UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

ANALYSIS OF SPACE, COGNITION AND PEDESTRIAN MOVEMENT

A DISSERTATION

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

DOCTOR OF PHILOSOPHY

By

YING ZHANG
Norman, Oklahoma
2019

ANALYSIS OF SPACE, COGNITION AND PEDESTRIAN MOVEMENT

A DISSERTATION APPROVED FOR THE
GRADUATE COLLEGE

BY

Dr. K. Meghan Wieters, Chair

Dr. Dean Hougen

Dr. Scott Gronlund

Dr. Jeffrey Widener

Dr. Charles Warnken

Acknowledgement

I would like to acknowledge several special people without whom this dissertation would not have been possible. I would like to express the deepest gratitude to my committee chair Dr. Meghan Wieters, whose profound knowledge and scholarly experience have guided me throughout my dissertation writing. I deeply appreciate her advice and support during the last several semesters, without which this work would not have been completed. I also appreciate Dr. May Yuan for offering me advice that helped me to design the empirical study and giving me her support for research grant applications. I also would like to express my thanks to Dr. Scott Gronlund for his comments of survey design and support of IRB application. Thanks to Dr. Dean Hougen and Dr. Guoqiang Shen for their comments and suggestions. Thanks also to Dr. Jeffrey Widener and Dr. Charles Warnken for kindly serving in the committee and offering advice after two former committee members left the university.

I also want to express my appreciation to Center for Spatial Analysis. Many thanks to my colleagues and friends Dr. Marguerite Keesee, Melissa Scott, and Leah Nash for encouragement and support throughout my graduate studies.

I want to thank my husband Chenxi, my daughter Yina and my parents for their love, support, and help throughout my graduate studies. Thanks to my friends in China and the United States. Special gratitude goes to participants who generously shared their experience, knowledge, and time.

Table of Contents

List of Tables

List of Figures

Abstract

Understanding the movement of people in urban areas is one of the most significant issues on spatial science with a wide range of applications in urban design, public health, public safety and intelligent transportation system. Urban planners, cognitive scientists, computer scientists, and geographers have contributed to an understanding of pedestrian movement from aspects of configurational analysis, knowledge representation, computational models, and space-time patterns respectively. However, no previous studies provide comprehensive solutions to pedestrian movement taking both space and cognition into account. Combining these disciplines allows us as researchers to not only explain correlations between spatial layouts and pedestrian flows but also understand how and why environmental perception and spatial knowledge are used by pedestrians to orient themselves and navigate through space.

My research proposes a theoretical framework of space, cognition and movement to fill in interdisciplinary gaps of pedestrian movement studies. The core of this framework lies in the hypothesis that where people choose to hold activities and how people choose to get there depends on individuals' cognitive maps of the environment. This cognitive map consists of the salient layout of spatial features as well as the prominent utilities afforded by these features. The analysis proceeds from three dimensions: (1) space syntax to characterize spatial configuration or structure, (2) space semantics to address the distribution of activities, and (3) spatial cognition to capture one's knowledge about the space.

The proposed framework was used to guide an empirical study conducted at the University of Oklahoma Norman Campus. Space was characterized by two aspects of space syntax and space semantics. For syntactical analysis, the study not only used measures of network centrality to examine network effects on pedestrian movement but also improved them by varying concepts of distance, adding distance decay effects, and weighting spatial heterogeneity of activities. Betweenness centrality calculated by the shortest length and weighted by distance decay effects resulted in the best description of observed pedestrian flows. In semantical analysis, functional centrality was described by density and diversity. Only functional density significantly contributed to modeling pedestrian flows. This study provided evidence that pedestrian movement depended on the spatio-functional interactions. The distribution of activities not only took the location advantage provided by spatial configuration but also reinforced network effects on pedestrian movement. This study not only examined aggregated patterns of pedestrian movement but also investigated individual variations in cognitive maps and wayfinding behaviors. The sketch map analysis suggested that as people became more familiar with the environment, the increase of completeness and accuracy was observed in their cognitive maps. Completeness was described by number of landmarks in sketch maps while accuracy concentrated on the relative positions between pairs of landmarks. Landmark served as the organizing concept of cognitive map. Betweenness centrality, functional density, and familiarity significantly contributed to modeling the presence of landmarks. When landmarks were used in navigation, this study developed a landmark-based pathfinding method. Landmark-based pathfinding resulted in a better description of routes selected by survey participants. In sum, individual cognitive maps, particularly the organization of landmarks, serve as the core in determining where pedestrians choose to hold activities and how to get there. Finally, the study developed the conceptual agent-based model (ABM) for pedestrian movement. The core of this ABM lies in a cognizing agent that is able to solve pathfinding tasks based on perceptual information and knowledge of cognitive map.

The research outcomes not only improve the understanding of spatial and cognitive factors on pedestrian wayfinding but also contribute to several disciplines. Architects and urban planners can adopt the framework of pedestrian movement to test, assess and improve existing spatial layouts and possible design alternatives. Computer scientists and Geographic Information System developers can use the specification of cognitive map to implement landmark based navigation system. Cognitive scientists and psychologists can apply the comprehensive model of pedestrian movement in research on human wayfinding behaviors for people with different perceptual abilities.

Keywords: Pedestrian Movement, Space Syntax, Space Semantics, Spatial Cognition, Network Centrality, Functional Density, Functional Diversity, Landmark, Agent

Chapter 1: Introduction

An urban area is a planned yet evolving settlement with rapid traffic flows of people, commodities and information. Understanding the movement of people in urban areas is one of the most significant issues on spatial science with a wide range of applications in urban design, public health, public safety and intelligent transportation system. Aggregated patterns of human movement result from the sum of individual behaviors for spatial navigation. Finding one's way in unknown or familiar environments is a common task that people experience in daily lives. The urban configuration can facilitate or limit one's navigation, depending on the structures and characteristics of physical elements in the city (Hillier & Hanson, 1989; Lynch, 1960). The impacts of spatial configuration on navigation behaviors are grounded in the way how people recognize this urban environment in their minds. More precisely, where to go and how to get to the destination are determined by spatial knowledge and spatial experiences through interactions with built environments. To date, however, the role of spatial configuration and spatial knowledge on pedestrian movement were examined separately in different fields and disciplines. Urban planners, cognitive scientists, computer scientists, and geographers have contributed to an understanding of pedestrian movement from aspects of configurational analysis (Hillier, Penn, Hanson, Grajewski, & Xu, 1993; Bin Jiang & Claramunt, 2002), knowledge representation (Lynch, 1960; Montello & Sas, 2006), computational models (Freksa, 1992; Kuipers, Tecuci, & Stankiewicz, 2003), and space-time patterns (Kwan, 1998; Miller, 1999) respectively. The knowledge gap about how do three domains - spatial configuration, spatial experiences, and spatial knowledge - interact with each other and their roles in shaping pedestrian movement has not been extensively explored.

The purpose for this study is twofold. On the one hand, we are concerned with the scientific question about how movement, particularly pedestrian movement, relates to space and cognition. Previous coarse-scale movement studies (Hu & Lo, 2007; Stead & Marshall, 2001) using aggregated, top-bottom approaches were weak in revealing spatial and temporal details and were criticized for ecological fallacy (Wrigley, Holt, Steel, & Tranmer, 1996) and modifiable areal unit problems (MAUP) (Openshaw, 1983). This study takes a bottom-up approach to explore how pedestrian movement relates to space and cognition. Specifically, how do spatial configuration and spatial experiences lead to differences in knowledge about the space, and moreover to the formation of movement patterns in space. On the other hand, we are proposing a practical tool through agent based modeling, which allows us to test the network, functional and psychological effects on pedestrian movement. This model can be used to guide the simulation of wayfinding tasks in real world or in layout plans even before the construction of built environments, which makes it possible to determine where on the network attracts more pedestrians, why pedestrians select particular routes and how to design the network to assist in pedestrian wayfinding.

This study attempts to bring spatial, behavioral and psychological dimensions into a single methodological framework for pedestrian movement. This framework aims to explain how a pedestrian finds a specific destination in a familiar environment when they have different environmental perception and bounded rationality due to limits of cognitive capabilities. The research design rests on the hypothesis that spatial configuration and spatial experiences influence the development of spatial knowledge, and furthermore, spatial knowledge contributes to pedestrian movement. Therefore, this study breaks the analysis into three components: space syntax, space semantics, and spatial cognition. Specifically, space syntax is characterized by the configurational layout of roads, buildings, open space and other spatial features, particularly how a spatial feature is separated or clustered with other spatial features in the network. Space semantics describes possibilities of functions or activities that can occur in the specific location, such as land use types of residential, commercial, industrial, transportation, and business regions or activities of living, working, commuting, shopping, eating and recreation. Spatial cognition refers to knowledge of space, particularly what critical spatial structures and meaningful places are stored in mind, and how to use these salient features along with environmental perception to guide pedestrian navigation. Based on these three components, the two key research questions are:

- What aspects of spatial cognition have measurable differences along with variance in spatial configuration measures (space syntax) and spatial affordance measures (space semantics)?
- What aspects of spatial cognition have measurable impacts on movement patterns?

This work proposes a comprehensive framework for pedestrian movement to analyze and simulate information needs for decision making in pedestrian navigation. This framework focuses on network and psychological effects on performing navigation tasks in a familiar environment. The major scientific contributions are:

- a theoretical framework of space, cognition and movement to fill in interdisciplinary gaps of pedestrian movement studies among fields of urban planning, geography, cognitive science and artificial intelligence;
- a methodological approach to derive and select syntactically and semantically salient features captured in cognitive map;
- a landmark-based pathfinding method to find the ‘optimal’ route with the least cognitive load, and
- a conceptual model for agent-based pedestrian wayfinding simulation that is grounded in human perception and cognition.

The research outcomes are expected to not only improve the understanding of spatial and cognitive factors on pedestrian wayfinding but also contribute to several disciplines. It is targeted in particular at researchers in the following areas:

- Architects and urban planners can adopt the framework of pedestrian movement to test, assess and improve existing spatial layouts and possible design alternatives.
- Computer scientists and Geographic Information System (GIS) developers can use the specification of cognitive map to implement landmark based navigation system.
- Cognitive scientists and psychologists can apply the comprehensive model of pedestrian movement in research on human wayfinding behaviors for people with different perceptual abilities.

The organization of this dissertation includes this chapter, Chapter 1, which has introduced the concepts, research questions, expected outcome, and the intended audience for this study.

Chapter 2 reviews previous research concerning the modeling of pedestrian movement. First, we discuss quantitative methods to describe syntactical properties of network where pedestrian wayfinding takes place. We then give an overview of affordance theories which provide functional interpretation of places over the network. Furthermore, we describe models of human spatial cognition which underlies all processes of wayfinding tasks. All of the presented theories and concepts are linked to the comprehensive framework of space, cognition and pedestrian movement developed in this study. Finally, we present relevant concepts from artificial intelligence and empirical studies using agent based modeling techniques.

Chapter 3 explains the methodology and approaches used in this work. An empirical analysis was conducted at the University of Oklahoma Norman Campus. The main task for the empirical study is to explain what kinds of syntactically and semantically salient features are captured by cognitive map and then used in wayfinding decision making.

Chapter 4 shows the results and analysis from the empirical study. First, we conduct syntactical analysis to explain network effects on pedestrian movement. Space syntax analysis here focuses on network centrality but is further improved by considering spatially heterogeneous origin-destination (OD) distribution and distance decay effects. We then describe the distribution of activity densities and perceived use of space. After that, we continue to examine the relationships between form and function, and identify impacts of spatio-function interactions on pedestrian movement. Furthermore, we show these syntactically and semantically salient features are expressed in cognitive maps represented by sketch maps. We specify methods to measure the salience of features from aspects from visual attraction, syntactical prominence and semantic significance. This study provides evidence that selected salient features, strongly correlated with human concept of landmark, play an important role in pedestrian wayfinding particularly destination preference and route selection. Finally, we develop a conceptual model of pedestrian movement using agent based techniques and allow pedestrian agents to understand knowledge of space in terms of cognitive map.

Chapter 5 first summarizes the work done in this study. We then present the major findings of our research. This chapter discusses limitation of this study and concludes with possible directions for future works.

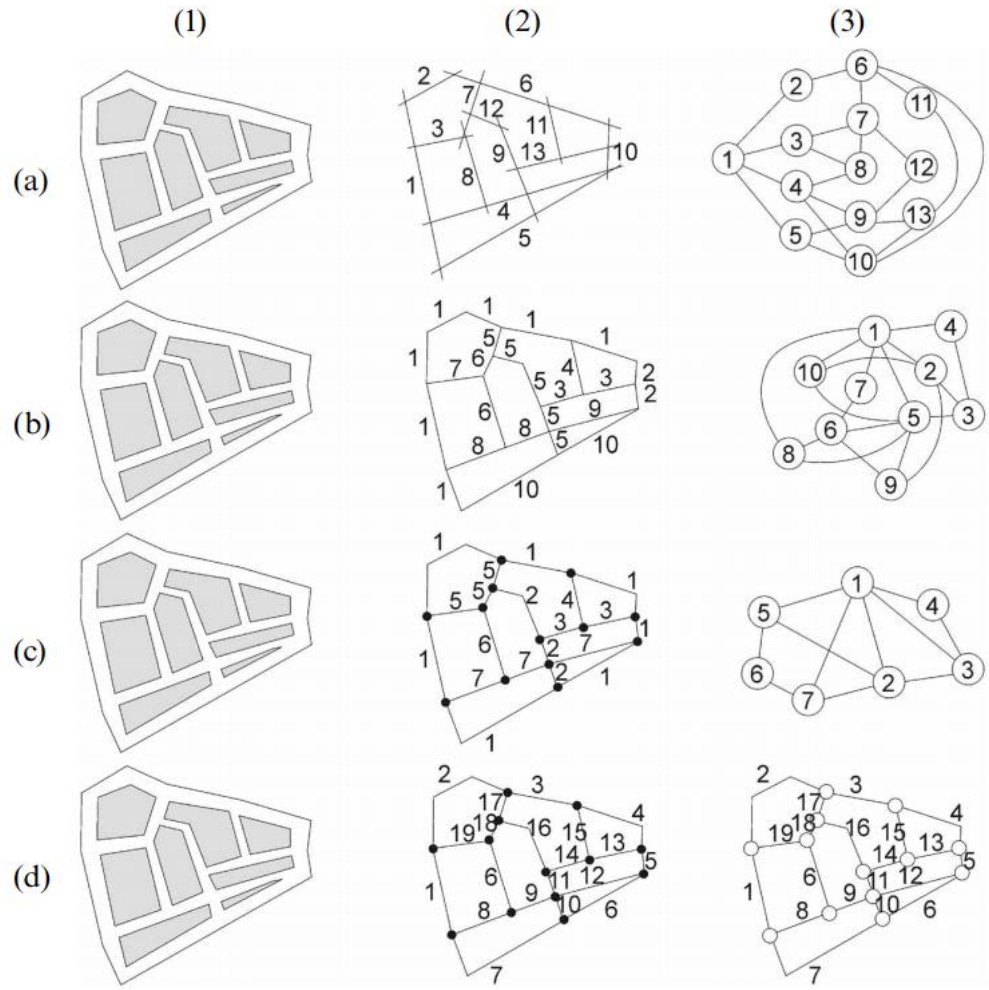
Chapter 2: Background

This chapter presents the scientific background on pedestrian movement research and relates it to the work done in this study. Spatial syntax describes the configuration of physical network in which pedestrian moves and is therefore introduced first. On one hand, pedestrian movement is constrained by the form of this walking grid. On the other hand, pedestrians interact with places over the network based on the meaning people assign to them. The chapter continues with the discussion of modeling places with affordances. Spatial knowledge underlies all processes of pedestrian movement. We then review different aspects relevant to spatial cognition: mental representation, computation models and sketch map analysis. The final part of this chapter is devoted to relevant concepts of agent based modeling.

2.1 Space syntax

Spatial configuration describes how spatial elements including buildings, open spaces and street networks are linked to construct a global pattern of urban form. This urban form is the environmental medium that people perceive, through which they further interpret the meanings of places. Space syntax analysis provides a quantitative framework to measure spatial configuration. There syntactical properties were found to be significantly correlated to pedestrian and vehicle movement in urban space (Hillier et al., 1993; Bin Jiang & Claramunt, 2002; Turner, Doxa, O'sullivan, & Penn, 2001).

The initial idea of space syntax analysis relies on the convex partition of urban space and the representation of axial lines. Axial lines are drawn as the longest and fewest straight lines passing through all convex elements within open space where people can freely move (Hillier & Hanson, 1989). For each axial line, it essentially represents directions of uninterrupted visual access and straight segments of movement. A collection of mutually intersected axial lines that pass through the whole free space constructs axial map. Syntactical measures with axial line based approach are derived from dual graph of axial map called connectivity graph (Bafna, 2003; Bin Jiang & Claramunt, 2002). Row (a) in Figure **1** demonstrates the mapping from the urban structure (column (1)) to the axial map (column (2)) and further the conversion to the connectivity graph (column (3)). As shown in row (a) column (1), urban structures are abstracted by grey areas of building blocks and white areas of roads. In row (a) column (2), network is identified though the longest straight paths available in road areas. Then the connectivity graph is established in column (3) for network analysis where nodes and edges represent axial lines and the intersections between lines respectively. Distances from an axial line to others are specified by number of turns (i.e., edges) between them. In order to increase representation resolution of street network, axial lines are chopped at each junction into axial segments (Dalton, 2001; Turner, 2001a). As for the transformed connectivity graph, nodes represent axial segments while edges are weighted by the angle of connecting pairs of axial segments. Although widely used in earlier studies of space syntax analysis, the generation of axial maps was criticized for sensitivity to boundary condition and deformation of urban grid (Bin Jiang & Liu, 2010; Ratti, 2004). Additionally, space syntax studies used to rely on hand-drawn axial map (Hillier & Hanson, 1989) until automatic generation of axial lines were developed (Batty & Rana, 2004; Bin Jiang & Liu, 2010; Turner, Penn, & Hillier, 2005). But how to generate axial map is still controversial which makes it hard to provide reliable and comparable results (Desyllas & Duxbury, 2001). Therefore, alternative representations of street network and visibility graph are put forward.

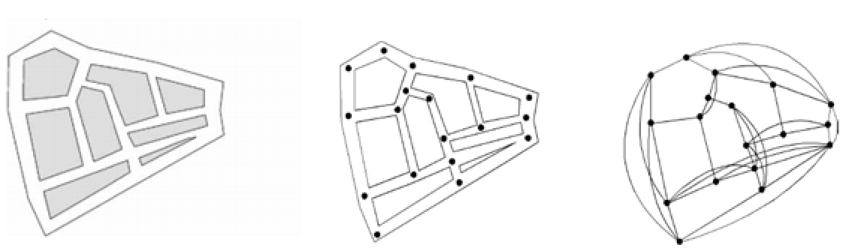


(Bin Jiang, 2007; Bin Jiang & Claramunt, 2004)

Figure 1 Comparison of axial map and street network based approaches
(a1, b1, c1, d1) urban structure; (a2) axial map; (b2) named streets; (c2) natural streets; (d2) street network; (a3, b3, c3, d3) connectivity graph

Street network based approaches provide an intuitive way of analyzing spatial configuration using road center line maps. In traditional representation of transportation modeling, urban network is perceived as a spatial graph (i.e., primal graph) whose nodes have precise positions of street junctions in two dimensions and edges are street segments. Street network based approaches provide a different perspective of space syntax analysis from axial line based approaches in that the primal graph can work with not only topological relations but also metric distances. The primal graph also overcomes the shortcoming of dual graph that a single value for a long axial line is too limited to represent complex urban structures (Ratti, 2004). However, Batty (2004) argued that measuring urban structure was not a primal but a dual problem of morphology. Primal representation of street network is neither the way how people perceive the urban structure nor able to uncover meaningful patterns of configuration (Bin Jiang, 2007). To simplify street network and construct dual graph of street network, individual segments are merged into meaningful streets, which leads to two additional representations of natural streets (Bin Jiang, 2007; Thomson, 2004) and named streets (Bin Jiang & Claramunt, 2004). As shown in Figure **1** row (c), natural streets are derived from merging adjacent street segments based on thresholds of continuation. Figure **1** row (b) represents named streets merging segments by street names.

