognitive variables must also be established before this position can be fully accepted. While this is not essential to accept an affordance based model, it would help to elaborate on the precise psychological mechanism(s) participating in the affordance of movement. Experiment 4 did demonstrate that pause behaviour was influenced by individual differences in cognitive ability, but it is only a general test of the influence of cognition on the affordance process. A more

rigorous test of this relationship could be established through real-time psychophysiology during navigation to establish whether attention or cognitive demands are systematically related to visuospatial properties in any way. This sort of approach would help to determine the interaction between individual differences and Depth Afforded Navigation in more specific terms and would further highlight potential sources of error in the predictive power of the proposed model.

Finally, the use of virtual reality may have produced behaviour that is not entirely descriptive of real-world navigation. Several factors of virtual reality interfaces, including the size of the field-of-view offered by the head-mounted display, requirement for the navigator to cease movement to visually explore the nearby environment, and inability to vary movement speed, may result in the character of the findings not generalizing to real-world spaces, at least when considering how gaze related to the affordance function. Prior work on the efficacy of the properties of space syntax has shown considerable agreement with real-world data (Penn, 2003). Likewise, some agreement between the prediction that spatial preference is influenced by the property of area have been shown in the real world (Dzubic et al., 2013). These studies provide some level of confidence that virtual reality studies do generalize to real-world behaviour. However, to effectively rule out this limitation, real-world studies will be necessary.

4.5 Concluding Comments

The present body of work extends our understanding of spatial navigation by identifying a specific spatial property that appears to guide navigation in a variety of contexts and independent of the task being performed, characteristic of an affordance function. Prominently, it has been demonstrated that a great deal of navigation and spatial preference can be accounted for through the unitary spatial variable of mean surface depth, specified here as Depth Afforded Navigation. This finding is consistent with current research suggesting that expanse and complexity appear important in the way that we navigate and perceive the world around us, placing in question the earlier suggestions that we navigate space due to specific preferred sight lines or magnitude of area. The present work also identifies a potential for direct perception to be useful in the understanding of complex navigation behaviour by establishing a framework that progressively tests the assumptions required by ecological perception. While further testing would better elucidate the precise character of the relationship between the affordance of movement and mean surface depth, the common mechanism of depth and complexity are likely explainable by a common spatial mechanism – the inexorable link between the structure of local visual space and its predictive relationship with that of the overall configuration of the environment. Using this model, it is possible to account for a wide variety of movement choices in both intelligible and unintelligible spaces, shifting focus toward distinct spatial variables and away from that of explicit configuration. In doing so, future work will be better able to understand the success of previous

techniques, such as Space Syntax, agent-based analysis, and isovist analysis in predicting spatial behaviour, and allowing a potential unifying theory to account for findings derived from a wide variety of seemingly disparate empirical works.

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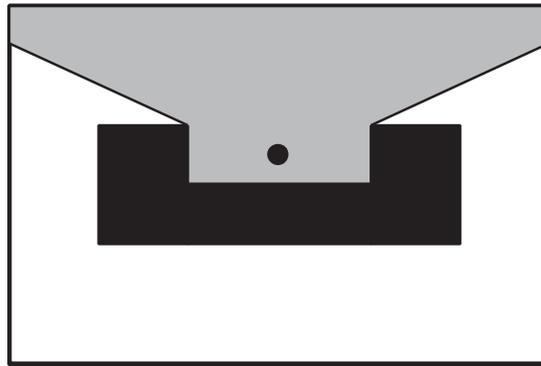
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Appendix 1

This supplement presents a more in-depth account of each variable used in Chapter Two. This is intended to accentuate the mathematical basis of each measure, as well as provide a visual depiction of how each measure captures a property of the structure of space. A table is also provided at the end of the appendix that summarizes what each measure captures, in general terms.