The third type of approaches is based on viewshed, which shifts syntactical analysis from street network to a single point of view. Viewshed based approaches provide a solution to combine axial lines and street network in the framework. As for the viewpoints representation of space syntax, nodes in connectivity graph can be either intersections of axial line (Batty, 2004) or junctions of road segments (Bin Jiang & Claramunt, 2002), which are essentially syntactical salient points. Edges represent inter-visibility or inter-accessibility between two points (see Figure **2**, below). This viewpoint representation is as efficient as axial line and street network approaches in describing urban structures. Additionally, it provides a richer interpretation for pedestrian movement as these syntactically salient points turn out to be critical locations of decision making (Batty, 2004; Bin Jiang & Claramunt, 2002). Viewshed based approaches are not limited to salient points of axial maps and street network but can cover every point in walking space. Specifically, visible areas from a point of view are described as 2-dimension isovist (Batty, 2001; Benedikt, 1979; Turner et al., 2001) and 3-dimension viewshed (Fisher-Gewirtzman, Shach Pinsly, Wagner, & Burt, 2005; Llobera, 2003; Morello & Ratti, 2009). Visibility graph is constructed by connecting mutually visible locations (Turner, 2001b). The advantage of thinking of space from the perspective of visibility is that it describes the extent of space that can be seen or moved from a point of view (Batty & Rana, 2004), which contributes to modeling individual pedestrian behaviors. When walking along a route, a pedestrian perceives a sequence of isovist/viewshed properties and captures a profile of visual field. This trace of visual fields does not only describe spatial experience associated with the route but also highlights salient locations over the rhythm of isovist/viewshed properties (Batty, 2001). In addition, viewshed based approaches introduce vertical dimension in space syntax analysis, which can be used to explain why taller buildings are perceived as the generator of more traffic flows (Ratti, 2004).



(Bin Jiang & Claramunt, 2002)
Figure 2 Viewshed based approach
left: urban structure; *center*: junctions of street segments; *right*: inter-visibility graph

As for dual graph of street network, syntactical analysis relies on topological accessibility of streets. Spatial configuration is specified by how a node (i.e., axial line, named street, or natural street) intersects with other nodes of neighborhoods. Depending on the distance used for neighborhoods, local and global properties are proposed. Local properties, including connectivity, control, local depth, local mean depth, and local integration, describe the degree of connectivity from a node to immediate neighborhoods within a specific distance. Global properties, including global depth, global mean depth, and global integration, evaluate structural salience of a node through the transversal of entire graph (see Table **1**, below). Integration in axial map, which refers to the normalized mean depth to neighboring axial lines, was found to be a significant indicator of predicting human movement in several empirical studies (Baran, Rodríguez, & Khattak, 2008; Hillier et al., 1993; Penn, Hillier, Banister, & Xu, 1998; Read, 1999). When compared local connectivity to global integration, another syntactical property called intelligibility are often used to describe the degree of ease of navigating in an environment (Hillier & Hanson, 1989; Kim, 2001). An intelligible environment is the one in which locally well-connected space tends to be well-integrated globally. Other syntactical properties, including small world metric and weighted PageRank, are related to the cluster or the concentration degree of a node (i.e., axial line, named street, or natural street) over network (see Table 1, below). The small world metric (Watts & Strogatz, 1998) refers to the probability that two connected neighbors of a given node are linked together. A high value suggests a clustered or centralized node in the network. The weighted PageRank examines the relevance and importance of a node in a directed network (Xing & Ghorbani, 2004). The basic idea behind PageRank is that highly ranked node is determined if other highly ranked nodes point to it. The weighted PageRank turned out to be better correlated with traffic flows than local integration in London street network (Bin Jiang, 2009).

The core of syntactical analysis in primal graph of street network lies in the concept of centrality (see Table **1**, below). Reach and closeness describe centrality as being near others through the shortest distance (Freeman, 1975; Wasserman & Faust, 1994). Central locations near others capture similar characteristics of network with depth and integration in dual graph. By comparing with virtually straight route, straightness in primal graph approximates measures of topological distance and describes centrality as being direct to others. Finally, as a large proportion of traffic flows are through movement, intermediate nodes between origin and destination control route selection strategically. Betweenness centrality describes the importance of a node as being passed through when linking all pairs of nodes in the network (Freeman, 1975; Porta et al., 2009; Sabidussi, 1966; Sevtsuk & Mekonnen, 2012). Central locations correspond to power in terms of attraction and control. Evidence was found that betweenness centrality is a better candidate of predicting moving flows than integration (Turner, 2007a). Primal graph makes options of metric distances possible in space syntax analysis, which is used to explain wayfinding behaviors of perceiving shortcuts. In our study, we investigate route selections using different wayfinding strategies. Space syntax analysis in primal graph provides an easy solution to modify the shortest distance into geometric distance of the least angle and topological distance of the fewest number of turns.

Table 1 Common space syntax metrics

Variables	Descriptions	Formulas	Sources
Connectivity	Number of directly linked nodes (i.e. immediate neighbors)	$\ell_{ik} = \begin{cases} 1, \ if\ i\ and\ k\ are\ connected \\ 0, \ if\ i\ and\ k\ are\ disconnected \end{cases}$ $CN_i = \sum \ell_{ik}$	Hillier and Hanson (1989); Bin Jiang and Claramunt (2002)
Control	Sum of connectivity reciprocals of immediate neighbors	$CR_i = \sum_K \frac{1}{CN_k},\ k \in K\ if\ \ell_{ik} = 1$	Hillier and Hanson (1989); Bin Jiang and Claramunt (2002)
Local depth	Sum of the topological turns to all local neighbors within a specific step	$LD_i = \sum_J d_{ij}$ d_{ij} *is the number of turns between i and j* $j \in J,\ if\ d_{ij} < n\ steps$	Hillier and Hanson (1989); Bin Jiang and Claramunt (2002); Penn et al. (1998)
Local mean depth	Local depth divided by number of local linked nodes (i.e. local neighbors within a specific step)	$MD_i = \frac{LD_i}{m_n - 1}$ m_n *is the number of nodes within n steps*	Hillier and Hanson (1989); Bin Jiang and Claramunt (2002); Penn et al. (1998)
Global depth	Sum of the topological turns to all nodes in the graph	$GD_i = \sum_E d_{ij}$ *E is the entire graph*	Hillier and Hanson (1989); Bin Jiang and Claramunt (2002); Penn et al. (1998)
Global mean depth	Global depth divided by the total number of nodes in the graph	$MD_i = \frac{LD_i}{M - 1}$ *M is the total number of nodes within the entire graph*	Hillier and Hanson (1989); Bin Jiang and Claramunt (2002); Penn et al. (1998)
Relative asymmetry (RA)	Standardized value of mean depth between zero and one (max: corner of chain/series connection; min: center of star/parallel connection)	$RA_i = 2(MD_i - 1)/(n-2)$ *k is the number of nodes*	Bafna (2003); Bin Jiang (2009)
Real relative asymmetry (RRA)	Standardized value of RA by dividing the RA of a formal grid/diamond of the same step	$RRA_i = \frac{RA_i}{D_n}$ $D_n = \frac{2\{n[\log_2((n+2)/3)-1]+1\}}{(n-1)(n-2)}$ *n is the number of node*	Bafna (2003); Bin Jiang (2009)

Local integration	Reciprocal of RRA or RA within a specific step	$LI_i = \frac{1}{RRA}$ *or* $LI_i = \frac{1}{RA}$ *within n step*	Hillier and Hanson (1989); Bin Jiang and Claramunt (2002); Penn et al. (1998)
Global integration	Reciprocal of RRA or RA within the entire graph	$LI_i = \frac{1}{RRA}$ *or* $LI_i = \frac{1}{RA}$ *within the entire graph*	Hillier and Hanson (1989); Bin Jiang and Claramunt (2002); Penn et al. (1998)
Intelligibility	Correlation between connectivity and integration	$I = \frac{\sum_{1}^{n}(CN_i - \overline{CN})(GI_i - \overline{GI})}{n-1}$ *n is the total number of nodes within the entire graph*	Bafna (2003); Hillier et al. (1993); Penn (2003)
Reach	Number of road segments accessible within a given search radius on the network	$R_i^r = Count(j \in G - \{i\}; d_{ij} \le r)$ *j is the others road segments* d_{ij} *is the shortest distance between i and j*	Sevtsuk and Mekonnen (2012); Wasserman and Faust (1994)
Closeness	Reciprocal of a sum of distances to all nodes within a given search radius through the shortest network paths	$C_i^r = \frac{1}{\sum d_{ij}},\ j \in G - \{i\}, d_{ij} \le r$	Crucitti, Latora, and Porta (2006); Sabidussi (1966); Turner (2007a)
Betweenness	Fraction of the shortest paths between pairs of other road segments that pass through the measured segment	$B_i^r = \sum \frac{n_{jk}[i]}{n_{jk}},\ j,k \in G - \{i\}, d_{ij} \le r$ $n_{jk}[i]$ *is the number of the shortest paths that pass by i*	Crucitti et al. (2006); Freeman (1975); Turner (2007a)
Straightness	Probability that connected routes deviate from the virtual straight route	$S^r[i] = \sum \frac{\delta_{ij}}{d_{ij}},\ j \in G - \{i\}, d_{ij} \le r$ δ_{ij} *is the straight Euclidian distance;* d_{ij} *is the shortest network distance*	Crucitti et al. (2006); Vragović, Louis, and Díaz-Guilera (2005)
Small world	Probability that two neighbors of a given node are linked	$S_i = \frac{Count(e_{mn})}{Count(e_p)}$ e_{mn} *are connected edges between neighbor m,n* e_p *are possible edges*	Bin Jiang (2009)
Weighted PageRank	Relevance and importance of individual road segment in clustered graph of network	$PR_i = \frac{1-d}{n} + d \sum_{j \in ON_i} PR_j \times \frac{w_j}{\sum w_c}$ ON_i *are nodes that point to i;* w_j *is the weight of j; c are couterpart of j*	Bin Jiang (2009)

Viewshed based approaches first provide quantitative methods to describe visual characteristics from a point of view: radial distance, maximum visible angle, radial variance, area, perimeter, occlusivity, roundness, jaggedness, bounding proportion, compactness, and convexity (Batty, 2001; Benedikt, 1979; Meilinger, Franz, & Bülthoff, 2012; Turner et al., 2001). When visibility analysis is extended to consider the third dimension of height, additional visual properties of vertical visual span, visual slope, height to width, visual voxel, shadow volume, visible volume and iso-vis-matrix are developed (Asami, Kubat, Kitagawa, & Iida, 2003; Fisher-Gewirtzman et al., 2005; Morello & Ratti, 2009; Ratti, 2005). These visual properties not only describe shapes of visual areas from a point of view but also express selections of reference points of visual prominence. For example, occlusive points in a visual field serve as salient points for pedestrian navigation as they characterize the discontinuity between optic flows (Turner, 2007b). Relation analysis between two visual locations is grounded on inter-visibility or accessibility. Inter-visibility is specified by direct linkage of mutually visible locations or locations of overlapping visible polygons (Turner et al., 2001). On one hand, the configurational properties derived from this visual connectivity graph are similar to ones used in dual graph approaches, including descriptions of being connected in terms of neighborhood size, visual integration and mean shortest path length, and descriptions of being clustered in terms of clustering coefficient (Turner et al., 2001). On the other hand, salient locations of visual prominence are identified by comparing visual properties at adjacent viewpoints (Llobera, 2003), which provides measures of local visually salient features for this study. As for descriptions of global visual awareness, a cumulative viewshed is constructed by adding each viewshed from every viewpoint in the walking space. Locations with local visual prominence and areas with a greater global visual presence are likely to be anchor points which serve as primary reference nodes in pedestrian wayfinding (Amedeo & Golledge, 1975). When pedestrians go through a sequence of visual points without obstacles to accessibility, the profile of visual fields describe 'true' visual experience, specifically how much of visual information is expanded or lost along the path.

Significant correlation between space syntax metrics and aggregated traffic flows was observed in studies across scales of space including shopping mall (Penn & Turner, 2001), museum (Choi, 1999), neighborhoods (Kim & Penn, 2004; Penn et al., 1998) and cities (Hillier et al., 1993; Read, 1999). These empirical studies suggested that 50-70% of the variance of movement flows could be explained by variance of syntactical properties of urban structures. This proportion of movement determined by spatial configuration is called natural movement (Hillier et al., 1993). With the development of viewshed based approaches, natural movement is able to be investigated at a finer resolution of individual navigation behaviors. From the perspective of visibility, the reason why syntactical properties correlated with observed movement lies in the fact that people tend to follow paths that minimize the turning of line of view in order to maximize trip efficiency (Hillier, 1999). Simulations using wayfinding strategies of following the longest visible line captured 50% of the variance in traffic flows, which implied that visual access provides critical environmental cues for navigation. Penn and Turner (2001)'s study in a shopping mall further compared two ways of route selection within field of view: the simple rule of randomly selecting next location with forward facing and the 'intelligent' rule of selecting the most integrated location. Simulated outcome with the simple rule of random selection resulted in a better correlation with observed movement, which implies that syntactical analysis better explains explorative behaviors of navigation. Similar finding was also confirmed in Bin Jiang and Jia (2011)'s study of GPS tracks from taxicabs in urban network.

In sum, space syntax essentially measures the structural salience of the route segments in a network. Evidence of natural movement does not only indicate that people can perceive distance by topological descriptions but also imply that route choices are determined by configurational relations to a larger network beyond local properties. However, syntactical properties only describes locations with no specific contents and thereby no measurable attraction. In other words, space syntax describes a way of urban growth that the spatial configuration is the primary generator of human movement and attractors for human activities just serve as multipliers that enhance the patterns from natural movement. On one hand, this proposition that attractors are a consequence of configuration conveys the idea of seeing cities from static perspective. Therefore, space syntax analysis cannot explain temporal details and individual variations in pedestrian movement. On the other hand, human activities do not evenly distribute over the network. When this uneven distribution of human activities conflicts with the primary pattern of natural movement, space syntax discarding meaning of space is rather limiting. Thus, we need to include discussions about sense of place represented by affordances.

2.2 Space semantics

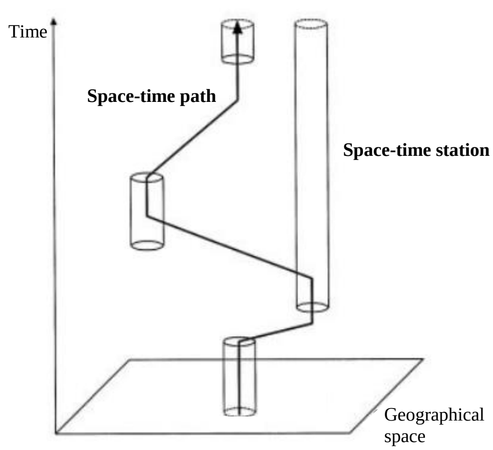
People interact with and communicate about locations based on meanings they assign to them. In other words, people infuse "a sense of place" into physical space (Tuan, 1977). Meanings turn space into places. As for pedestrian movement, the sense of place influences decisions about destination choices and route selections. Specifically, pedestrian movement is attracted by meaning of space as how individuals perceive functions afforded by locations. Urban space can support a variety of functions related to land use types, such as residential, commercial, industrial, and transportation. The function of a place is determined by human activities or actions that it can occupy. Affordance based model of place fills in absence of semantic dimension of space.

The concept of affordances was originally developed by Gibson (1977) when investigating how people visually perceive the environment. Gibson (2013) argued that affordances are measurable invariant property of an environment but is meaningful only when a user perceives it. The core of affordance lies in possibilities for activities provided by an environment and perceived by the user (i.e., pedestrian). This study focuses on affordances tied to locations. As for pedestrian movement, natural movement generated by spatial configuration relies on walkability affordances. Additionally, affordance is neither a property of a pedestrian nor of an environment but instead a relational property that fits between them (Jordan, Raubal, Gartrell, & Egenhofer, 1998; Wells, 2002). The term "fit" indicates that a pedestrian is capable of perception and activities/actions. Pedestrians with visual impairments rely on auditory and haptic hints and comprehend a different interpretation of spatial configuration (Kitchin, Blades, & Golledge, 1997). Pedestrians using wheelchairs afford different walking surface. External environmental conditions such as light, shadow, and weather also influence the perception of affordance. Raubal and Winter (2002b) found that landmark selection for navigation were different between day and night, and between foggy and sunny days (Raubal & Winter, 2002a). From the perspective of agent-environment mutuality (Zaff, 1995), spatial qualities such as color or size are meaningless unless the pedestrian can perceive affordance from them. Therefore, a top-down approach of pedestrian movement is not sufficient to capture sense of place perceived by pedestrian and not able to explain how people conduct perceptual wayfinding. Understanding meaning of space emphasizes an agent center perspective. Modeling perceptual wayfinding focuses on activity/action relevant properties of environment that can be utilized by the pedestrian.

Examples in the original idea of affordance such as 'sittability' or 'climbility' derive action possibilities from physical properties relevant to agent's capabilities. But physical properties are not sufficient to explain affordance in complex behaviors of pedestrian movement. A pedestrian moves within spatiotemporal schedules and contexts with social and institutional rules. Although physical properties afford walkability, the utilization of this perceived affordance may not be accomplishable within space-time constraints or not be socially permitted. In addition, route planning is essentially a cognitive process of making decisions about destinations and routes which is neglected in Gibson's theory of affordances. In order to compensate these deficiencies, Raubal and Moratz (2008) proposed an extended model of affordances to break concept of affordance into three parts: physical, social-institutional, and mental. Most of Gibson's examples of affordances fall within the category of physical affordances. Social-institutional affordances (Raubal, Miller, & Bridwell, 2004; Raubal & Moratz, 2008) essentially describe contextual properties relevant to the pedestrian's socioeconomic and cultural backgrounds. For example, only pedestrians having membership get the access to the fitness center. Taking physical and social-institutional affordances as perceptual input, mental affordances refer to cognitive interpretation which influences decision about what perceived affordances to be utilized and further what actions or activities to be executed. This extended model of affordances goes beyond environment as perceived and serves to represent cognitive processes in pedestrian movement. Norman (2002) argued that affordance is the result of mental interpretation, in which past experiences and obtained knowledge are applied to perceptual information. A collection of perceived use of space from previous environmental experiences highlights functionally meaningful places. These semantically salient locations further serve as anchor points for future navigation. However, this extended model does not specify the temporal context of affordances. In order to understand affordances with time constraints, the inclusion of time geography studies in the background discussions is needed. Time geography studies will help to provide descriptions of situational context within a net of constraints.

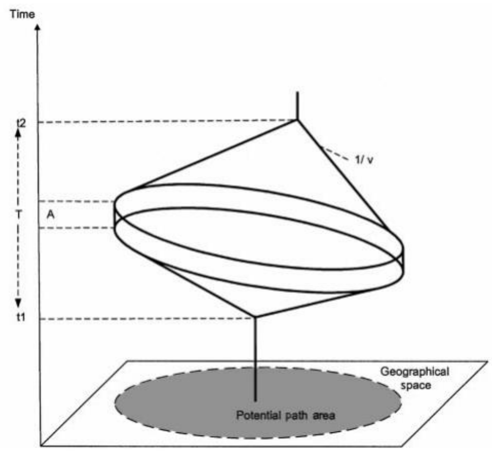
Time is an important component in describing affordances as the situational interpretation of the environment (Rasmussen & Pejtersen, 1995). Compared with slow transformation of spatial configuration, functions of places and patterns of human activities change rapidly. Time geography suggests that human activities are conditioned by three type of constraints: capability constraint, coupling constraint, and authority constraint (Hägerstraand, 1970; Miller, 1999). Specifically, capability constraints which describe limitations on activities due to inherent abilities and/or lacking tools are related to physical affordances. Authority constraints which describe limitations on activities due to the control of certain institutions are associated with social-institutional affordances.