Describing Space Using Isovists

An isovist describes the shape of local visual space using a visibility polygon. The visibility polygon can be described in a number of ways, broadly classified here as capturing the extent of the polygon, shape, and other more complex factors. The mathematical basis for each measure is presented below. A figure is presented that on Page 156 for visual reference of all the variables at once. Below, a simple environment is presented and will be used to demonstrate each variable. The location of a person is indicated by a black dot, the shaded grey region is the visibility polygon, and the shaded black region is the footprint of a building.



Area

The area of an isovist can be computed through the *shoelace method*:

$$I_{AREA} = \frac{1}{2} \left| \sum_{i=1}^{n-1} x_i y_{i+1} + x_n y_1 - \sum_{i=1}^{n-1} x_{i+1} y_i - x_1 y_n \right|$$

where n is the number of sides of the polygon and (x_i, y_i) are the vertices of the polygon. Below, the area of the visibility polygon is depicted as hatch marks.



Perimeter

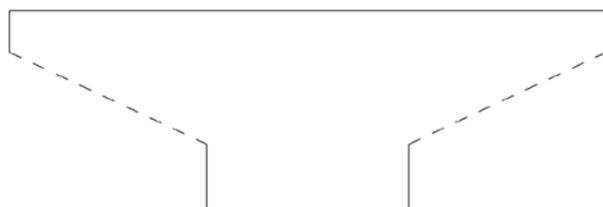
The perimeter is calculated as the sum of the distance between each point and its immediate neighbour on the isovist. The perimeter of a polygon is presented as dashed lines.



Occlusivity

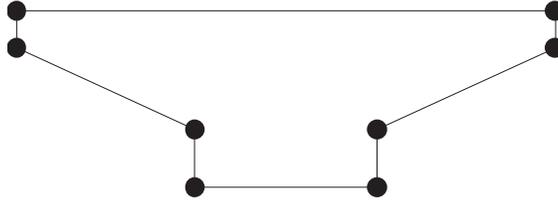
$$I_{occ} = \frac{P_{occ}}{P}$$

where P_{occ} is the perimeter lying on solid boundaries or occlusions and P is the total perimeter. The P_{occ} is depicted as solid lines. Lines lying in open space are depicted as dashed lines. Lines against a surface are depicted as solid.



Number of Vertices

The number of vertices is a simple count of the number of vertices necessary to define the polygon. This is depicted as black dots.

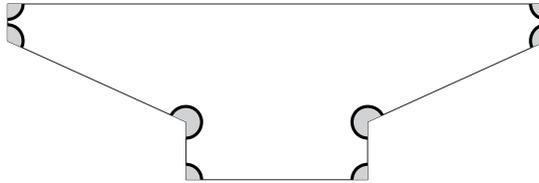


Tortuosity

The tortuosity, or degree of angular variation experienced as one traverses the isovist polygon, is computed as follows:

$$I_{TORT} = \frac{\sum_{i=1}^n \text{atan}\left(\frac{y_{i+1} - y_1}{x_{i+1} - x_1}\right)}{n \pi}$$

where n is the number of vertices and (x_i, y_i) are the vertices of the polygon. Each distinct angle is depicted as angular braces.

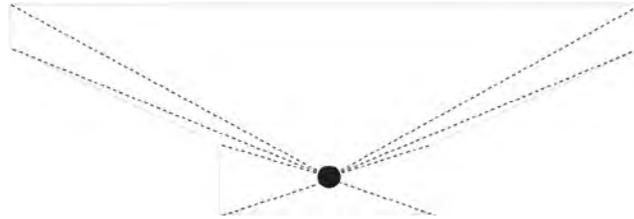


Entropy

The normalized entropy is computed as follows:

$$I_{ENT} = \sum_i N p_i \log\left(\frac{1}{p_i}\right)$$

where i is each distinct distance, N is the total number of vertices, p_i is the probability of observing a point at that distance within the sample. It can be normalized by dividing by N . This is depicted by the dashed lines radiating out to each distance, depicting the pattern of distances observed in the isovist.