What are not covered in extended theory of affordances are the coupling constraints which deal with interactions of an individual with others people or entities in a space-time context (Raubal et al., 2004; Shaw & Yu, 2009). Coupling constraints require a pedestrian to reach a certain location within a time limit and stay for enough duration in order to engage in an activity, such as taking classes or attending a meeting. In order to represent a space-time context of activities, time geography provides a useful method of the space-time path (Hägerstraand, 1970; Raubal et al., 2004) which delineate a sequence of activities at various locations over a period of time in a 3-dimension graph (see Figure **3**, below). Slopes of segments in space-time path represent moving efficiency (Miller, 2004). The steeper the slope is, the more time is required for moving per unit space. Vertical tube as shown in Figure **3** illustrates a stationary state in space called space-time station (Raubal et al., 2004). When considering interactions between a pedestrian and a place, vertical tube can also be used to represent the spatiotemporal context of physical properties and social-institutional rules, such as opening hours. Conjunction on the space-time path indicates that a pedestrian and other people are co-present to engage in a social activity or a pedestrian reaches to utilize an opportunity of the activity. While space-time path describes sequential relations of activities conducted, space-time prism as shown in Figure **4** illustrates opportunities of activities offered by a space-time context. Time geography distinguishes fixed and flexible activities by the ease to rescheduling and relocation. Fixed activities such as working are imposed by more strict coupling constraints. As illustrated in Figure **4**, if space and time of fixed activities are determined, the projection of space-time prism to geographical space demonstrates all locations accessible with reference to the travelling velocity of a pedestrian. Locations within this potential path area that support relevant functions results in a feasible opportunity set of places for the flexible activity. Space-time prism lies in the core of space-time queries from a person-specific perspective (Kwan, 1998). It goes beyond what perceived function of space is as described by the concept of affordance and illustrate whether a pedestrian is able to utilize and engage in the perceived possibility of activities with spatiotemporal constraints. Finally, the integration of time geography and affordance theory makes representing temporal details of pedestrian movement possible.



(Raubal et al., 2004)

Figure 3 Space-time path and space-time station



(Kwan, 1998)

Figure 4 Space-time prism and potential path area
(t1, t2: space and time of fixed activities; A: minimum duration required for the flexible activity; v: travel velocity)

Wayfinding simulation is the next component of affordances within the literature to discuss. Agent-environment mutuality lies in the core at understanding meaning of space in terms of affordances. An affordance based model of place was developed to represent knowledge in the world in the agent simulation of perceptual wayfinding at the airport (Raubal, 2001, 2008; Raubal & Worboys, 1999). It also implemented in crowd simulation system to model perception of available actions in evacuation scenarios (Pelechano, Allbeck, & Badler, 2008; Sokhansefat, Delavar, & Banedj-Schafii, 2012). Furthermore, the concept of affordance is used to explain and evaluate effectiveness of environmental signage on indoor wayfinding performance (Vilar, Rebelo, & Noriega, 2014). Most of these wayfinding simulations using the affordance based model are conducted in an indoor scenario and focus on perceptual knowledge of explorative behaviors in an unfamiliar environment. The types of affordances modeled are limited to physical affordances relevant to actions such as ‘go-to’ and ‘turn’. When considering navigation on an urban network, pedestrians are situated within a more complex environment with social and institutional rules. Pedestrians are also engaged in types of activities in a spatiotemporal context. Therefore, how to integrate the concept of affordances and insights from time geography in modeling pedestrian movement is still challenging.

In sum, space semantics in terms of affordances transforms a location on physical network into a meaningful place. From the perspective of affordances, places are locations with functional significance. Pedestrians travel to places and utilize possibilities of activities they can afford. In order words, space is meaningless to pedestrians unless they can perceive and utilize affordances from it. Affordances are essentially the person centered interpretation of possibilities for activities situated within a spatiotemporal context. Space-time prism from time geography serves as the theoretical foundation to represent spatiotemporal contexts and conduct space-time queries. However, this affordance based model of place has not been applied to wayfinding simulation in complex urban network. Additionally, although discussed in the extended model of affordances, the cognitive process behind mental affordances is unclear. How past experiences are utilized in mental affordances, how mental affordances make decisions from alternatives and how to model the process of mental affordances are open to question. Cognitive psychologists and geographers have conducted studies of spatial cognition about the acquisition, organization and utilization of spatial knowledge. The concept of affordances is essentially grounded in ecological approaches to understand cognitive processes.

2.3 Spatial cognition

How a person moves essentially depends on how much the individual knows about the environment. There are two levels of spatial knowledge: (1) intuitive knowledge of the immediate environment at a perceptional level and (2) knowledge of the global structure at a cognitive level which results from a long term exposure to the environment (Golledge, 1997). Spatial knowledge stored in mind construct a cognitive map although it is not necessarily conceptualized in the form of a classical map (Tolman, 1948; Tversky, 1992). Cognitive collage, rubber sheet map, and cognitive atlases are other metaphors developed based scattered information from multiple sources of perception (Mark, 1993; Tversky, 1993). Cognitive map (i.e., mental map) in this study refers to mental representation of environmental structures along with subjective meaning of places. Space syntax and space semantics are sources of spatial knowledge. For the purpose of modeling pedestrian movement, we will review relevant studies about mental representation of spatial configuration, landmarks and anchor point theory, and computational model of spatial cognition.

Navigation particularly wayfinding is impossible without some kinds of mental representation for spatial configuration. Siegel and White (1975) classified mental representation for a new environment by three stages of construction: landmark knowledge, route knowledge, and survey knowledge. Landmark knowledge comprises salient, typically familiar features in the environment. Route knowledge consists of a sequence of landmarks with associated topological information. Survey knowledge is characterized by an understanding of the spatial layout of an environment and capabilities to locate landmarks and routes with reference of Euclidean distances and directions. However, this model is criticized for the strict sequence of knowledge development (Montello, 1998). Montello and Sas (2006) argued that spatial knowledge was acquired and stored as soon as the beginning of the first moving experience but the extension and elaboration continued over a long time period. As for salient features captured, Lynch (1960) extracted five elements in mental maps of a city by interviewing residents of three cities: nodes, landmarks, paths, edges, and districts. Nodes, paths and districts are spatial elements accessible on the moving path. Landmarks and edges serve as external strategic references for navigation, which are typically visually or semantically salient but not necessarily accessible to pedestrians (Conroy-Dalton & Bafna, 2003). This study about the image of the city also provides an analytical method of sketch map which is later widely used to represent the understanding of spatial layouts (Kim & Penn, 2004; Rovine & Weisman, 1989).

Physical structures captured in cognitive map were found to be fragmented and systematically distorted. Pedestrians make spatial decisions based on fragmentary knowledge. The level of details in cognitive map is influenced by degree of syntactical salience and familiarity. Specifically, spatial features located in areas with a higher integration resulted in a higher frequency of appearance in cognitive map (Kim, 2001). Detailed descriptions of the spatial layout was observed in familiar areas, while unfamiliar areas were associated with sparse information (Appleyard, 1970). As spatial knowledge is obtained from separate traveling experiences, cognitive map captures salient features of different spatial scales. The integration of separately learned routes into configurational knowledge was found to be more difficult in between-route inferences than within-a-route (Montello & Pick, 1993). In addition, the perception of spatial configuration is distorted systematically in cognitive space (Tversky, 1992). Spatial distortion results from tendency of simplification, error of alignment, and effects of hierarchical organization. Specifically, irregular shapes of spatial objects tended to be regularized (Glicksohn, 1994). Alignment tended to be simplified as lining up. Horizontal and vertical coordinates were favored in identifying directions. Faster judgement of directions and smaller estimate of distance are associated with a pair of in-region locations than a between-region pair. Stevens and Coupe (1978) found that estimated direction between San Diego, California and Reno, Nevada was biased by the fact that Nevada is east of California. McNamara (1986) observed similar outcomes in a room divided by barriers. Evidences of fragmentary knowledge and spatial distortion suggest that salient features captured by cognitive map are loosely connected in a hierarchical structure.

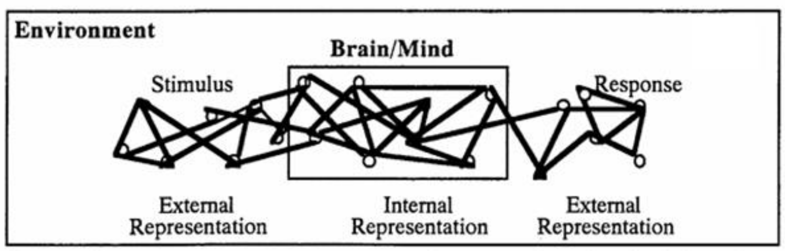
Landmarks are crucial elements in mental representation of the environment. The concept of landmark was used in various different ways in the literatures (Couclelis, Golledge, Gale, & Tobler, 1987; Lynch, 1960; Sorrows & Hirtle, 1999a). What is in common is that landmarks have salient characteristics that distinguish them from other spatial objects and serve as an important role in conceptual organization and navigation assistance. This study extends the point notion of landmarks and includes linear and areal entities. We focus on why a feature serves as a landmark and how landmarks are used in pedestrian navigation.

The concept of landmarks is grounded on distinctiveness of the feature. In other words, landmark saliency does not depend on individual qualities but on relative properties of contrast to nearby elements in the environment. Lynch (1960) argued that landmarks were identified because of local contrast to close features and high chances of being visible from many locations. Besides singularity and prominence of spatial location described by Lynch (1960), Sorrows and Hirtle (1999b) elaborated the list of characteristics that make a landmark salient: singularity, prominence, contents and prototypicality. Content salience refers to common understanding of cultural or historical significance. Similar to content salience, prototypicality is characterized by typical properties that represent a category. Sorrows and Hirtle (1999b) further categorized landmarks into visual, structural, and cognitive ones. As for measures of feature salience, Raubal and Winter (2002b) proposed a model to extract landmarks for route directions by visual, semantic, and structural attraction and conducted an empirical study in Vienna to test methods of visual and semantic salience (Nothegger, Winter, & Raubal, 2004). In order fill in the missing measures of structural attraction, Klippel and Winter (2005) investigated the conceptual complexity of using landmarks in route directions and derived the measure of structural salience from the ease of use. In addition, syntactical properties of centrality are used to measure structural salience. Takes and Kosters (2014) suggested that centrality in terms of degree, betweenness, closeness, and PageRank were intuitive measures to select landmarks over a network. Claramunt and Winter (2007) conducted network analysis in named street network and used closeness centrality and betweenness centrality to investigate structural salience of places, paths, and districts in the image of the city. With GPS information widely used in mobile devices, landmark selection is shifted from measuring feature salience to learning from a collection of geotagged images (Kurashima, Iwata, Irie, & Fujimura, 2010; Shi, Serdyukov, Hanjalic, & Larson, 2011). In this study, salience of landmarks is determined by visual properties (visual contrast), syntactical properties (prominence of location), and semantic properties (content and prototypicality).

Landmarks serve not only as an organizing concept in the formation of cognitive map but also as a navigational tool. Pedestrian navigation consists of locomotion and wayfinding (Montello & Sas, 2006). Locomotion refers to identifying a path towards a perceptible destination within an immediate environment without running to obstacles. Wayfinding aims to reach a destination through route planning. The route planning depends on an understanding of distal locations not directly accessible to perceptual systems. As for locomotion, pedestrians rely on landmarks to identify destination of the route. As for wayfinding, landmarks are used to identify decision points, origin and destination of a route, provide hints for self-orientation, confirm route progress, and signal crucial actions (Richter, 2007; Sorrows & Hirtle, 1999b). Landmarks have been used in pedestrian navigation services to enhance wayfinding instructions (Beeharee & Steed, 2006; Bessho, Kobayashi, Koshizuka, & Sakamura, 2008). Pedestrians were found to prefer landmark-enhanced instructions to metric based directions (Rehrl, Häusler, & Leitinger, 2010). Additionally, landmark-based route instructions result in better performances in navigation than map or distance-and-turn based directions due to advantages of being easy to follow, less cognitive load, shorter learning time, and reduction of confusion (Beeharee & Steed, 2006; Goodman, Gray, Khammampad, & Brewster, 2004; Millonig & Schechtner, 2007). However, most of existing landmark-based pedestrian navigation system depends on collective knowledge for landmark selection, which is not adaptive to knowledge of individual pedestrian.

Preferences of wayfinding strategies are different by gender and level of familiarity for an environment. On one hand, males demonstrated greater preference for directional cues while females relied on positional cues (Chai & Jacobs, 2010). When asked for direction, males tended to recall the distance and cardinal information while females preferred to use landmarks (Brown, Lahar, & Mosley, 1998). However, gender differences in preference of environmental cues did not lead to significant discrepancy in navigation performances (Ward, Newcombe, & Overton, 1986). On the other hand, for a navigation task in a multi-level building, inexperienced participants preferred the central-point strategy while more experienced pedestrians used the floor strategy (Hölscher, Meilinger, Vrachliotis, Brösamle, & Knauff, 2006). Central-point strategy relied on the most well-known parts. The floor strategy selects routes that first head towards the vertical position of the destination. Experienced subjects also outperformed the inexperienced in terms of better route plan and shorter searching time (Hölscher et al., 2006). Familiarity also influences navigation performance due to effects of emotions and mood. In modeling evacuation behaviors, familiarity with the building layout generated a level of confidence that allowed the occupants to detour and search for alternative routes in congestion (Gwynne, Galea, Lawrence, & Filippidis, 2001). Instead pedestrian under panic suffered from disorientation and eventually were stuck in traffic.

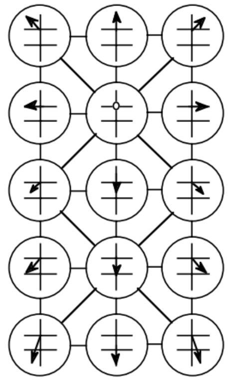
Computation models of spatial cognition are developed in order to better understand cognitive processes, test empirical observations, and reproduce spatial behaviors. Three types of models are reviewed here: synergistic models, qualitative models, and robotic models. Synergetic models (see Figure **5**, below) represent spatial cognition as a complex self-organized system consisting of mind and environment. Internal and external representations are expressed by pairs of stimulus and response. The dynamics of cognitive processes and the construction of cognitive map are manipulated by interactions between internal representation of the environment and external representations of knowledge in mind (Portugali, 1996). An update of spatial knowledge is conducted by adjusting values of parameters in mind based on response from the environmental stimulus. Complexity of synergetic models lies in temporally recursive operations under a large number of self-organized principles. The notion of synergetic is implemented in agent based modeling as the self-organized principle of disaggregated agents.



(Portugali, 1996)

Figure 5 Synergetic network mediating internal and external representations

In qualitative models, cognitive processes are represented by a collection of qualitative statements and logical operations. Spatial-conceptual neighbor and wayfinding chroeme are two examples. Because of complexity in spatial tasks and limited capabilities of human cognition, spatial-conceptual neighbor model suggests only distinct environmental properties are stored in memory. Significant properties include uniqueness of spatial objects, topology of spatial arrangement, and conceptual structure, which are represented by the unit of spatial-conceptual neighbor. The spatial-conceptual neighbor is represented by a pair of spatial relations that have a direct transition from one relation to the other, such as “a is left of b” and “a touches b on the left” (Freksa, 1992). As shown in Figure **6**, the model of spatial-conceptual neighbor also includes length information in terms of qualitative distance (A. U. Frank, 1998). The spatial-conceptual neighbor is useful in spatial reasoning particularly when working with spatial relations under uncertainty or with incomplete knowledge. Wayfinding chroeme model (Klippel, 2003) further adds functionality at adjunctions to spatial relations. As illustrated in Figure **7**, the functionality lies in physical affordances in terms of actions to be performed relevant to the spatial relation. Qualitative models grounded in the qualitative abstraction of spatial relations contribute to an understanding of spatial reasoning and the forming of procedural knowledge.



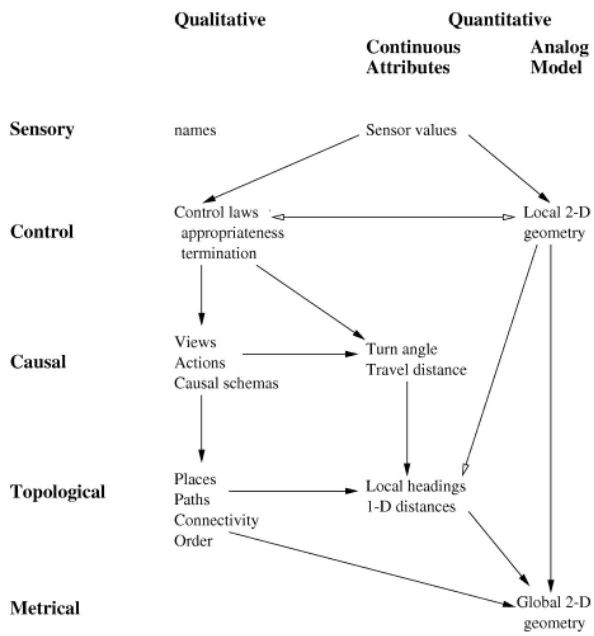
(Freksa, 1992)

Figure 6 Fifteen qualitative orientations and locations specified by spatial-conceptual neighborhood

(Klippel, 2003)

Figure 7 Wayfinding chroeme

Robotics develops models of spatial cognition in order to investigate elements needed for an automatic system of spatial behaviors. TOUR model is a robotic model that integrates procedural knowledge, topological knowledge, and metrical knowledge (Kuipers, 1978). Specifically, procedural knowledge is represented by commands of turning and going. Topological knowledge describes connections between routes while metric knowledge refers to an understanding of distances and orientations. But TOUR model discards representation of survey knowledge. In order to overcome this limitation of TOUR model, an alternative spatial semantic hierarchy model develops an extended structure for spatial knowledge, in which knowledge at control, causal, topological, and metrical levels is chained through logical interactions (see Figure **8**, below). Robotic models provide an engineer approach to capture and construct the mental representation of spatial configuration by explorative behaviors of robots.



(Kuipers, 2000)

Figure 8 Spatial semantic hierarchy

In sum, from the perspective of information processing approaches, mind serves as the central control system of cognitive processes, which takes perceptual information as an input and responses with instructions of actions. The cognitive map stored in mind consists of physical locations and their spatial relations (i.e., spatial syntax). From the perspective of ecological approaches, spatial knowledge does not rely on internal processing of cognitive map but is perceived and utilized through interactions with the environment. In other words, all information needed for cognitive processing is present in the environment and no memory is stored in mind. Specifically, cognitive processes rely on opportunities provided by the environment (i.e., affordance) (Heft, 1996). A pedestrian must actively search an environment in order to perceive an affordance. Ecological approaches provide a better explanation to fast responses in functionally specific behaviors such as reading directional signage and perceiving use of space. In this study, we argue that syntactical information and semantic interpretation are both the sources of spatial knowledge. Constructing cognitive map depends on hybrid approaches which support central storage and processing of environmental structures along with internal abstraction of subjective meaning for places. Wayfinding chroeme (Klippel & Winter, 2005) provides a promising model that integrates spatial relations and physical affordances although it is only used to describe route information. Visually, syntactically and semantically salient features are stored in cognitive map as landmarks which serve as the most predominant cues for pedestrian navigation. Pedestrian navigation systems enriching route instructions with landmarks lead to better navigation experiences and performances. However, whether landmark-based route instructions predict or outperform the intuitive way of pedestrian navigation remains to be investigated. In addition, these landmark-based pedestrian navigation services are grounded on collective knowledge of space and not adaptive to knowledge of individual pedestrian.

2.4 Agent based modeling

Agent-based modeling (ABM) provides a bottom-up approach to examine pedestrian movement patterns from simulation of individual pedestrian navigation. ABM is also an intuitive way to model complex behaviors of pedestrian navigation which inherently autonomic and distributed (de Smith, Goodchild, & Longley, 2009). Within ABM, navigation is grounded on cognitive map of individual pedestrian. A typical structure of ABM consists of agents, an environment, and relationships between agents as well as between an agent and the environment.

The agent in ABM has some typical features: autonomy, heterogeneity, explicit space, local interactions, bounded rationality, and non-equilibrium dynamics (Bonabeau, 2002; Macal & North, 2005). With respect to the form of intelligence, agents are classified into reactive agents (i.e. behavior-based agents) and deliberative agents (i.e. intelligent agents), which leads to different modeling architectures (Franklin & Graesser, 1997; Wooldridge & Jennings, 1995). On one hand, the idea of reactive agents is close to ecological approaches of cognitive processes. Specifically, intelligence does not depend on the complex mental computation but on physical interactions with an environment. No abstract representation of the environment is stored in memory. Reactive moving agents were used to simulate flock behaviors (Reynolds, 1987; Spector, Klein, Perry, & Feinstein, 2003) and reactive robots wandering around without collisions (Brooks, 1986). On the other hand, the idea of deliberative agents is close to information processing approaches. Deliberative agents rely on a mental representation of the world stored in memory to pursue a long-term complex goal.