Rectangularity

The rectangularity is determined by first calculating the minimum bounding rectangle (depicted in light grey). Next, it is computed as:

$$I_{RECT} = \frac{I_{AREA}}{R_w R_H}$$

where R is the width and height of the minimum bounding rectangle (depicted in light grey) against the I_{AREA} where is depicted as hatched lines.

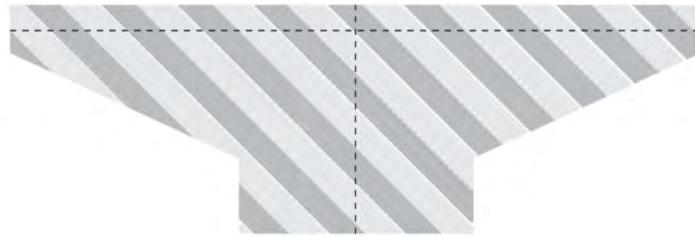


Compactness

The compactness is represented by the relation between the area of the isovist to the circumference of a circle (which itself is defined by the diameter of the isovist):

$$I_{COMP} = \frac{I_{AREA}^2}{2\pi\sqrt{i_{max} + i_{min}}}$$

where i represents the maximum and minimum span of the polygon. Within the thesis, the span was determined by computing the minimum and maximum antipodal distance through the *rotating calipers* algorithm but other methods also exist. The maximum and minimum span are depicted as dashed lines. Area is depicted as the hatched region.



Circularity

The circularity is an approximation of how much the isovist's shape matches that of a circle of matching perimeter (depicted, approximately, as a grey circle against the isovist as a visual analogue). The formula is as follows:

$$I_{CIRC} = \frac{4\pi I_{AREA}}{I_{PERI}^2}$$

where I_{PERI} is the perimeter of the isovist, and I_{AREA} is the area. This method is a basic form of the *isoperimetric quotient*, which describes how much a curve approximates a circle.



Convexity

Convexity is the relation between the area of the isovist to that of a convex hull:

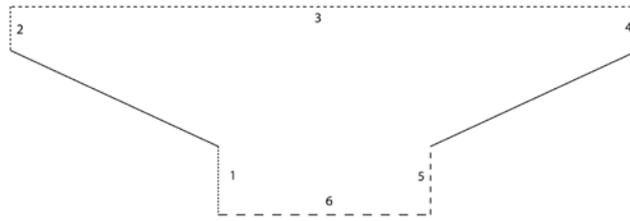
$$I_{CONV} = \frac{I_{AREA}}{I_{HULL}}$$

where I_{AREA} is the area of the isovist and I_{HULL} is the area of a convex hull sufficient to enclose all points on the polygon. The convex hull was determined through *rotating calipers*. The convex hull is depicted in light grey against the hatched region, which is the area of the original isovist.



Surface Count

Surface count is simply the count of each unique surface that defines the isovist. These are depicted as dashed lines of different widths and have been numbered to highlight those which are unique.

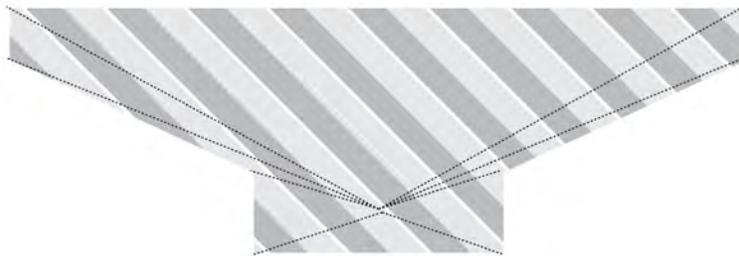


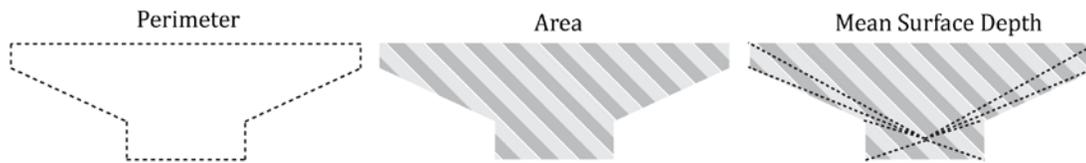
Mean Surface Depth

Mean surface depth is computed as:

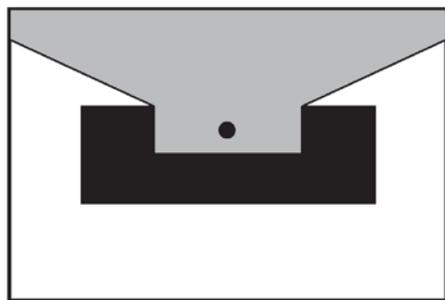
$$I_{MSD} = \frac{I_{AREA}}{SC}$$

where I_{AREA} is the area of the isovist divided by the surface count (SC). Each unique surface depth is depicted as a triangular segment of the isovist.

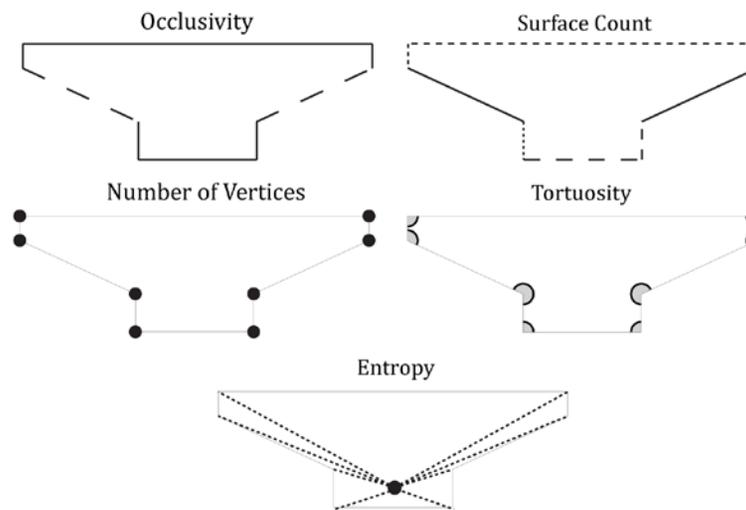




VARIABLES OF EXTENT



VARIABLES CAPTURING ELEMENTS OF STRUCTURE

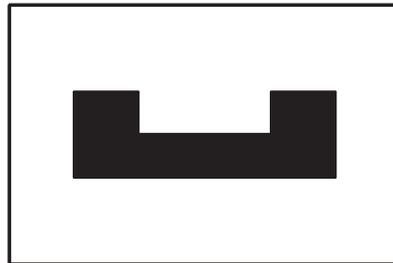


VARIABLES OF SHAPE

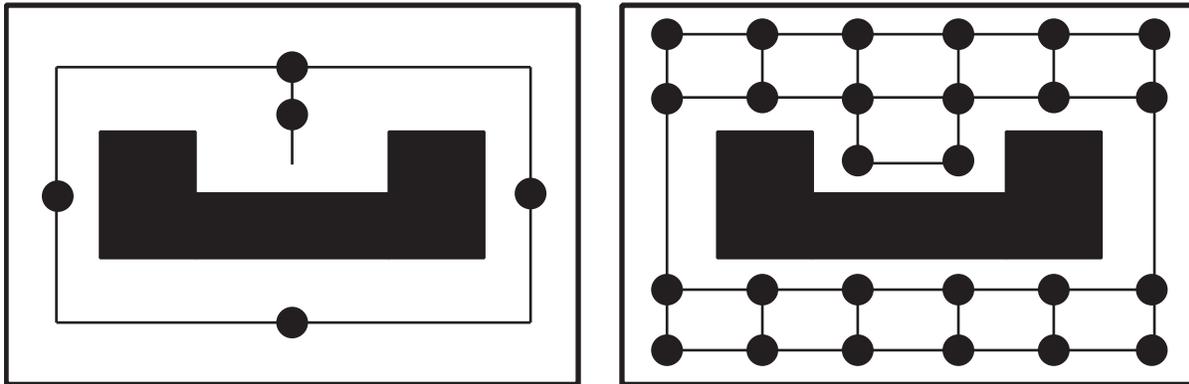


Describing Space Using Space Syntax and Accessibility:

The structure of the layout is again presented below but this time without an isovist:



The axial map and accessibility graph of the simple environment are presented on the left and right respectively.



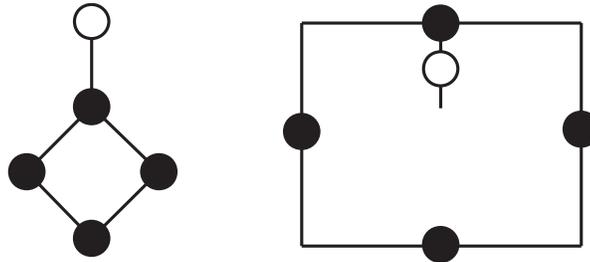
Dots on the axial map indicate each axial line. Dots on the accessibility graph indicate nodes in the graph (locations that can be occupied). The lines connecting each dot depict movement possibilities. Many of these measures can be computed out to a certain distance (traversing a certain number of nodes), making the methods either more precise at predicting behaviour or reducing the computation time.

Space Syntax Measures

To the left of each axial map is a simplified depiction of the graph, where the shape of the path or edge has been discarded. This is sometimes termed a *j-graph* in space syntax analysis.

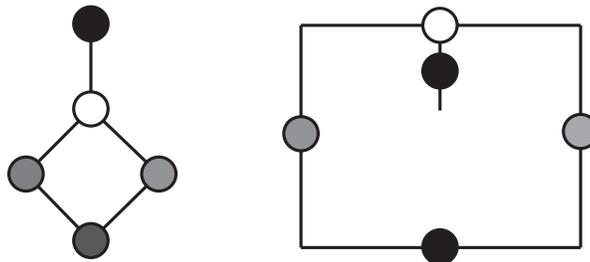
Connectivity

Connectivity is the simple count of how many other paths each path intersected with. This is depicted in the figure where white is low and black is high.



Mean Depth

The mean depth of each unique path (each dot) is the distance of the shortest path necessary for to travel to reach all other paths in the graph divided by the number of paths traversed. This is depicted where white is low and black is high.



Integration

Integration is the mean depth divided by a diamond graph of matching size. This is not depicted in the figure. The method and its relation with the normalizing factor drawn from the diamond graph is thoroughly described elsewhere (Park, 2005).

Angular Deviation

The angular deviation of the graph is defined as:

$$G_{ADEV} = \frac{1}{n} \sum_{i=1}^n \text{atan}\left(\frac{y_{i+1} - y_1}{x_{i+1} - x_1}\right)$$

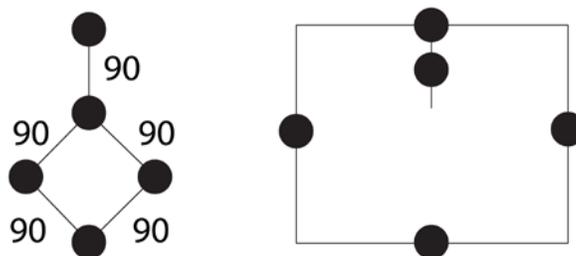
where n is the number of axial lines and (x, y) is slope of each line. This is depicted on the *j-graph*.

Angular deviation is then weighted by mean depth.

$$G_{AVAR} = \sqrt{\frac{\sum_{i=1}^n \text{atan}\left(\frac{y_{i+1} - y_1}{x_{i+1} - x_1}\right) - G_{ADEV}}{n - 1}}$$

where (x, y) is the slope of each axial line, G_{ADEV} is the mean angular deviation, and n is the total number of axial lines.