Learning and adaptive behaviors are observed in pedestrian navigation. Three types of learning paradigm are usually applied in computational models: supervised learning, unsupervised learning, and reinforcement learning. In the supervised learning, the correct answer is offered after each action. Learning agents are trained to produce output close to the known correct answer. As for the unsupervised learning, no explicit target output is associated with each attempt (Dayan, 1999). The intelligence emerges from the underlying structures of data patterns. Reinforcement learning (RL) provides a trial-and-error approach to model learning capabilities, which benefits from shorter response time. In response to actions, the learning agent receives feedback in terms of rewards or punishments instead of the correct answer to be learned. A typical RL model consists of four components: reward, value, policy, and environment (Samson, Frank, & Fellous, 2010).

In sum, pedestrian navigation is a situated, yet planned task. On one hand, locomotion part conducts simple reactive behaviors in response to direct perception of environmental cues without information retrieval from memory. On the other hand, wayfinding partially relies on a cognitive map collected from past experiences to search for an 'optimal' route. ABM provides an integrated framework to coordinate heterogeneous agents and serves as an intuitive framework to model pedestrian navigation. One of the most significant strengths of ABM lies in the flexibility of simulating complex scenarios of pedestrian behaviors, particularly simulating special cases which are hard to be tested in reality such as evacuation during emergent disasters. In geospatial models, complexity of spatiotemporal objects has been identified in changes of internal structure, changes of movement and changes of geometry (Goodchild, Yuan, & Cova, 2007). ABM essentially captures the fourth dimension of complexity which lies in propagation from individuals to the aggregated whole. This propagated complexity essentially results from a hierarchical nature of spatiotemporal behaviors.

2.5 Summary

This chapter reviews relevant concepts and studies in urban planning, time geography, ecological psychology, cognitive science, and artificial intelligence, which builds the theoretical foundation for this interdisciplinary study about pedestrian movement. The literature review reveals three important points:

1. Space syntax can be utilized as a tool to quantify configurational properties of network structures. Evidences show significant correlation between network syntax and aggregated traffic flows. Spatial configuration places constraints on navigation behaviors because it encourages or impedes route selections through cognitive representation of network structures. Cognitive map in spatial cognition captures spatial syntax of configuration in real environments.

2. Pedestrian movement is attracted by places of activity opportunities. Commercial activities and museum visits benefit from central locations in spatial configuration which suggest higher chances of traffic flows passing through. Some researchers even argue that spatial configuration is the primary generator of attractors for human activities although this point of view discards individual variations and temporal details. People do not have information about all opportunities. Environmental perception and cognitive constraints play an important role in determining which opportunities are accessible to them. Time geography provides useful methods to represent pedestrians' activity patterns and analyze possibilities of activities within the spatiotemporal contexts.

3. Salient features embedded in spatial configuration and captured by spatial experiences are loosely connected as landmarks in cognitive map. Landmarks serve as the most predominant cues for pedestrian navigation and are used to enrich route instructions. Individual preferences of wayfinding strategies have been observed between genders and by levels of familiarity for an environment. But existing pedestrian navigation services are not adaptive to knowledge of individual pedestrian and short of task specific route search.

We also summarize content categories of previous studies related to space, cognition and pedestrian movement. As show in Table **2**, most of studies emphasize up to three aspects of content categories. Studies from three aspects of space syntax, space semantics and spatial cognition, such as Sorrows and Hirtle (1999b) and Claramunt and Winter (2007), concentrates on evaluating structural and semantic salience of environment features and identifying salient elements stored in cognitive map. However, whether and how these salient features are used in assisting pedestrian navigation is not examined. Studies from three aspects of space syntax, space semantics, and pedestrian movement, such as Kwan (1998) and Dijst and Kwan (2005), illustrate how people's choice of activities is determined by individual action spaces and space-time accessibility. These studies do not take cognitive constraints into account and rest on assumption that people are able to capture all opportunities in the environment. In studies from other three aspects of space semantics, spatial cognition and pedestrian movement, such as Raubal (2001), pedestrians rely on environmental cues to perform perceptual wayfinding but are not able to construct cognitive map. In contrast, in studies from three aspects of space syntax, spatial cognition, and pedestrian movement, such as Turner (2007b) and Gwynne et al. (2001), pedestrians are able to have memory of spatial layouts and decide where to go using stored information. Due to the lack of space semantics, these studies only deal with explorative behaviors or are conducted in experimental settings of emergency evacuation when the only goal is to find exits. Few existing models (Pelechano et al., 2008) provide comprehensive solutions to pedestrian movement taking both space and cognition into account.

Based on the literature review, it is intuitive to bridge space syntax, space semantics and spatial cognition in a comprehensive framework for pedestrian movement. The conceptual framework developed in this study aims to integrate syntactical analysis and semantic knowledge abstraction in modeling cognitive map and further examine whether and how identified landmarks are used in pedestrian navigation. Empirical studies within the campus area make it possible to verify whether collected landmarks can be identified by evaluating the salience of features and how this same group of participants uses these identified landmarks to choose destinations and select routes. The conceptual framework is finally used to develop the prototype form of an agent based model for pedestrian navigation.

Table 2 Content categories of literatures

Studies	Syntax	Semantics	Cognition	Pedestrian movement
Lynch (1960)	X		X	X
Ward et al. (1986)			X	X
Rovine and Weisman (1989)			X	X
Hillier et al. (1993)	X			X
Heft (1996)			X	X
Kwan (1998)	X	X		X
Montello (1998)			X	X
Penn et al. (1998)	X			X
Choi (1999)	X			X
Read (1999)	X			X
Sorrows and Hirtle (1999b)	X	X	X	
Dalton (2001)	X			X
Desyllas and Duxbury (2001)	X			X
Gwynne et al. (2001)	X		X	X
Kim (2001)	X		X	
Penn and Turner (2001)	X			X
Raubal (2001)		X	X	X
Asami et al. (2003)	X	X		
Bafna (2003)	X		X	
Klippel (2003)			X	X

Kuipers et al. (2003)			X	X
Goodman et al. (2004)			X	X
Miller (2004)	X	X		
Nothegger et al. (2004)	X	X	X	
Raubal et al. (2004)		X	X	X
Dijst and Kwan (2005)	X	X		X
Hölscher et al. (2006)	X		X	X
Millonig and Schechtner (2007)			X	X
Montello and Sas (2006)			X	X
Montello (2007)	X		X	X
Claramunt and Winter (2007)	X	X	X	
Turner (2007a)	X			X
Turner (2007b)	X		X	X
Pelechano et al. (2008)	X	X	X	X
Bin Jiang (2009)	X			X
Morello and Ratti (2009)	X		X	
Porta et al. (2009)	X	X		
Shaw and Yu (2009)	X	X		
Rehrl et al. (2010)			X	X
Bin Jiang and Jia (2011)	X			X
Meilinger et al. (2012)	X		X	X
Lerman, Rofè, and Omer (2014)	X			X
Takes and Kosters (2014)	X		X	X
Li, Xiao, Ye, Xu, and Law (2016)	X	X		X
Batty (2017)	X	X		X
Summers and Johnson (2017)	X	X		

Chapter 3: Conceptual framework and methodology

This chapter describes in details the empirical and analytical methods used in this study. It begins with the construction of conceptual framework. The conceptual framework breaks analysis into three components: space syntax, space semantics, and spatial cognition. The proposed conceptual framework is then utilized to guide the empirical study. Study area, data collection, and survey design are outlined. The analytical method specifications start with measures of network centrality and functional centrality. They are followed by the sketch map analysis. Finally, the chapter compares calculated routes using different criteria and the routes chosen by survey participants to examine the concepts of distances and uses of landmarks in route selections.

3.1 Conceptual framework

Central to this discussion on space, cognition and pedestrian movement is the premise that space syntax and space semantics of an environment influence the development of spatial cognition which guides moving behaviors. In other words, where people choose to hold activities and how people choose to get there depend on individuals' cognitive maps (i.e. spatial cognition) of the environment in which the layout of roads, buildings, open space and other features (i.e. space syntax) as well as the actual or potential utilities of these features (i.e. space semantics) are representative elements.

Due to the interdisciplinary nature of pedestrian movement studies, the conceptual framework as shown in Figure **9** is built on a comprehensive treatment of space syntax, space semantics and spatial cognition. We use specific concepts from the fields of urban planning (i.e., space syntax), time geography (i.e., potential path area), ecological psychology (i.e., affordances), cognitive science (i.e., cognitive map), and artificial intelligence (i.e., agents) to design the process model. The analysis is conducted from three dimensions: (1) space syntax to characterize spatial configuration or structure, (2) space semantics to address functions and affordance of space for activities that individuals experience and interpret, and (3) spatial cognition to capture one's knowledge about the space. On one hand, space syntax is assumed static because the built environment features and network structures changes slowly over time. On the other hand, space semantics characterized by perceived activity space within the potential path area is determined by space-time contexts and is modified by experiences within that environment. Space syntax can influence semantic salience of a place, depending on characteristics of activities. For example, commercial activities are more likely to choose locations of structural salience. Both space syntax and semantics serve as cues to activate one's cognitive map. This cognitive map consists of the salient layout of spatial features as well as the prominent utilities afforded by these features. These salient features with visual attraction, syntactical prominence and semantic significance are identified as landmarks in cognition map. Landmarks deform the grid layout of network and serve as the most predominant cues for pedestrian navigation. Based on cognitive map, wayfinding decisions are made by the pedestrian agent, particularly determining where to go and how to get there. A successful navigation corresponds to a sequence of explorative and purposive actions ending at the perceived destination. With more exposure to an environment, one's cognitive maps are also gradually updated and further modify spatial behaviors.

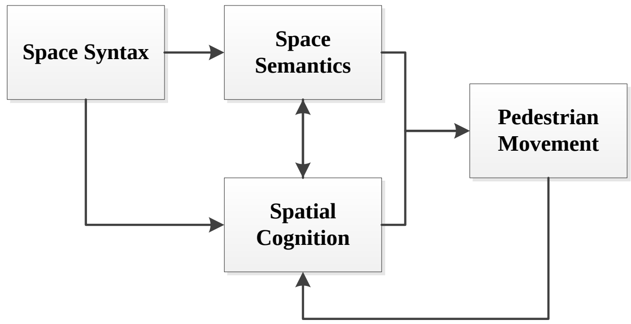


Figure 9 Conceptual framework of pedestrian movement

3.2 Study area

The empirical study was conducted at the University of Oklahoma Norman campus which can be regarded as a miniature version of an urban neighborhood. In the year 2015 when data was collected, 27,261 students, 1,660 faculty members and 3,916 staff members attended the campus which consisted of 210 buildings (Figure **10**) covering a considerable portion of the city Norman, Oklahoma. This study area is a 3.8 km^2 pedestrian-friendly neighborhood. The core academic area with the densest campus activities is located in the northern part of this study area.

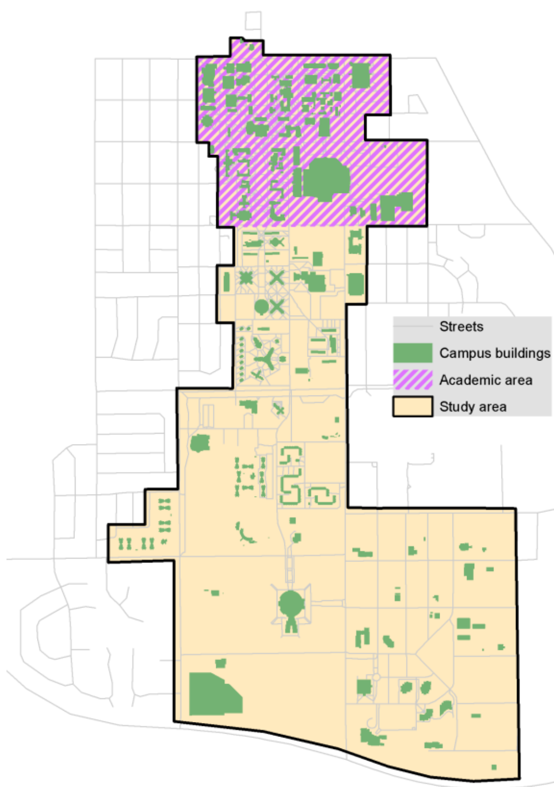


Figure 10 OU Norman campus and the street network

3.3 Data description

To address how space and cognition affect the distribution of pedestrian movement, it is necessary to compile data from different sources and merge them into a single database. First, pedestrian volumes were collected by on-site observations. Second, a survey was conducted with faculty, staff, and students to collect data about activity patterns, route selections and sketch graphs of campus layouts. Third, the general distribution of human activities was described by WiFi usage acquired from the information technology department.

3.3.1 Gate counts of pedestrian flows

Gate counts are used to establish the flows of pedestrians at sampled locations within the campus area over the course of a day. A gate is a conceptual line across a street while gate counts refer to the number of pedestrians crossing that line in either direction. Pedestrian observation concentrated on the 0.8 km^2 academic areas where the majority of campus activities occurred on weekdays. Specific 67 gates (Figure **11**) within the academic areas were observed for five minutes during weekdays at two periods of time including mid-morning period between 10:00 am and 12:00 noon and mid-afternoon period between 2:00 pm and 4:00 pm. This study employed six people to carry out the observation, each of whom covered 11-12 gates since most of gates were not far apart. Within each time period, two rounds of observation were carried out including one round from gate 1 to 12 and the other reverse round from gate 12 to 1. As shown in Figure **11**, the average observed flows of pedestrians ranged from high flows of 1,044 pedestrians per hour (i.e., 87 per five minutes) to low flows of 60 pedestrians per hour (i.e., 4 per five minutes). When examining the statistical properties of the observed pedestrian flows, this study found that most of street segments have low volume while only a small proportion of segments have high volume. Specifically, as shown in Figure **12**, 25% of segments contributed to about 50% of the observed pedestrian volume.

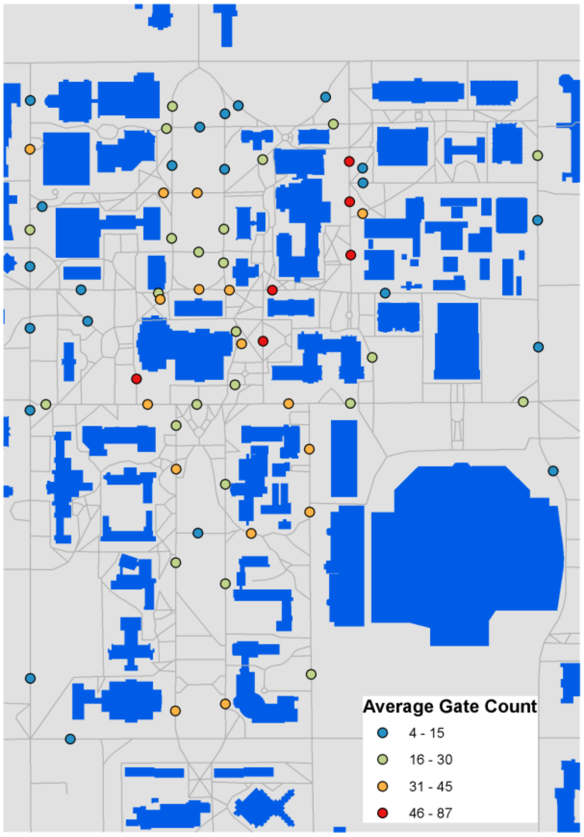


Figure 11 Average gate counts using 5-minute samples at 67 sampled locations

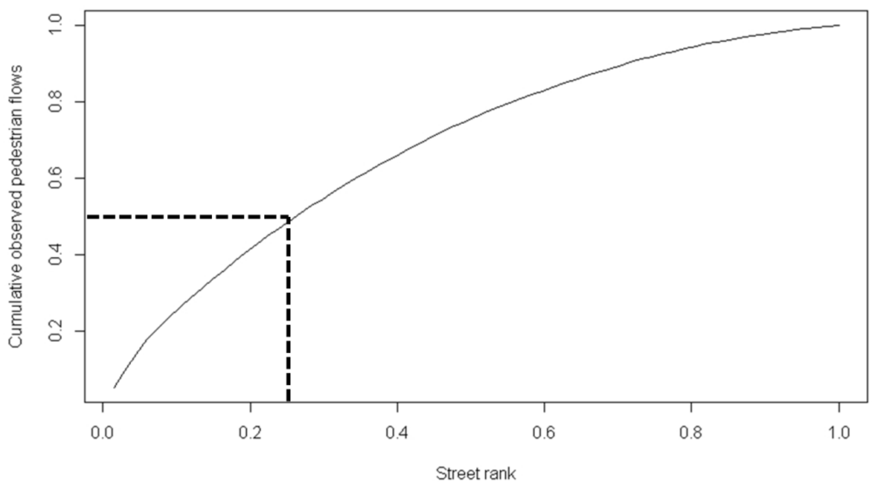


Figure 12 Cumulative distribution of observed pedestrian flow with ranked segments

3.3.2 Survey

An interview survey was conducted to obtain data about activity patterns, route selections and sketch graphs of OU Norman campus. The survey had been reviewed and approved by the Institutional Review Board (IRB) at the University of Oklahoma. The purpose of this survey is to identify how people of different groups use space for types of activities, how individuals choose the route to a destination, and what spatial objects stored in memory are physically and psychologically important to the subject. Therefore, participants were asked to (1) draw a sketch map about the physical layout of OU Norman campus from memory; (2) response to questions about their spatial experience at OU, their perception of use of campus space, and their route selection to specific destinations. More specifically, the task of sketch map was the first part of survey interview so that the map was drawn from memory without reference to other map products. Voluntary participants were given 8.5’’×11’’ sheet of plain white paper and asked to sketch an image of OU campus including everything he/she remembered about the campus area. The participants were instructed that the purpose of this sketch map was to help a visitor to explore and navigate on campus. No time limit was set for this task as related studies suggested that most of participants would finish it within 15 minutes (Blades, 1990; Poppinga, Magnusson, Pielot, & Rassmus-Gröhn, 2011). As the second part regarding perceived use of campus space, participants first indicated their most frequent activities on campus and identified all or the top three areas that they would go for varied types of activities. The choices of location were collected for nine type of activities which covered most of common activities on campus: (1) hanging out with friends or colleagues, (2) looking for something for fun or entertainment (e.g., movies, billiards, watching TV), (3) self-studying, (4) organizing group study or group meeting, (5) looking for open lectures or seminars, (6) eating lunch, dinner or snacks, (7) doing physical exercises or physical activities (e.g., Frisbee, walking, weight-lifting), (8) parking or taking public transit, and (9) taking a nap or break. The last part of the survey was the route selection task. Theses voluntary participants were asked to draw the preferred route that they may take between two campus buildings. The route selections tasks were followed by an open question about the reasons for choosing the specific route. This study specifically conducted two route selections tasks: the route between Bizzell Memorial Library and Sarkeys Energy Center and the route between Sarkeys Energy Center and Dale Hall. These selected buildings were best known by OU students, staff, and faculty. The detailed survey design is stated in Appendix A.

The survey was conducted by face-to-face interviews through a convenient sampling on Norman main campus. The convenient sample for survey participation used any subjects that were available to participate in the research study. The recruitment of volunteers included advertisement on bulletin boards in campus buildings, brief announcement before class with the permission of instructors, and email invitation to all faculty, all staff, and all students through the OU mailing system. The survey was scheduled at noon on every Monday, Wednesday, and Friday in different survey locations between 10/5/2015 and 12/4/2015. Overall 126 volunteers participated in the survey interview. Compared with other empirical studies using the sketch map methods (Table **6**), this sample size provided an appropriate number of observations for the purpose of this study. Additionally, the surveys also collected each participant’s demographic characteristics such as gender, race, role, the number of years and self-report of familiarity level with the campus layout. Although the survey interview were conducted through convenient sampling, compared with OU facts, no systematical bias by participant types (Table **3**), gender (Table **4**) or race (Table **5**) were observed in the sample of participants.