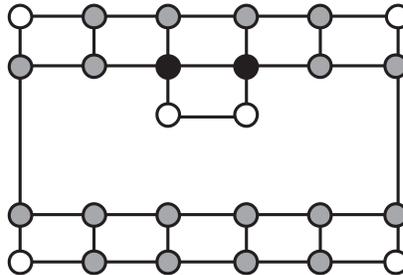
All dots on the graph are depicted in black as the mean angular deviation is constant for this axial map.



Accessibility Measures:

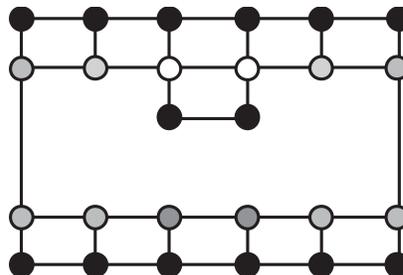
Degree Centrality

The degree of each node in the graph is the number of edges incident upon the node. This is depicted where black is high and white is low.



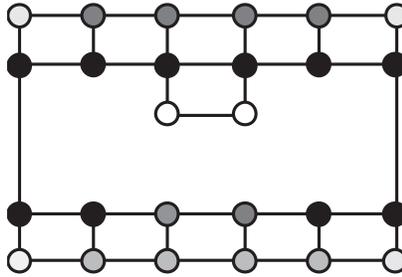
Closeness Centrality

Closeness centrality is the reciprocal of mean depth. It is normalized by $n-1$. This is depicted where black is high and white is low.



Betweenness Centrality

Betweenness centrality is defined as the sum of the total number of shortest paths that traverse a particular node, divided by the total number of shortest paths. It is normalized by $(n-1)(n-2)/2$ where n is the total number of nodes. This is depicted as black where betweenness is high and white when low.



Eigenvector Centrality

For the accessibility graph, eigenvector centrality is determined as:

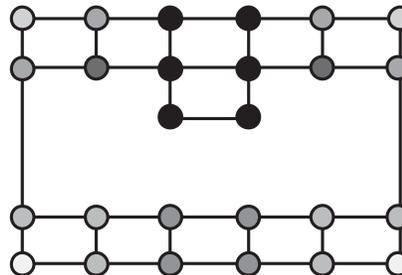
$$x_v = \frac{1}{\lambda} \sum_{t \in M(v)} x_t$$

$$x_t = \frac{1}{\lambda} \sum_{v \in G} A_{v,t} x_v$$

such that, $A^t x = \lambda x$

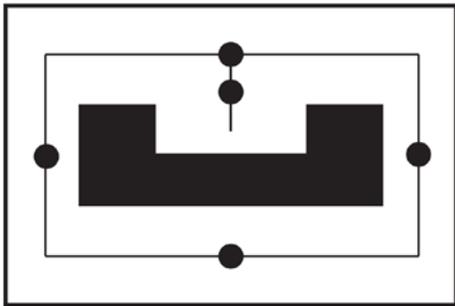
where for graph G , each node t and v , the eigenvector centrality is determined for the neighbourhood, $M(v)$ of t , with the adjacency matrix A and (with 1s indicate an edge exists between nodes and 0 indicates no edges), and eigenvalue of λ . As seen above, this is recursive, reducing the a graph to a weighted sum of the amount of connection between a node and its neighbours.

This is depicted on the accessibility graph where black indicates locations of high eigenvector centrality and white low.