Table 3 Comparison of participant type for sample frame and sample

Role	Total Sample frame Fall 2015	% of Participant Type for Sample frame	Survey Participants Sample (Actual)	% of Participant Type for Sample
Faculty	1,660	5.1%	7	5.6%
Staff	3,916	11.9%	13	10.3%
Student	27,261	83.0%	106	84.1%
Total	32,837		126	

Table 4 Comparison of gender for sample frame and sample

Role	Sample Frame				Sample					
	Fall 2015 Male		Fall 2015 Female		Male Participants		Female Participants		Other	
Faculty	900	54.2%	760	45.8%	3	42.9%	4	57.1%	0	0.0%
Staff	856	21.9%	3,060	78.1%	3	23.1%	10	76.9%	0	0.0%
Student	13,939	51.1%	13,323	48.9%	53	50.0%	52	49.1%	1	0.9%

Table 5 Comparison of races for sample frame and sample

Races	Total Sample frame Fall 2015	Survey Participant Sample (Actual)
White	69.9%	62.7%
Native American	8.7%	4.2%
Asian	6.4%	10.6%
Black	6.5%	7.0%
Hispanic	8.0%	12.0%
Others	0.6%	3.5%

Table 6 Empirical studies using sketch map methods and sample sizes

Studies	City/Area (Country)	Sample size
Lynch (1960)	Boston, Jersey City, Los Angles (United States)	60
De Jonge (1962)	Amsterdam, the Hague, Rotterdam (Netherlands)	72
Gulick (1963)	Tripoli (Lebanon)	35
Tversky (1981)	Palo Alto (United States)	47
Yan (1990)	Beijing (China)	432
O'Neill (1991)	Building floor plan	63

Yeung and Savage (1996)	Orchardscape (Singapore)	291
Kim and Penn (2004)	Hampstead Garden Suburb (London, United Kingdom)	76
Haq and Girotto (2003)	University hospital and city hospital	96
Yun and Kim (2007)	Yonsei University (Seoul, South Korea)	39

3.3.3 Spatial distribution of WiFi usage

In this study, WiFi usage is selected to represent spatial distribution of human activities on campus. An earlier study at MIT found that 73% of students use their laptops equipped with WiFi on campus every day or some days of the week (Sevtsuk, 2009). The popularity of campus WiFi has been further enhanced with the development of ubiquitous WiFi infrastructure and smart phones. Therefore, WiFi usage serves as a proxy measure to describe daily working and living patterns on campus. The WiFi usage on campus was collected by the department of information technology at OU (OU IT) for two weeks between 11/9/2015 and 11/24/2015. OU IT provides us with the average daily WiFi usage by building during work days. This WiFi usage is determined by the number of users within the coverage of the access point although these users may not actually be using the access point. In the data that was made available to us, wireless traffic in 59 buildings on OU campus was observed (Figure **13**). These buildings include most of academic offices and classrooms but exclude housing, parking and utility facilities.

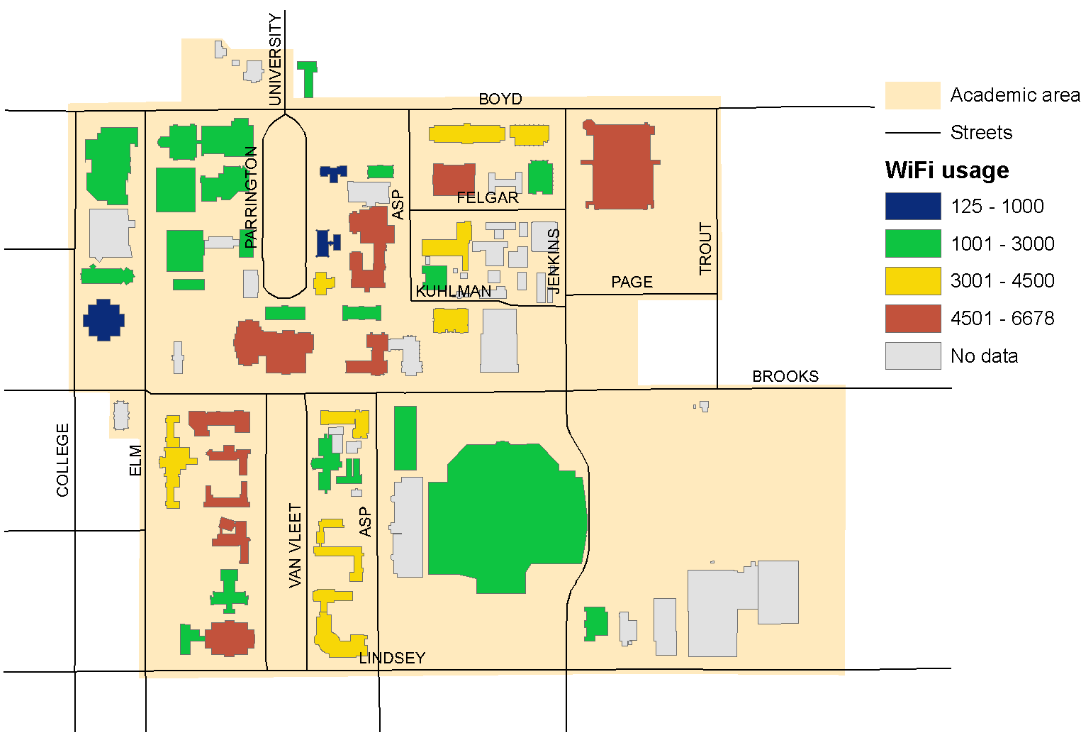


Figure 13 Spatial distribution of daily average WiFi usage in campus academic area

3.4 Method specification

Based on the conceptual framework as shown in Figure **9** above, the analysis proceeded from three dimensions: network centrality analysis, functional centrality analysis, and sketch map analysis. The specific method and data would vary for different analytical aspects (see Table **7**, below). The definition of variables will be discussed in details in the following subchapters. The first part is to examine relationships between the specific aspects of space and the patterns of pedestrian flows. Space is characterized by network centrality and functional centrality. The study uses the observed pedestrian flows as the dependent variable with two kinds of explanatory variables including syntactical variables describing the structural centrality of network and semantic variables describing the contextual characteristics for pedestrian movement in the study area. The second part is to investigate how these syntactically and semantically salient features are expressed in the sketch map of campus layouts. The study also examines the influences of spatial familiarity on the forming of cognitive map. A logistic regression model is used to assess the impacts of network centrality, functional centrality, and familiarity on predicting the presence of landmarks. The third part is to investigate how landmarks are used in individual route selections and develop a landmark based approach of pathfinding.

Table 7 Data and method in the analytical dimensions

Analytical dimensions	Analytical chapters	Data	Collection methods	Variable	Analytical method
Space syntax	Chapter 4.1: Network effects on pedestrian movement	Street network	Campus GIS database	Degree	▪ Correlation analysis
				PageRank	
				Closeness	
				Betweenness	
Space semantics	Chapter 4.2: Impacts of spatio-functional interaction on pedestrian movement	WiFi usage	IT department database	Number of users connected to WiFi	▪ Kernel density estimation ▪ Correlation analysis
		Activity pattern	Survey interview	Perceived functional densities	▪ Multiple regression methods
				Perceived functional diversity	▪ Multiple regression methods
Spatial cognition	Chapter 4.3: The image of OU campus	Sketch map	Survey interview	Campus boundaries	▪ ANOVA
				Number of landmarks (buildings, paths, intersections) drawn	▪ ANOVA ▪ Logistic regression
				Topological accuracy	▪ ANOVA

Pedestrian movement	Chapter 4.4: Individual wayfinding behaviors	Route selection	Survey interview	Route drawn for route selection tasks	▪ Frechet distance ▪ ANOVA
				Criteria for route choices	▪ Frequency distribution
		Sketch map		Landmarks based pathfinding	▪ Frechet distance ▪ ANOVA
Survey respondents	Chapter 4.3 & 4.4	Familiarity	Survey interview	Self-reported familiarity	▪ ANOVA ▪ Logistic regression
				Number of years working or study at OU	▪ ANOVA ▪ Logistic regression

3.4.1 Network centrality analysis

The core of space syntax studies lies in the proposition that spatial configuration of urban street network is the primary generator of pedestrian flows. Spatial configuration is characterized by network centrality which identifies important street based on its position in the network. The association between space syntax and pedestrian movement are examined by the correlation analysis between network centrality measures and observed pedestrian flows.

3.4.1.1 Street based representation

As described in Chapter 2.1, spatial syntax analysis is grounded on the representation of urban structures. Street based analysis of spatial configuration is chosen over axial lines based representation in this study for a variety of reasons. First, road centerlines have been easily available for use within geographical information systems. The space syntax community still argues about the necessity and exact definition of axial lines (Batty & Rana, 2004; Ratti, 2004). Secondly, this intuitive way of using road centerlines as the skeleton network is able to represent precise positions of street intersections and edges. In contrast, the construction of axial map relies on refinement of researchers in deciding whether or not a certain split of axial line in the environment is important (B Jiang & Sun, 2008). The choice of minor shift in configuration leads to significant differences in analytic results (Ratti, 2004). Thirdly, street network allows us to work with varied concepts of distances for navigation choices such as metric, topological, and geometric distances. Axial map based analysis depends on the notion that pedestrian movement is shaped by topological properties of urban grids.

3.4.1.2 Measures of centrality in street networks

Space syntax literatures provide a set of quantitative measures to describe spatial configuration of urban structures and identify important segments that lie at the central positions over the network. Network centrality in this study is described from four aspects: 1. degree centrality as being adjacent to others (i.e., connectivity as it is called in axial map analysis); 2. PageRank as being clustered with other central segments (i.e., eigenvector centrality); 3. closeness centrality as being close to others (i.e., integration as it is called in axial map analysis); and 4. betweenness centrality as connecting two other nodes (i.e., choice as it is called in axial map analysis). On one hand, both degree centrality and PageRank are grounded on link analysis. Specifically, degree centrality is based on the idea that important nodes have the largest number of linkages connecting them to different directions. As shown in equation (1) below, the measure of degree centrality for a node is determined by the number of nodes adjacent to it (Wasserman & Faust, 1994). Two nodes are adjacent if they are linked by an edge. Nodes with a large number of first neighbors are considered as the central locations in the network graph. PageRank provides a recursive view that a highly ranked node is likely to receive connection from other highly ranked nodes (Bin Jiang, 2009). The computational iteration starts from equal PageRank scores for all nodes and ends when convergence is reached. For each iteration, a node either selects a connected node with probability of d or jumps to a randomly chosen node with probability of $1-d$. The damping factor d can be set between 0 and 1 but 0.85 is widely used in ranking web pages (Brin & Page, 1998). This study uses a weighted PageRank (Bin Jiang, 2009) in equation (2) where a PageRank score is not evenly divided over nodes that it connects with but is distributed by the proportion of their degree centrality. In other words, a node with a higher degree centrality contributes more to the propagation of PageRank scores. On the other hand, closeness and betweenness (Crucitti et al., 2006) go beyond the identity of one node and emphasizes the distribution of centrality by passing through all nodes in the network. Closeness is determined by the sum of distances to all the other nodes through the shortest paths (see equation (3) below). Closeness conceives of a network position as accessibility to all the others. Betweenness shown as equation (4) is based on the idea that a central node lies in the position traversed by many shortest paths between all pairs of nodes. Betweenness suggests that a network position has strategic control and influence on the others.

$$Degree_i = \sum \ell_{ij} \tag{1}$$

where i and j are street segments

$$\ell_{ij} = \begin{cases} 1, & if\ i\ and\ j\ are\ connected \\ 0, & if\ i\ and\ j\ are\ disconnected \end{cases}$$

$$PageRank_i = \frac{1-d}{n} + d \sum_{j \in ON_i} PageRank_j \frac{w_j}{\sum_{m \in C_j} w_m} \qquad (2)$$

where $PageRank_i$ *and* $PageRank_j$ *are rank scores of node* i *and* j;

d *is a damping factor which is usually set to* 0.85 *in ranking web pages*;

n *is the number of nodes that point to* i;

ON_i *are nodes that point to* i;

w_j *is the weight of* j (*i.e.*, $Degree_j$);

C_j *are couterpart of* j.

For example, node $e1$ *are connected with node* $e2$ *and* $e3$, *PageRank of node* $e1$ *are calculated as below*:

$$PageRank_{e1} = \frac{1-d}{2} + d(PageRank_{e2} \frac{Degree_{e2}}{Degree_{e2} + Degree_{e3}} + PageRank_{e3} \frac{Degree_{e3}}{Degree_{e2} + Degree_{e3}})$$

$$Closeness_i^r = \frac{N-1}{\sum d_{ij}},\ j \in G - \{i\}, d_{ij} \le r \qquad (3)$$

where d_{ij} *is the shortest distance between i and* j;

N *is the number of nodes within neighbor distance of* r;

G *are all nodes within neighbor distance of* r.

$$Betweenness_i^r = \sum \frac{n_{jk}[i]}{n_{jk}},\ j,k \in G, d_{ij} \le r, d_{ik} \le r \qquad (4)$$

where n_{jk} *is the shortest path between segment j and k*

$n_{jk}[i]$ *is the number of the shortest paths that pass by* i;

d_{ij} *is the shortest distance between i and* j;

G *are all nodes within neighbor distance of* r.

Network centrality is essentially grounded on three assumptions: (1) pedestrians choose the route with the shortest length, (2) probabilities of traveling from one node to any other nodes are equal, and (3) the distribution of origin-destination (OD) pairs corresponds to that of network edges. This study goes beyond the centrality measures in the previous space syntax studies and challenges these assumptions by taking into account the varied distance concepts, the distance decays effects, and the spatial heterogeneity of human activities.

3.4.1.3 Varying distance concepts in centrality analysis

Most of network centrality analysis, particularly the calculation of closeness and betweenness, depends on shortest distance measured metrically (Crucitti et al., 2006). However, empirical evidence from cognitive science studies suggested that geometric and topological factors were also involved in navigational choices (Hillier et al., 1993; Montello, 2007). Therefore, this study extends the notion of the shortest distance in network centrality to metric, topological, and geometric concepts. As shown in Figure **14**, criterions of metric, topological, and geometric distance search for the shortest route of least lengths, fewest turns, and least angle changes respectively. Figure **14** represents the shortest route by length (a), turn (b), angle changes (c) from location A to location B.

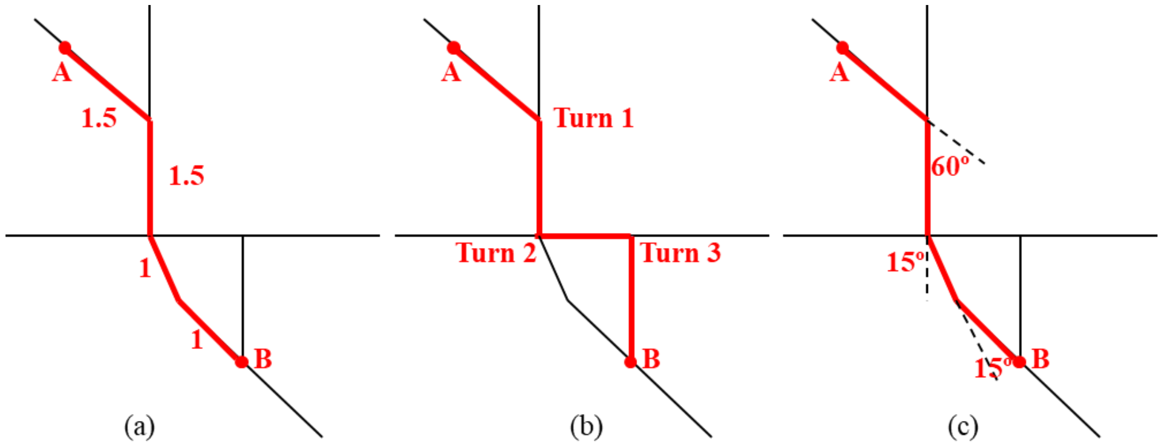


Figure 14 Types of the shortest routes
(a) metric distance; (b) topological distance; (c) geometric distance

Additionally, this study examined network centrality measures within a set of defined radiuses since previous space syntax studies suggested that local measures of centrality applied to smaller sample areas resulted in better performance in predicting pedestrian flows (Bin Jiang & Liu, 2009). Only pairs within these defined radiuses were used to calculate the shortest distances. As illustrated in Figure **15**, these radiuses of analysis were also determined by metric, topological and geometric distances. In Figure **15**, red dash lines described neighboring radius of distances from segment E. Specifically, local centrality measures were calculated for neighbors within 500, 750, 1000, 2500, 5000, and 10000 feet. Topological neighbors were analyzed for every third radius from 3 to 15 turns. Geometric neighbors included segments within directional changes of 90, 180, 270, and 360 degrees. This gives 90 different mathematical interpretation of the network centrality (see Table **8**, below): closeness and betweenness measures applied to the shortest length, fewest turns and least angle changes within specific metric, topological, and geometric radiuses of analysis.

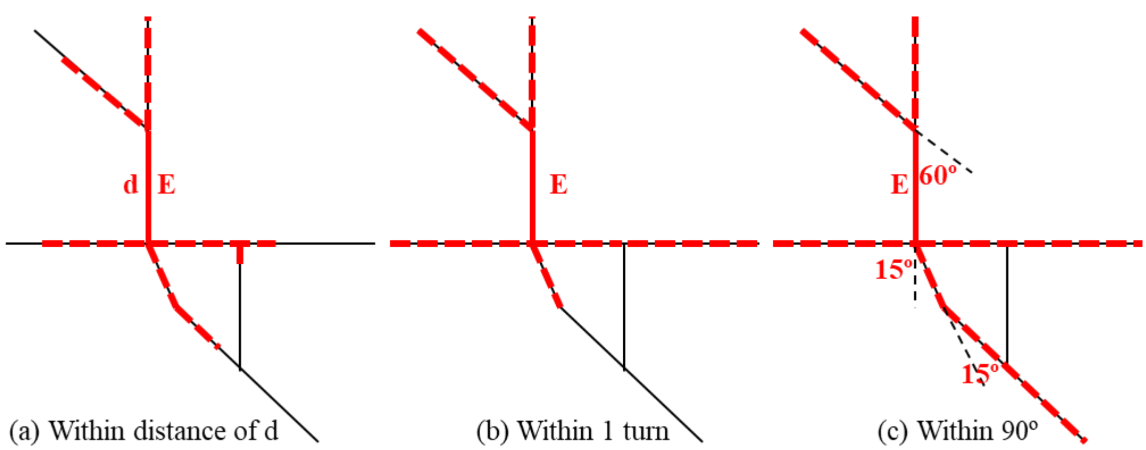


Figure 15 Radius of analysis by metric, topological and geometric distances

Table 8 Closeness and betweenness within metric, topological and geometric radiuses

Network centrality	Criteria of the shortest distance	Metric radius	Topological radius	Geometric radius
Closeness Betweenness	Metric (shortest length)	Metric_M500, Metric_M750, Metric_M1000, Metric_M2500, Metric_M5000, Metric_M10000	Metric_T3, Metric_T6, Metric_T9, Metric_T12, Metric_T15	Metric_G90, Metric_G180, Metric_G270, Metric_G360
	Topological (fewest turns)	Topo_M500, Topo_M750, Topo_M1000, Topo_M2500, Topo_M5000, Topo_M10000	Topo_T3, Topo_T6, Topo_T9, Topo_T12, Topo_T15	Topo_G90, Topo_G180, Topo_G270, Topo_G360
	Geometric (least angle change)	Geom_M500, Geom_M750, Geom_M1000, Geom_M2500, Geom_M5000, Geom_M10000	Geom_T3, Geom_T6, Geom_T9, Geom_T12, Geom_T15	Geom_G90, Geom_G180, Geom_G270, Geom_G360

3.4.1.4 Distance decay effects

Pedestrian navigation is not simply random walk over the network. Studies about human mobility patterns suggest that the distribution of trip lengths is governed by the distance decay effects (Brockmann, Hufnagel, & Geisel, 2006). The concept of radius in local measures of network centrality is essentially a practice of truncating the analysis after a maximum distance. This truncating prioritizes segments close to the target segment while ignores segments falling outside the radius, which is a kind of distance decay. This study attempts to further generalize radius of analysis and bring together betweenness centrality and distance decay effect. Distance decay refers to the idea that the further away from the target object, the less likely it will make an influence. This distance decay effect has been widely identified in many geographic phenomena and been expressed by the first law of geography (Tobler, 1970). The general distance decay function is formulated as the equation (5). When applied to the calculation of betweenness centrality, distance decay functions are used to describe the probabilities that the shortest paths occur (see equation (6) below). That is, the probability that the shortest path passes through the target segment follows a power law distribution given the length of the shortest distance. The choice of distance decay coefficient β in equation (6) represents different types of spatial structures and spatial behaviors (Hansen, 1959). This study tries different β values between 0.5 and 2.5 to search for the best betweenness centrality weighted by distance decay effect in explaining observed pedestrian flows.

$$I_{ab} \propto \frac{1}{d_{ab}{}^{\beta}} \qquad (5)$$

I_{ab} *is the spatial interaction between a and b*;

d_{ab} *is the distance between two objects a and b*;

β *is a decay coefficient*.

$$Betweenness_i^r = \sum \frac{\Pr(T \mid j,k) n_{jk}[i]}{\Pr(T \mid j,k) n_{jk}},\ j,k \in G \qquad (6)$$

$$\Pr(T \mid j,k) = \frac{1}{d_{jk}{}^{\beta}}$$

j,k *are pairs of segments over the network* G;

d_{ij} *is the distance between segment* j *and segment* k;

n_{jk} *is the shortest paths from segment* j *to segment* k;

$n_{jk}[i]$ *is the number of those shortest paths that pass through* i;

$\Pr(T \mid j,k)$ *is the probability that a trip between segment* j *and segment* k;

β *is the distance decay coefficient*.

3.4.1.5 Spatial heterogeneity of activities

Campus activities are not uniformly distributed and will influence the potential OD distribution of pedestrian movement. The hypothesis that spatial configuration independently contributes to the pedestrian flows has not been empirically tested by controlling activities patterns variations. Thus, this study continues to inspect how the distribution of activity density influences the network effects on pedestrian movement. Specifically, a spatial variable is introduced to betweenness centrality, which accounts for the spatial heterogeneity of campus activities. In this study, the spatial distribution of campus activities was approximated by the average daily WiFi usage. When activities are considered as a part of centrality measures, the probability of a trip is determined by a gravity model which is proportional to activity densities at two segments and inversely proportional to their distance (see equation (7) below). More specifically, each segment does not equally contribute to the probability of the shortest paths. Instead, the weight of each segment is determined by the daily WiFi usage of the nearest building. Since a typical wireless router travel 150 feet or less in a closed area that has obstructions, weights were assigned to segments located within 150 feet of campus buildings. This weighted betweenness suggests that if two segments are located near areas with higher density of campus activities, the trip between them are more likely to occur. Due to data availability of WiFi usage and areas of pedestrian observation, the investigation of betweenness centrality weighted by activity density was conducted in campus academic areas as shown in Figure **13** above. By using comparison of correlation coefficients in the unary linear regression, this study was able to explore the effectiveness of global betweenness, local betweenness, betweenness weighted by distance decay, and betweenness weighted by distance decay and activity density for modeling pedestrian movement.

$$Betweenness_i^r = \sum \frac{\Pr(T \mid j,k) n_{jk}[i]}{\Pr(T \mid j,k) n_{jk}}, \; j,k \in G \qquad (7)$$

$$\Pr(T \mid j,k) = \frac{w_j w_k}{{d_{jk}}^{\beta}}$$

j,k *are pairs of segments over the network* G;

d_{ij} *is the distance between segment* j *and segment* k;

n_{jk} *is the shortest paths from segment* j *to segment* k;

$n_{jk}[i]$ *is the number of those shortest paths that pass through* i;

$\Pr(T \mid j,k)$ *is the probability that a trip between segment* j *and segment* k;

β *is the distance decay coefficient*;

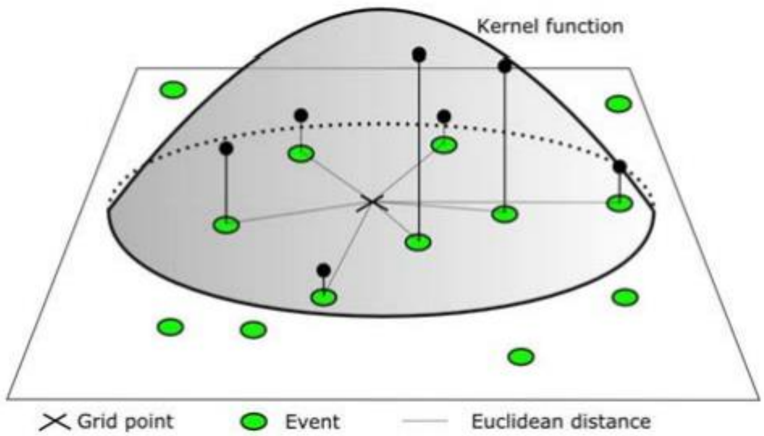
w_j *and* w_k *are the weight of segment* j *and* k (*i.e. WiFi usage of the nearest building*).

3.4.2 Functional centrality analysis

The semantic aspect of analysis is to examine whether the variation of pedestrian flows is reflected in the intensity of land use, in our case the functional centrality of campus activities, and how the spatio-functional process contributes to the pattern of pedestrian movement. Functional centrality in this study is characterized by two aspects of volume and variety and is measured by density and diversity respectively. The general distribution of activity densities on campus is described by the average daily WiFi usage. In order to examine patterns of activities for different purposes, perceived use of space collected by survey interview is used to calculate functional density and diversity of campus activities. First, kernel density estimation and correlation analysis were used to examine the effectiveness of functional centrality in predicting pedestrian flows. Second, the study investigated the extent to which the changes of network centrality and functional centrality were explained by each other. Third, multivariate regression methods were employed to assess the interactions between spatial and functional elements on modeling pedestrian movement.

3.4.2.1 Kernel density estimation

Since the street network and WiFi usage were two distinct spatial features, the kernel density estimation (KDE) method was applied to the distributions of both centrality measures and WiFi usage in order to transform them into one unit of analysis. The core of KDE lies in the idea that the surroundings of a place make it special. As a spatial smoothing method, the KDE estimates the density at the center using the observations within a neighborhood around it. Specifically, in Figure **16**, the kernel density at the grid point is estimated to be the sum of event observations within the bandwidth (equation (8)). The choice of bandwidth is a critical parameter in KDE which influences the level of smoothness. Previous studies about kernel density of urban services used the bandwidth of 300 meters (i.e., 984 feet) (Porta et al., 2009). Considering the average nearest distance between the building centroids is 261 feet, this study explored different bandwidths of 200, 400, 500, 600 and 800 feet. Within the bandwidth, KDE weights nearby observations more than far ones based on a kernel function. Although this kernel function can be described by standard Gaussian (Levine, 2006) or quartic functions (Silverman, 2018), the choice of it does not significantly affect the detection of spatial patterns (Epanechnikov, 1969). This study utilized the default quartic function implemented in ArcGIS (equation (9)). KDE essentially generates two continuous surfaces with the same resolution to represent these two distinct spatial features. As the study area, the academic area consists of 9,094 grid cells each of which is a 30 feet × 30 feet square. Each cell contains multiple values of kernel densities for different variables. Pearson's correlation is then computed based on cell-by-cell pairs of values in order to determine the extent to which variables were proportionally related to each other.



(Timothée, Nicolas, Emanuele, Sergio, & Stéphane, 2010)

Figure 16 Kernel function of the kernel density estimation

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{dist(x, x_i)}{h}\right) \quad (8)$$

$$K(r) = \begin{cases} (3\pi)^{-1}(1-r^2)^2, & if \ \ r^2 < 1, \\ 0, & otherwise. \end{cases} \quad (9)$$

K is the kernel function;

h is the bandwidth;

n is the number of events within the bandwidth;

$dist(x, x_i)$ *is the distance between grid point and event at location i.*

3.4.2.2 Functional density

The functional density refers to the number of perceived opportunities for activities within a specific radius. Opportunities of activities distinguish trips for different purpose. This study considered the following set of possible activities that occurred on campus: (1) hanging out with friends or colleagues, (2) looking for something for fun or entertainment (e.g., movies, billiards, watching TV), (3) self-studying, (4) organizing group study or group meeting, (5) looking for open lectures or seminars, (6) eating lunch, dinner or snacks, (7) doing physical exercises or physical activities (e.g., Frisbee, walking, weight-lifting), (8) parking or taking public transit, and (9) taking a nap or break. In order to standardize activities of different types in the same scale, weights of opportunities equal to the number of participants choosing the location for an activity divided by the maximum number of participants identifying affordance for this specific type of activity among all locations (equation (10)). Since this study focuses on the cumulative perception of use of space, the opportunity number for each location is assumed to be the same as 1.

$$Den_{i,r} = \sum_{j=1}^{J} \sum_{k=1}^{K} o_{j,k} \frac{n_{j,k}}{n_{\max}}, d_{ij} < r \qquad (10)$$

$o_{j,k}$ *is the number of opportunity for type k activity at location j;*

$n_{j,k}$ *is the number of participants suggesting location j affords activity of type k;*

$n_{\max}$ *is the maximum number of participants suggesting one location affords activity of type k;*

d_{ij} *is the distance between location i and j.*

3.4.2.3 Functional diversity

The functional diversity is another aspect of functional centrality which measures the equal distribution for different types of campus activities. Information entropy is one of the most common indices of measuring land use mixing (L. D. Frank & Pivo, 1994). This study applied entropy to measuring the diversity of campus activities. More specifically, area percentages of different land uses were transformed into the percentage of participants suggesting different types of activity affordances (equation (11)). Higher functional diversity suggests more heterogeneous distribution of campus activities while zero value of functional diversity indicates homogeneous distribution.

$$Div_{i,r} = \frac{-\sum_{k=1}^{K} P_{i,k} \ln(P_{i,k})}{\ln(K)}, d_{ij} < r \qquad (11)$$

$$P_{i,k} = \frac{n_{j,k}}{\sum_{k=1}^{K} n_{j,k}}$$

$n_{j,k}$ *is the number of participants suggesting location j affords activity of type k;*

K is the total number of activity types;

d_{ij} *is the distance between location i and j.*

3.4.3 Sketch map analysis

Sketch map method has been widely used to externally represent cognitive map as what a person knows about a specific place and also how these thoughts influence their behaviors, specifically in this study the pedestrians' wayfinding. The sketch map analysis in this study consists of two parts. The first part is to investigate the aggregated pattern captured by a collection of sketch maps. The study examined what salient features were drawn in sketch maps and how network and functional centrality contributed to the forming of landmarks. The second part focuses on the individual sketch maps. The study inspected the influence of spatial familiarity on landmark salience and the relationship between activity space and sketch map.

3.4.3.1 Boundary delimitation

Regions like campus areas are perceived and expressed imprecisely in terms of vague concepts with fuzzy boundaries (Montello, Goodchild, Gottsegen, & Fohl, 2003). As the first part of analysis, this study used the sketch maps drawn by survey participants to estimate the individual referent of OU campus space. The method of boundary delimitation is grounded on the concept of action space (Horton & Reynolds, 1971) which describes a choice set of places for which individual possess sufficient knowledge to assign preference. Specifically, the analytical expression of a convex hull was used to approximate perception of the campus boundary. For each survey participant, the convex hull referred to the smallest convex polygon that contained all spatial features drawn in sketch map (see Figure **17**).

(a) (b)

Figure 17 Raw-data of sketch maps and related convex hull
(a) Raw-data sketch maps for one participant; (b) convex hull of spatial features in the participant's sketch map

3.4.3.2 Code scheme of sketch maps

The spatial features captured by sketch maps allow identification of which places were important to pedestrians. Conventional analysis of sketch maps is grounded on the disaggregation of represented elements outlined by Lynch (1960): nodes, landmarks, paths, edges, and districts. However, the concept of these components is confusing without the context of movement patterns. Whether a place is a node or a landmark is not able to be interpreted from the map alone because the identification requires additional information about purposive behaviors of the pedestrian (Walmsley & Jenkins, 1993). For example, the library can be a landmark if it is used as a reference point in navigation, but it will be a node if it serves as the strategic focus points for orientation in day-to-day life. This study concentrated on landmarks for pedestrian navigation. The term of landmark in this study is used to denote all salient structures in the environment. Specifically, a landmark is not only a simply defined feature such as a building, an attraction or a clock tower, but also a node of street intersection, a path of any kind and an area like parking lot or landscape garden. In terms of frequency of appearance, as shown in Table **9**, the sketch maps for campus areas were dominated by buildings, which was a consistent finding with previous studies (Banai, 1999; Tu Huynh & Doherty, 2007).

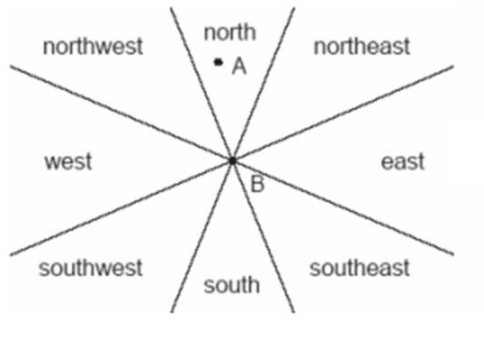
Table 9 Sketch map elements drawn by survey participants

Landmarks	Mean
Buildings	21.5
Paths	6.6
Street intersections	6
General areas	3.3
Other simple features	1.7

Note: 126 survey participants

3.4.3.3 Topological accuracy

Successful wayfinding depends on the integration and memory of landmarks and streets in spatial relations (Lee & Tversky, 2005). Empirical studies also suggest that topological knowledge is generally more important than metric knowledge for effective navigation (Hillier & Hanson, 1989; Rovine & Weisman, 1989). As the third part of analysis, sketch maps were assessed in terms of topological accuracy. Since buildings and paths were the dominant elements captured by sketch maps, the topological accuracy in this study focused on spatial relations between pairs of buildings and street intersections included in sketch maps. For each pair of analysis, the absolute bearing was calculated to determine the degree of angle in a clockwise direction from the north. The directions were then translated into the qualitative descriptions by the cone-based model as shown in Figure **18** (Liu, Wang, Jin, & Wu, 2005). Each cone was 45˚. When directions drawn in sketch maps were compared with the actual directions, same qualitative descriptions were considered as being ‘matched’ with a score of 2. If the qualitative descriptions were different but the angle in between was less than 45˚, directions were considered as ‘partially matched’ with a score of 1. Pairs of directions that were not matched obtained the score of 0 (see Figure **19** below).



(Liu, Wang, Jin, & Wu, 2005)

Figure 18 Cone-based model for cardinal directions

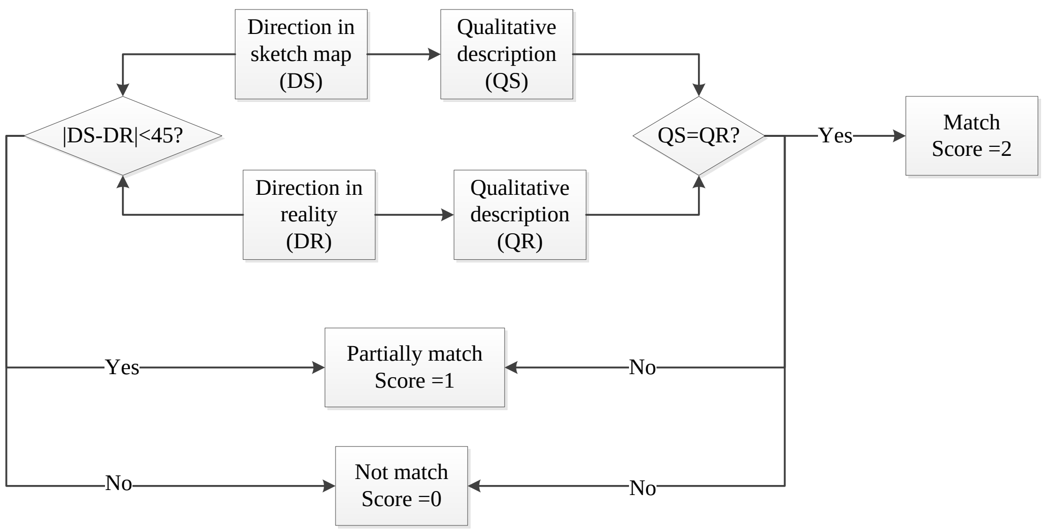


Figure 19 Calculation of score for topological accuracy

3.4.3.4 Spatial familiarity

The complexity of the sketch map is related to individuals' experience of places and personal preferences (Appleyard, 1970). In previous studies, personal experiences were characterized from five aspects: familiarity, travel model, location of home, associativity, and socio-economic characteristics (Long, Baran, & Moore, 2007). This study focused on pedestrian movement and considered the influence of spatial familiarity and locations of anchor points on the forming of spatial knowledge represented by sketch maps.

Familiarity was described by two aspects: how long they have studied or worked on campus and self-assessment of how familiar they are with the campus areas. Figure **20** illustrated the frequency distribution of spatial familiarity for survey respondents. The survey sample included a good combination of respondents staying at OU for a long period of time and those new to the environment. Of 126 survey participants, 29% worked or studied at OU for less than one year, 25% for 1-2 years, 9% for 2-3 year, 12% for 3-4 years, and 25% for more than 4 years. With the number of staying years increased, respondents were more likely to report they were very familiar with the environment. For respondents staying at OU for less than one year, only 10% of them reported they were very familiar while about 50% of respondents for more than 4 years reported very familiar. Most of respondents reported that they were above the average level of familiarity with campus areas. Therefore, the following analysis combined the groups of very unfamiliar and unfamiliar.

Spatial familiarity plays an important role in pedestrian navigation as it influences the knowledge acquisition and strategies followed. O'Neill (1992)'s study provided empirical evidence that as familiarity with an environment increased, wayfinding performances improved in accuracy and latency, and the degree of complexity of the layout became less important. In this study, the analysis of variance (ANOVA) was conducted to investigate whether the completeness and accuracy of sketch map were significantly different among groups of participants with different levels of spatial familiarity. Tukey's HSD (honestly significant difference) test was then applied to test whether the means were significantly different from each other.

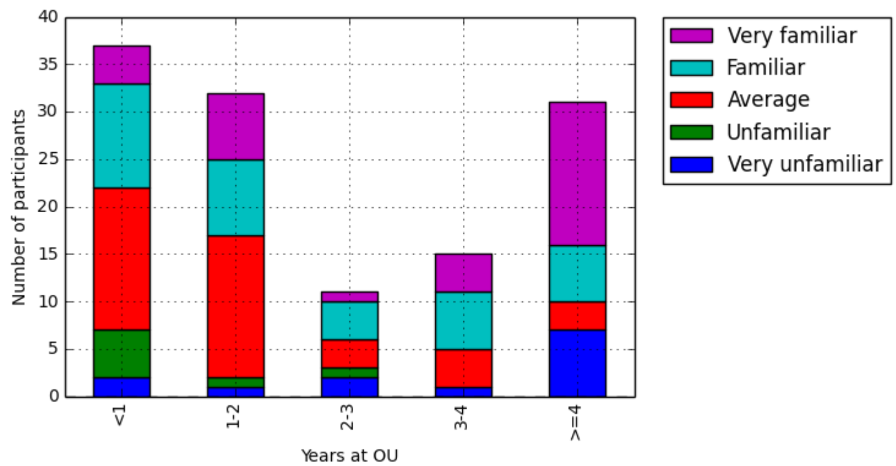


Figure 20 Frequency distribution of spatial familiarity

3.4.3.5 Anchor points

Anchor points closely relate to landmarks in terms of cognitively salient cues in the environment. Couclelis et al. (1987) argued that landmarks described the travel cues from a collective perspective while anchor points were more personalized and captured in individual cognitive maps. For example, locations of home and work would be too personal to be meaningful for other people. In this study, places where survey participants took the classes and worked were considered as personal anchor points. Distance to the anchor point served as a moderating variable in modeling the probability that a spatial feature was captured in cognitive map. For multiple anchor points, the minimum distance was used as the independent variable in logistic regression models.