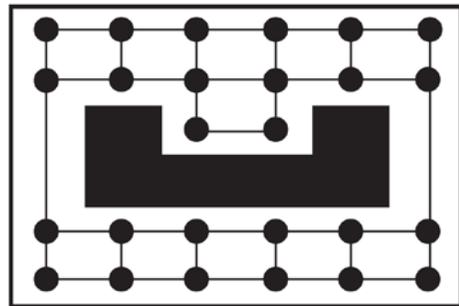




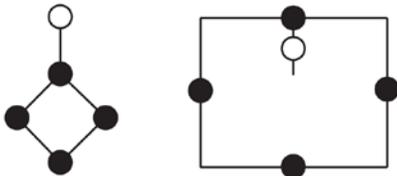
AXIAL MAP



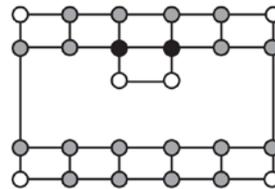
ACCESSIBILITY GRAPH



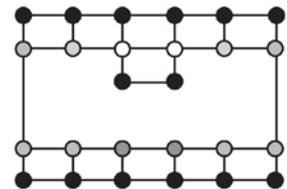
Connectivity



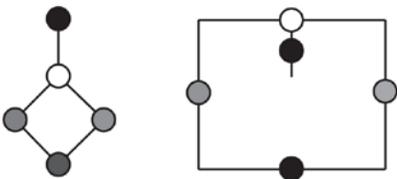
Degree



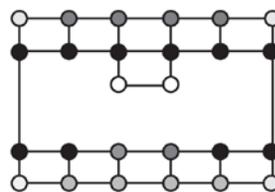
Closeness



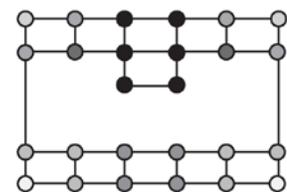
Mean Depth



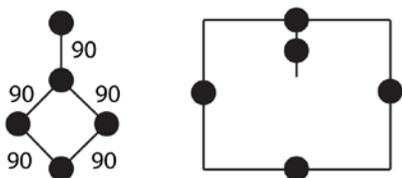
Betweenness



Eigenvector



Mean Angular Distance



The general interpretation of each of these measures is as follows:

	Scope	Description
Axial Maps		
Connectivity	Local	Number of adjacent paths
Mean Depth	Global space	Mean distance traversed to reach all other paths
Integration	Global space	Mean depth weighted by a symmetric diamond graph
Mean Depth-3	Global space	Mean depth, considering only those paths within 3 steps
Integration-3	Global space	Integration, considering only those paths within 3 steps
Angular Analysis		
Mean Deviation	Global space	Mean turn angle necessary to reach all lines within a radius of 3
Mean Variance	Global space	Mean variance in the turn angle experienced when traveling to all lines within a radius of 3
Accessibility Graph		
Degree	Local space (metric)	Number of directions available to travel at a specific point
Closeness	Global space (metric)	Mean number of meters traversed to reach all other locations by shortest paths
Betweenness	Global space (metric)	Mean number of paths crossing through the point when traveling to all other positions in the graph
Eigenvector	Global space (metric)	How well the position is connected to other equally connected positions
Isovist		
Vertices	Local space	Number of edges in the visible area
Area	Local space	Extent of the visual field
Perimeter	Local space	Size of boundary
Occlusivity	Local space	Relative amount of boundary lying in closed space
Entropy	Local space	Magnitude of randomness in the position of isovist vertices
Tortuosity	Local space	Angular variation per unit of perimeter
Convexity	Local space	Amount of deviation away from a perfect convex polygon
Circularity	Local space	Amount of deviation away from a perfect circle
Rectangularity	Local space	Amount of deviation from a rectangle of matching size
Surfaces	Local space	Number of discrete edges or surfaces lying in obstructed space
Surface Depth	Local space	The ratio of the surrounding area to the number of surfaces visible