3.4.3.6 Logistic regression of landmarks

The probability that a spatial feature is captured by the cognitive map is determined by its salience. The salience of features in this study was characterized from two aspects:

syntactical prominence and semantic significance. Logistic regression models were used to assess the likelihood that a spatial feature was present in the cognitive maps (see equation (12)-(14) below). Specifically, the dependent variable was binary coded as whether a spatial feature was present or absent in sketch maps. For logistic regression models in this study, the dataset of spatial features included all campus buildings, all streets with names, and all street intersections. General areas were excluded in logistic regression analyses as it usually related to vague regions with ambiguous boundaries. Independent variables included betweenness centrality, functional density, number of years at OU, level of familiarity, and minimum distances to anchor points. Since the probability *P* increased when the value of y increased, a positive sign of coefficient indicated that the explanatory variable contributed to increasing the probability of presence in sketch maps while a negative sign implied the opposite effect. The fit of logistic regression models was evaluated by McFadden R^2. As a part of the calculation for this pseudo R^2, the log likelihood value for the fitted model is divided by the log likelihood value for the null model with only an intercept (equation (15)). The value of McFadden R^2 ranges from 0 to 1. This pseudo R^2 is typically low and is not interpreted in the same way as R^2 in a linear regression model. The larger value indicates that the fitted model produces much better prediction than the intercept model.

$$y = a + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n \qquad (12)$$

$$y = \ln[\frac{P}{1-P}] = \mathrm{logit}(P) \qquad (13)$$

$$P = \frac{e^y}{1+e^y} \qquad (14)$$

$x_1, x_2, \cdots, x_n$ *are explanatory variables*;

$b_1, b_2, \cdots, b_n$ *are coefficients*;

P is the probability of presence of landmarks in sketch maps.

$$R^2_{McFadden} = 1 - \frac{\log(L_f)}{\log(L_{null})} \qquad (15)$$

L_f *is the maximized likelihood value for the fitted model*;

L_{null} *is the maximized likelihood value for the null model with only intercept*.

3.4.4 Route selections analysis

Spatial knowledge plays an important role in wayfinding decisions of where to go and how to get there. People tend to use the cognitively stored and recalled information more than the supplement materials such as maps and GPS, especially when wayfinding occurs in the familiar environment. The study continues to examine the interactions between spatial cognition and pedestrian navigation, particularly how individual wayfinding behaviors are influenced by the cognitive maps and how the increase of spatial experience contributes to the update of cognitive maps. The analysis focuses on impacts of route selection criteria and landmarks captured by the cognitive maps. First, we will look into the individual choices of the route selection. Additionally, we will examine how levels of familiarity influence the perception of distance. Finally, the study investigates how personal landmarks provide the navigation cues for individual route selections.

3.4.4.1 The perception of distances

Previous work gives evidence that human navigator does not exclusively choose the shortest path by length (Golledge, 1995; Hochmair, 2004). The cost of traveling is essentially determined by the perception of distance (Montello, 1997). This perception of distance is not only shaped by the metric properties of network but also topological and geometric attributes (Montello, 2007). This study focuses on the concept of travel distances, particularly the perception of distance made by each pedestrian.

In order to understand the perceived distances by pedestrians, the performance of each participant in route selection tasks was observed and measured. Survey participants drew their preferred routes of Bizzell Memorial Library - Sarkeys Energy Center and Sarkeys Energy Center - Dale Hall. The chosen routes by survey participants were then compared to the target routes calculated. Specifically, for each route selection task, three types of target routes were generated: metric route of the shortest length, topological route of the fewest number of turns, and geometric route of the least angle change (see Figure **21** below). The study also considered three entrances of Dale Hall, six entrances of Sarkeys Energy Center and two entrances of Bizzell Memorial Library. Frechet distance was used to measure the difference between the chosen route drawn by survey respondents and three target routes. The concept of Frechet distance can be illustrated as a man walking a dog on a leash (Alt & Godau, 1995). Suppose the man moves on one curve while the dog on the other with varied speeds, the Frechet distance is the shortest length of leash that will be sufficient for traversing both curves (Alt & Godau, 1995). As backtracking is not allowed, the Frechet distance also takes into account the location and order of points along the curves. As shown in the equation (16), for every possible function $\alpha(t)$ and $\beta(t)$, the largest distance between the man and its dog was found as they walk along their respective path. Finally, the Frechet distance refers to the smallest distance among these maximum distances. This study utilized the discrete Frechet distance algorithm (Eiter & Mannila, 1994) which resulted in a good approximation of the continuous measure (see Figure **22**, below). Frechet distance essentially describes the geometric similarity between two line features. Larger Frechet distance indicates that the route drawn by the participant deviated more from the calculated route. Small Frechet distance means that the target route calculated by the perception of distance better predicts the route to be taken.

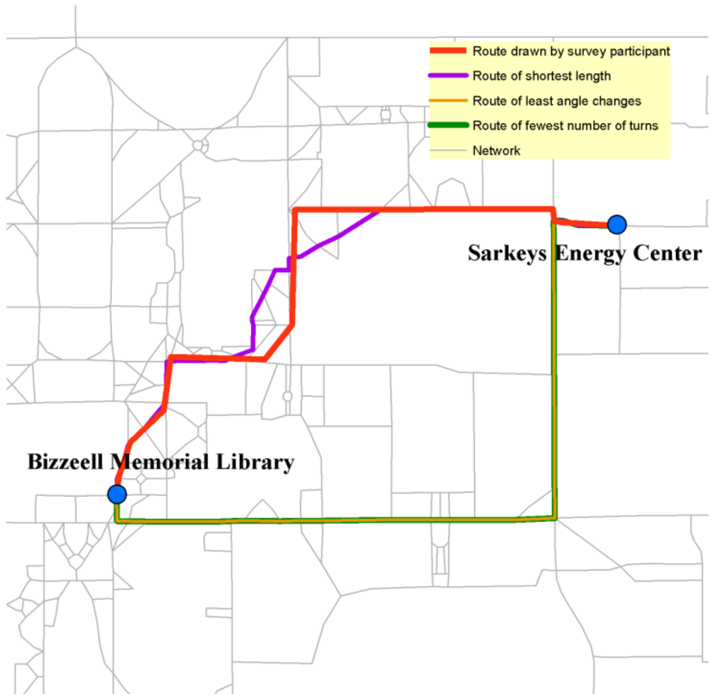


Figure 21 Comparing route drawn by survey participant and target routes of shortest length, fewest number of turns and least angle changes

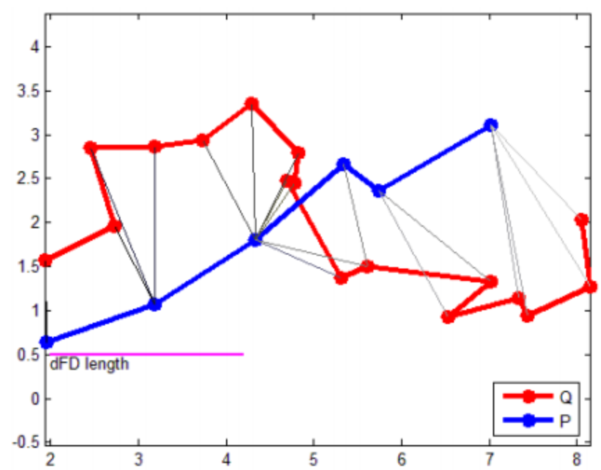
$$F(P,Q) = \min\{\max\{d(P(\alpha(t)), Q(\beta(t)))\} \qquad (16)$$

$\alpha[0,1] \rightarrow [a, a'], \beta[0,1] \rightarrow [b, b'], t \in [0,1]$

$P:[a,a'], Q:[b,b']$ *are curves*

$P(\alpha(t)), Q(\beta(t))$ *are positions on the curves*

d is the distance between two curves.



(Eiter & Mannila, 1994)

Figure 22 Discrete of hypothetical routes

3.4.4.2 Usage of landmarks in route selections

Landmarks are not only an organizing concept of spatial knowledge as described in sketch map analysis but also provide environmental cues to find the way and serve as an essential component of route instructions. Therefore, this study focused on not only what features served as landmarks but also how these landmarks were used in pedestrian navigation, particularly to support route selections.

Although landmarks provide important navigation cues for pedestrians, very few path-finding algorithms start with the availability of landmarks. This study incorporated landmarks as the weight of street segments for route selection. This weight depended on the number of visible landmarks within a neighboring radius of the street segment. Lovelace, Hegarty, and Montello (1999) distinguished types of landmarks: landmarks of reorientation at decision points, route landmarks confirming to be on the right way, and distant landmarks. Previous studies found that distant landmarks were only used in navigation by a novice for coarse reference (Lynch, 1960; Raubal & Winter, 2002b). This study concentrated on local landmarks that were visible within a neighboring radius of the street segments. As shown in Figure **23** below, the view analysis with isovist was used to identify visible landmarks from the center of each street segment. Considering the average length of segments, the neighboring radius used in this study was 1,000 feet. The pathfinding aimed to not only minimize the distance to be traversed but also maximize number of landmarks. Specifically in the landmark-based path finding calculation, the equation (17) was used to determine the cost of each segment. For each survey respondent, the view analysis was conducted within the personal landmarks captured in cognitive maps. For example, in Figure **24**, using the personal landmarks drawn, the landmark based approach resulted in better prediction of the route drawn by the survey participant #51.

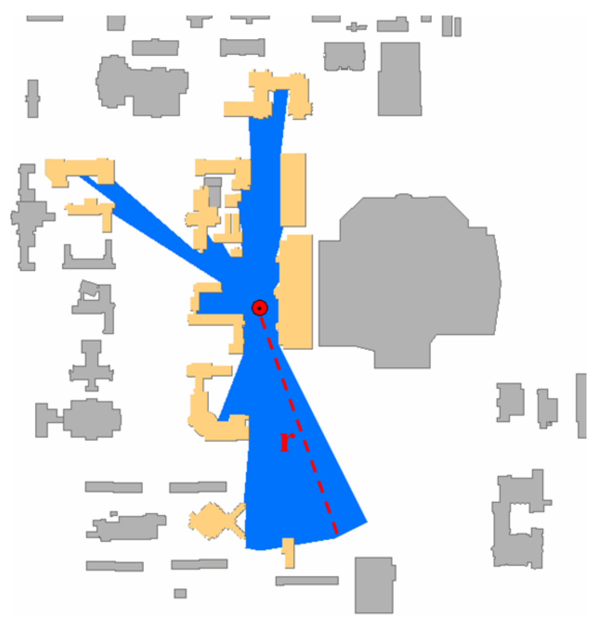


Figure 23 Visible landmarks within neighboring radius at the center of a street segment

$$W = \frac{D}{L_r + 1} \qquad (17)$$

W is the cost of the segment;

D is the length of the segment;

L_r is the number of accessible landmarks within r distance;

r is the neighboring radius.

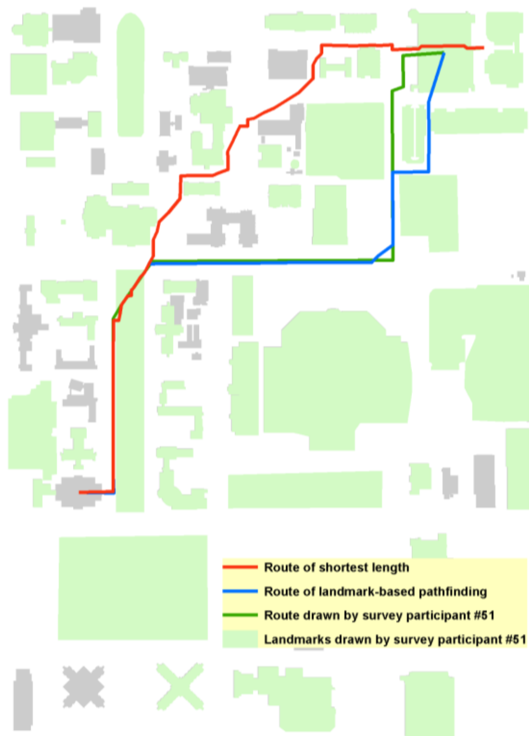


Figure 24 Comparing route drawn by survey participant and target routes of shortest length and landmark-based approach

3.5 Summary

The purpose of this chapter is to introduce a theoretical framework of space, cognition and movement and utilize it to guide the empirical study. Space is characterized by two aspects of space syntax and space semantics. For syntactical analysis, the study not only uses measures of network centrality to examine network effects on pedestrian movement but also improve them by varying concepts of distance, adding distance decay effects, and weighting spatial heterogeneity of activities. In semantical analysis, functional centrality is described by density and diversity. Using the centrality measures, the study is able to derive syntactically and semantically salient features and model the presence of landmarks in cognitive map. The chapter finally develops a landmark-based pathfinding method to identify the optimal route that balances demands of minimizing the travel distance and reducing the cognitive energy of processing.

Chapter 4: Results

The analysis in this chapter follows three objectives. The first is to examine the extent to which interactions of spatial and functional elements contribute to pedestrian movement. The second is to assess what factors significantly explain the presence of landmarks in cognitive map. The third is to investigate how landmarks can be utilized in route selections and develop a landmarks-based approach for pathfinding. The chapter starts with the correlation analysis between observed pedestrian flows and measures of network centrality and functional centrality. Then the multivariate regression models are used to establish the relationships between spatio-functional interactions and pedestrian flows. In the following sketch map analysis, the completeness and accuracy of sketch maps are compared among groups with different levels of familiarity. The logistic regression is utilized to identify significant factors in predicting the presence of landmarks in cognitive maps. The final analysis is grounded on the idea that pedestrians prefer routes not only of shortest distances but also familiar to them.

4.1 Network effects on pedestrian movement

4.1.1 Correlation between pedestrian flows and network centrality

We first conducted correlation analysis between observed pedestrian flows and eight syntactical measures including degree, PageRank, along with closeness and betweenness that are applied to three types of distances. As shown in Table **10**, betweenness and closeness were significantly correlated to observed pedestrian flows, which indicated that pedestrian flows strongly corresponded with the most accessible and direct streets. Betweenness turned out to be the best candidate of network centrality to predict pedestrian flows. This result was consistent with previous findings by Turner (2007a). Furthermore, the best significant correlation was obtained when distances were measured by the shortest length. When distances were calculated by fewest turns and least angle change, network effect on pedestrian flows was not significant.

Table 10 Correlations between network centrality and observed pedestrian flows

Centrality	Distance	Correlation
Degree		0.13
PageRank		0.16
Closeness	Metric (shortest length)	0.3**
	Topological (fewest turns)	0.06
	Geometric (least angle change)	0.09
Betweenness	Metric (shortest length)	0.41**
	Topological (fewest turns)	0.02
	Geometric (least angle change)	0.07

Significance: *** = 0.001, ** = 0.01,* = 0.05

4.1.2 Multiple regression analysis on network centrality

The strength of each centrality measure explaining the observed pedestrian flows was further evaluated through multiple regression analysis. Degree, PageRank, closeness and betweenness were selected as the explanatory variables. As for closeness and betweenness, paths between pairs of nodes were selected by the shortest length. When four measures of network centrality were included in the model, a strong collinearity (VIF>4) was detected among degree and PageRank (Table **11**). Global betweenness was the only significant variable explaining the variation in pedestrian flows. When degree and PageRank were dropped from the model, only the coefficient of betweenness remained significant to the number of pedestrian flows. This global betweenness variable explained 16% (p=0.003) of the variation in the pedestrian flows (Table **12**).

Table 11 Multiple regression of pedestrian flows on network centrality measures

	Coefficients	p	VIF
Degree	5.7	0.24	7.2
PageRank	-88440.64	0.21	6.9
Closeness	6022.08	0.45	2
Betweenness	224.53**	0.01	2.2
R^2 = 0.18, p = 0.01, n = 67 segments			

Table 12 Multiple regression of pedestrian flows on closeness and betweenness

	Coefficients	p
Closeness	26170.48	0.8
Betweenness	202.2	0.01
R^2 = 0.16, p = 0.003, n = 67 segments		

4.1.3 Local betweenness and closeness within radius of analysis

The study continued to examine local measures of centrality, particularly closeness and betweenness within the area of analysis. On one hand, local measures of closeness resulted in better correlation with pedestrian flows than global measures. Significant correlations between pedestrian flows and local measures of closeness ranged between 0.31-0.38 for the least length interpretation of distances and between 0.27-0.3 for the least angle changes. Closeness centrality was not significantly correlated with pedestrian flows when distances were measured by the fewest number of turns. As shown in Table **13**, closeness centrality showed the best correlation with pedestrian flows when the shortest distances were measured by length and radius of analysis was 5,000 feet. This closeness demonstrated a weak positive linear relationship with pedestrian flows (correlation=0.38). On the other hand, correlation analysis of betweenness gave a consistent picture that the local measures outperformed global measures in explaining pedestrian flows. Specifically, correlations for local measures of betweenness ranged between 0.24-0.52 when it applied to the least sum of length, between 0.37-0.44 for the fewest number of turns, and between 0.29-0.4 for the least sum of angle changes. These correlation coefficients implied that betweenness was better correlated with pedestrian flows than closeness. The best correlation was obtained when the shortest distances were determined by the least sum of length and radius of analysis was 1,000 feet. This betweenness centrality showed a moderate positive relationship with pedestrian flows (correlation=0.52).

Table 13 Correlations between observed pedestrian flows and local measures of betweenness and closeness

Criteria of the shortest distance	Betweenness		Closeness	
	Range of significant correlation	Radius of best correlation	Range of significant correlation	Radius of best correlation
Metric (shortest length)	0.24-0.52***	1,000 feet	0.31-0.38**	5,000 feet
Topological (fewest turns)	0.37-0.44***	500 feet	None	None
Geometric (least angle change)	0.29-0.40***	500 feet	0.27-0.3**	750 feet

Significance: *** = 0.001, ** = 0.01,* = 0.05

4.1.4 Adding distance decay effects

Although both global and local analysis of centrality suggested that betweenness was the best measure to capture the network effects on pedestrian flows, the correlation coefficients were still not satisfactory. The study continued to examine gaps between measures of betweenness and pedestrian flows by taking the distance decay effects into account. Distance decay effects were modeled by a power law function which described the probabilities that the shortest paths occurred. Decay coefficient between 0.5 and 2.5 were applied in this study, which influenced how the probabilities decrease as the distance increase. As shown in Table **14** below, all measures of weighted betweenness centrality were significantly correlated with observed pedestrian flows. Distance decay effect is a crucial factor in analyzing network effects on pedestrian flows. Additionally, correlation between weighted betweenness centrality and observed pedestrian flows achieved a maximum of 0.70 when distance decay coefficient β was 2.0. This was the consistent finding with Gao, Wang, Gao, and Liu (2013)'s study that the urban traffic flows followed the power law distance decay with an exponent of 2.0. Furthermore, this weighted betweenness centrality outperformed global and local measures of betweenness centrality in correlation analysis. In sum, weighted betweenness centrality with distance decay effects was the best candidate to describe network effects on pedestrian flows. Distance decay effects were best described by the power law function with an exponent of 2.0.

Table 14 Correlation analysis between weighted betweennness centrality and observed pedestrian flows given different distance decay coefficient β

B	Correlation
0.5	0.63***
1	0.57***
1.5	0.66***
2	0.70***

2.5	0.63***

Significance: *** = 0.001, ** = 0.01,* = 0.05

4.1.5 Weighting spatial heterogeneity of activities

Heterogeneous distribution of activities is another factor that influences network effects on pedestrian movement. The study considered the spatial distribution of activities as weight of betweenness centrality. As discussed in Chapter 3.4, weights of activities in centrality measures were determined by the average daily WiFi usage of the nearest building. As shown in Table **15**, betweenness centrality weighted by density of campus activities was significantly correlated with observed pedestrian flows and demonstrated a strong positive relationship with observed pedestrian flows (correlation=0.71). However, compared with correlation of 0.7 for betweenness centrality weighted by only distance decay effect, adding activity density to centrality analysis did not contribute more to explaining variation in observed pedestrian flows.