Appendix 2

Detailed results of EFA for Study 1

Factor:	Unrotated Matrix					Rotated Matrix										h ²
						Pattern Matrix					Structure Matrix					
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	
Connectivity	0.85		0.51			0.91					0.99	-0.43	0.31	0.55	0.34	0.98
Integration-3	0.84		0.52			0.92					0.98	-0.41	0.31	0.53	0.38	0.97
Mean Depth-3	-0.82		-0.45			-0.92					-0.93	0.44		-0.56	-0.33	0.87
Ang. Variance	0.75		0.45			0.93					0.88	-0.44		0.46		0.79
Closeness	0.50								0.55		0.46	-0.36		0.57		0.39
Betweenness	0.51	0.60			-0.32			0.87					0.90	0.41	0.57	0.82
Eigenvector	0.47	0.56	0.34		-0.35			0.90					0.88	0.38	0.51	0.79
Vertices	0.83			0.46					0.99		0.60	0.56	0.53	0.96	0.31	0.98
Area	0.56	0.77								0.81	0.38		0.72	0.36	0.96	0.97
Perimeter	0.82	0.34		-0.32				-0.41		0.68	0.60	-0.61	0.62	0.57	0.84	0.96
Entropy	0.41			0.49					0.88					0.67		0.50
Convexity	-0.55	0.64	0.42					0.95			-0.34	0.96		-0.45		0.97
Circularity	-0.67			0.39				0.79		-0.31	-0.50	0.83		-0.49	-0.33	0.77
Rectangularity	-0.53	0.58	0.41	0.30				0.92			-0.32	0.92		0.42		0.90
Surfaces	0.75								0.35	0.49		0.52	-0.56	-0.60	0.78	0.70
Depth		0.80		-0.33						0.90		0.32				0.75
λ	6.90	3.05	1.87	1.43	0.80											
% Variance	43.3	62.4	74.1	83.1	88.1											

Correlation Matrix

Factors:	1	2	3	4	5
1	-	-0.48	0.31	0.58	0.36
2		-	-0.23	-0.57	-0.15
3			-	-0.50	0.56
4				-	0.26

Note. All factor loadings below 0.30 have been suppressed.

Detailed results of EFA for Study 2

Factor:	Unrotated Matrix					Rotated Matrix										h ²
						Pattern Matrix					Structure Matrix					
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	
Connectivity	0.82	-0.43	0.35			0.99					0.99	-0.41	0.55		0.54	0.97
Integration-3	0.80	-0.44	0.34			0.96					0.98	-0.40	0.54		0.54	0.96
Mean Depth-3	-0.76	0.45				-0.89					-0.93	0.41	-0.54		-0.49	0.87
Ang. Variance	0.68	-0.37	0.31			0.88					0.86	-0.36	0.40		0.49	0.74
Closeness	0.52							0.57			0.48	-0.32	0.59		0.31	0.42
Betweenness	0.54	0.70			-0.35				0.94				0.41	0.98	0.60	0.97
Eigenvector	0.48	0.63							0.73				0.40	0.84	0.57	0.73
Vertices	0.81			0.54					0.99		0.50	-0.54	0.98	0.36	0.58	0.96
Area	0.83	0.44								0.86	0.51	-0.50	0.67	0.63	0.98	0.95
Perimeter	0.90						-0.35			0.68	0.58	-0.78	0.72	0.40	0.92	0.98
Entropy	0.37			0.60				0.91		-0.33			0.62			0.50
Convexity	-0.63		0.70					0.98			-0.30	0.97	-0.46		-0.40	0.97
Roundness	-0.69		0.46					0.70			-0.49	0.83	-0.54		-0.50	0.74
Rectangularity	-0.60		0.67					0.98				0.93	-0.41		-0.39	0.90
Surfaces	0.80			0.34					0.71		0.48	0.61	0.87	0.42	0.61	0.80
Depth		0.39	0.39	-0.47					-0.57	0.88				0.40	0.56	0.60
Λ	7.47	2.26	2.03	1.63	0.68											
% Variance	46.7	60.1	73.4	83.6	87.9											

Correlation Matrix

Factors:	1	2	3	4	5
1	-	-0.41	0.53	0.11	0.54
2		-	-0.58	-0.16	-0.53
3			-	0.32	0.58
4				-	0.52

Note. All factor loadings below 0.30 have been suppressed.