Table 15 Correlation between types of betweenness and observed pedestrian flows

Types of betweenness	Correlation
Global betweenness	0.41***
Local betweenness (radius = 1000 feet)	0.52***
Betweenness weighted by distance decay (distance decay coefficient =2)	0.7***
Betweenness weighted by distance decay and activity density	0.71***

Significance: *** = 0.001, ** = 0.01,* = 0.05

4.2 Impacts of spatio-functional interactions on pedestrian movement

4.2.1 Estimating kernel densities of daily WiFi usage

The distribution of campus activities determine what places pedestrian choose for destinations, which further contributed to the patterns of pedestrian movement. The average daily WiFi usage per building was used to represent the general distribution of campus activities. More specifically, this study first applied kernel density estimation (KDE) method to point features of daily WiFi usage and generated a density surface which showed where campus activities were concentrated. Bandwidths of 200, 400, 500, 600, 800 feet were applied to calculate kernel densities. As shown in Figure **25**, the choice of small bandwidth (200 feet) demonstrated high variability and was not able to capture the general pattern of distribution. However, the increase of bandwidth resulted in the loss of spatial precision. In these density surfaces, two hot spots in areas of South Oval and Oklahoma Memorial Union were observed.

In order to examine the effectiveness of activity distribution for modeling pedestrian movement, the kernel densities of WiFi usage were then applied to correlation analysis with observed pedestrian flows. Correlation results in Table **16** suggested that the distribution of WiFi usage was significantly and positively correlated with pedestrian flows. Kernel densities of all bandwidths provided a consistent picture. The correlation coefficient was best captured when bandwidth was 400 feet.

Table 16 Correlation between kernel density of WiFi usage and observed pedestrian flows with different bandwidths

Bandwidth	Correlation
200	0.34***
400	0.63***
500	0.58***
600	0.55***
800	0.48***

Significance: *** = 0.001, ** = 0.01,* = 0.05

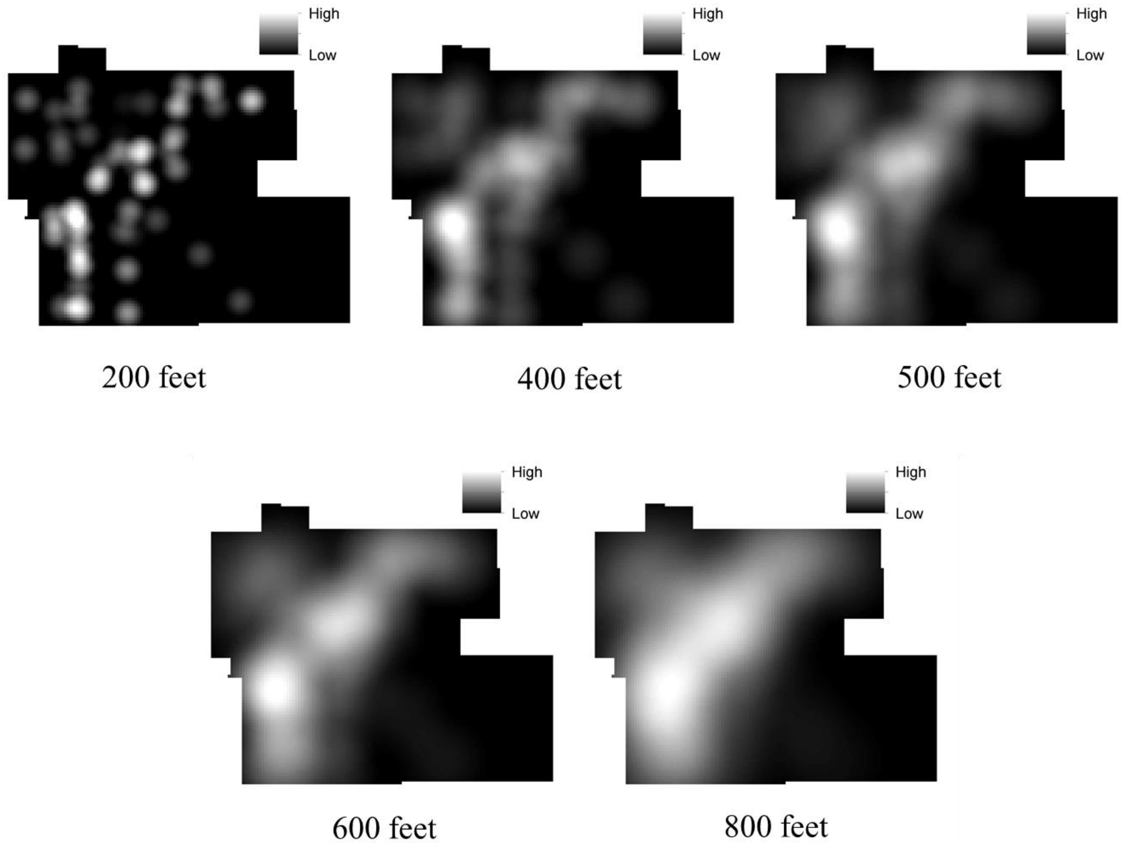


Figure 25 Kernel densities of average daily WiFi usage

4.2.2 Correlation betweenness centrality and WiFi densities

The study continued to examine whether network structure and functions were mutually dependent. As discussed earlier, the kernel density estimation method was then used to transform network centrality and activity density into the same unit of analysis so that the relationships between them could be evaluated at the same scale. More specifically, bandwidths of 200, 400, 500, 600, and 800 feet were applied to calculate kernel densities of betweenness centrality and average daily WiFi usage. This study used the betweenness centrality weighted by distance decay as it was found to be the best candidate of centrality measures in explaining pedestrian flows. Zero value of WiFi density suggested no anticipated activities occurred in the area while zero value of betweenness indicated no anticipated movement was present. Since this study focuses on the association relationship along the street network, cells of zero values in either centrality layer or WiFi density layer were excluded.

As shown in Table **17** below, betweenness centrality was significantly correlated with the general distribution of campus activities in terms of WiFi usage. Analysis using KDE with 200 feet bandwidth demonstrated weak correlation because KDE with this small bandwidth was not able to capture general areas where campus activities were concentrated. When bandwidth was increased to 400 feet, a strong positive correlation was observed. KDE results using other different bandwidths showed very similar patterns but with a stronger smoothing effect. Comparing Figure **25** and Figure **26**, the spatial pattern of WiFi usage was consistent with those of the density of street betweenness centrality, which showed the hot spots in areas of South Oval and Oklahoma Memorial Union.

Table 17 Correlation between kernel density of WiFi usage and betweenness centrality

Bandwidth	Correlation
200	0.07***
400	0.60***
500	0.72***
600	0.79***
800	0.88***

Significance: *** = 0.001, ** = 0.01,* = 0.05

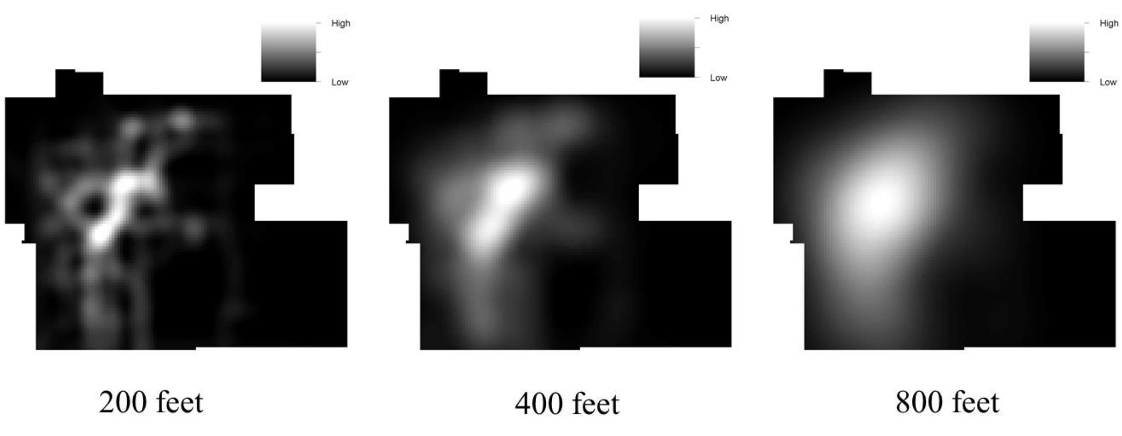


Figure 26 Kernel densities of betweenness centrality weighted by distance decay (decay coefficient = 2)

4.2.3 Street network and perceived uses of campus space

Although the correlation analysis suggested that the choice of destinations contributed to the pattern of pedestrian flows, the distribution of WiFi usage was not able to explain how people utilized places for different purposes. The function of a place is determined by possibilities of activities that it can afford. Thus, this study continued to investigate functional centrality at a finer resolution. More specifically, we considered the following 11 types of campus activities in Table 18. Location choices for each activity by 126 voluntary survey participants were used to represent perceived uses of campus space and further measure the functional centrality. This study also distinguished fixed and flexible activities by the degree of freedom for pedestrians involved. On one hand, pedestrians were often required to work or take the class at a specific location for a designated duration, which was difficult to reschedule or relocate. On the other hand, pedestrians were able to choose where to shop, recreate or socialize at any idle times between classes or work hours. As for fixed activities on campus, this study applied the number of enrollment and employers to represent the distribution of classes and work related activities.

The analysis started with the interdependence between street network and these perceived possibilities of activities. The bandwidth of 400 feet was applied to kernel density estimation as it was able to capture the general pattern of campus activities without losing much spatial resolution. Table **18** shows all correlations between activities densities of 11 categories and betweenness centrality. Four important findings could be obtained. First, betweenness centrality showed significant correlations with the distributions of all activities. Secondly, among all types of activities, hanging out with friends, self-study, group study and nap demonstrated the strongest correlation with betweenness centrality. Thirdly, activities of parking or taking public transit were negatively correlated with betweenness centrality. Fourthly, flexible activities were clearly ranked higher than fixed activities. The study also tested the analysis with bandwidths of 200, 600 and 800 feet. Although the correlation coefficients were different for other bandwidths, activities resulted in the same ranking by correlation.

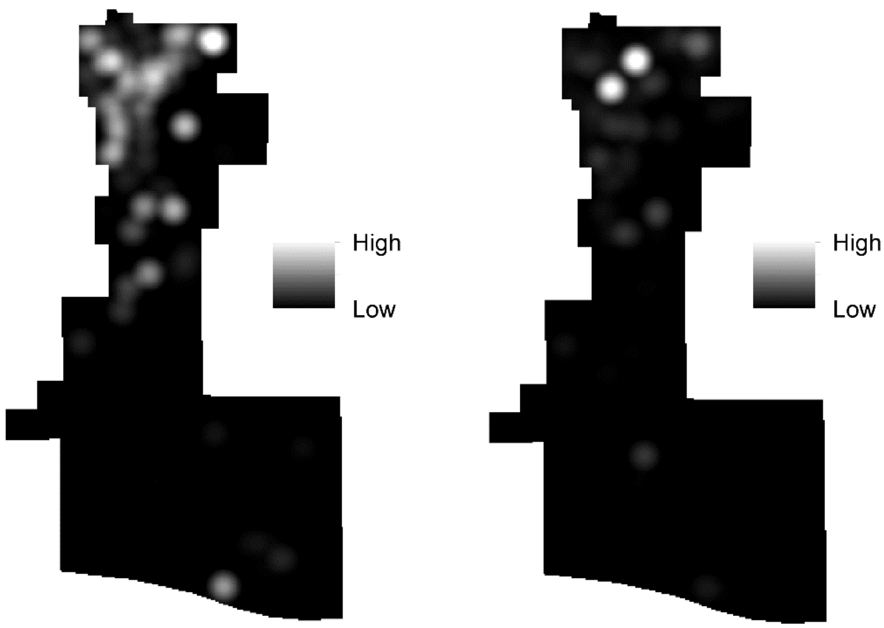
Table 18 Correlations between types of activities and betweenness centrality

Types of activities	Correlation
Parking or public transit	-0.308***
Take the class	0.125***
Physical exercises	0.374***
Fun or entertainment	0.384***
Work	0.401***
Eating lunch, dinner or snacks	0.436***
Open lectures or seminars	0.456**
Hanging out with friends	0.609***
Self-study	0.628***
Group-study	0.643***
Nap	0.697***

Significance: *** = 0.001, ** = 0.01,* = 0.05

4.2.4 Estimating functional centrality

Functional centrality describes how important a location is based on its surrounding affordances, which is characterized in this study by density and diversity. The study first continued to estimate functional density by standardizing densities of each activity and summing them up as described in equation (10). Figure **27**(a) illustrated the patterns of functional density for fixed activities at OU campus, which distributed all over the academic areas. The distribution of functional density for flexible activities in Figure **27**(b) showed two highlighted areas of Bizzell Memorial Library and Oklahoma Memorial Union.

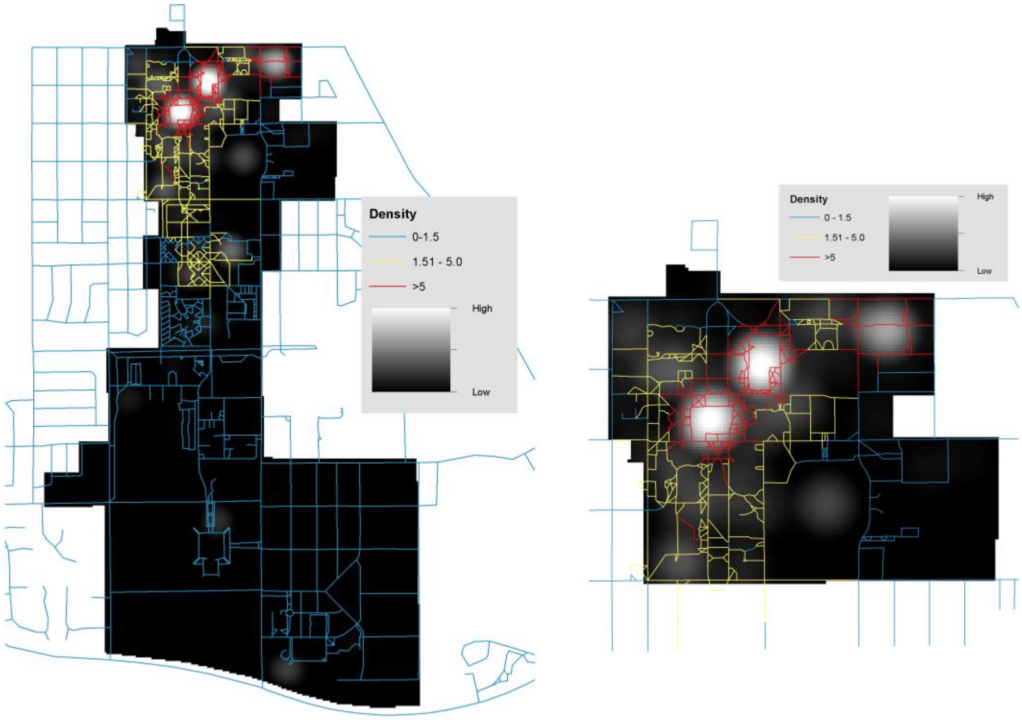


(a) (b)

(bandwidth = 400 feet)

Figure 27 Functional densities of fixed activities and flexible activities
(a) fixed activities (b) flexible activities

The study then validated the reliability of functional density in explaining the distribution of campus activities and examined its effectiveness in modeling wayfinding behaviors. Figure 28 illustrated the functional density of all activities, which showed hot spot areas in Bizzell Memorial Library, Oklahoma Memorial Union, and Sarkeys Energy Center. When correlation analysis was conducted between WiFi density and functional density in academic areas, the result indicated that the perceived use of campus space was significantly and moderately correlated with the actual distribution of campus activities with a coefficient of 0.50. The analysis in study focused on the functional centrality over the street network as shown in Figure **28**.



(a) (b)

Figure 28 Functional density at OU campus
(a) OU Norman campus (b) academic areas

Functional diversity describes the mixture patterns of perceived affordances in terms of activity possibilities. In Figure **29**, the distribution of functional diversity over the street network was represented. It was shown that areas with the most heterogeneous distribution of campus activities were Cate Centers, South Oval, Oklahoma Memorial Union, Engineer Quad and Sarkeys Energy Center, which were similar areas identified by large functional density. However, the inherent difference between these two dimensions of functional centrality can be demonstrated by their frequency distributions. As shown in Figure **30**, the statistical pattern of functional density indicated that only a small number of streets occupied high density of activities while most of other streets were located in areas with low activity density. The distribution of functional diversity suggested that most of streets were close to a good mixture of activities. Areas with lower diversity of activities were also with lower density of street network.

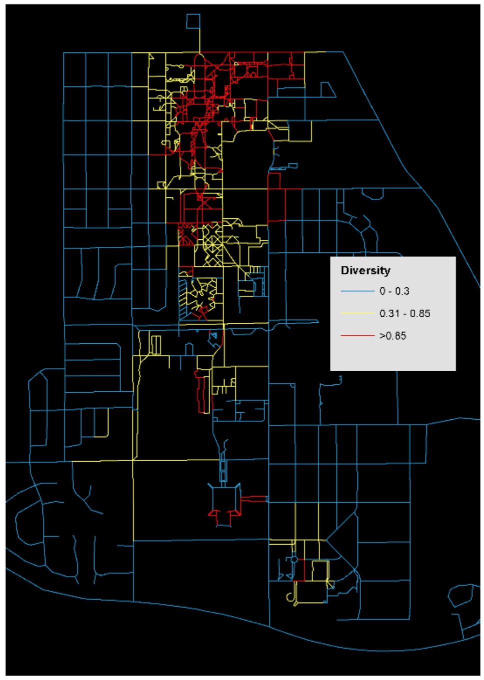
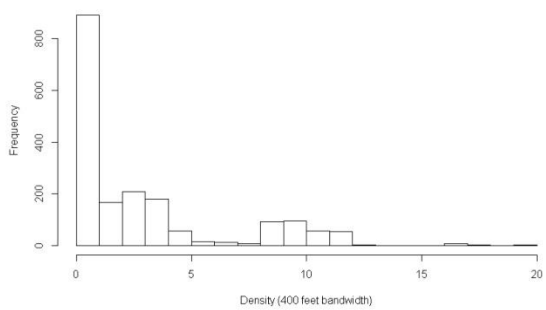
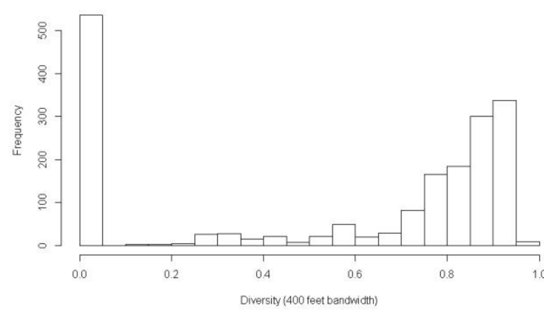


Figure 29 Functional diversity over the street network at OU campus





(a) (b)

Figure 30 Frequency distributions of functional centrality
(a) functional density (b) functional diversity

4.2.5 Multiple regression analysis on functional centrality

Multiple regression analysis was then conducted to assess the influence of functional centrality on pedestrian movement. Specifically, functional density and functional diversity were independent variables while the gate count was the dependent variable. The regression result (Table **19**) suggested that functional density was the only significant variable that contributed to predicting pedestrian flows. However, this model of functional centrality only captured 15% (p-0.004) of the variation of observed pedestrian flows.

Table 19 Multiple regression of pedestrian flows on measures of functional centrality

	Coefficients	p
Density	1.57	0.006
Diversity	0.001	0.99
R^2 = 0.15, p = 0.004, n = 67 segments		

4.2.6 Spatio-functional interactions

Previous analysis found that the pattern of pedestrian flows was not able to be explained by the single dimension of network centrality or functional centrality. The study hypothesized that pedestrian movement was grounded on the interactions of form and function. Therefore, a multivariate regression method was applied to explore the impact of network centrality and functional centrality measures on the variation of observed pedestrian flows. Betweenness centrality with distance decay effect was used to describe network centrality. Two regression models were generated. In the first regression model, functional centrality is represented by the actual distribution of campus activities described by the WiFi density at bandwidth of 400 feet. The second regression model used the density and diversity to characterize functional centrality perceived by pedestrians. The regression results were shown in Table **20**, which indicated that both models captured over 50% of the variation in observed pedestrian flows. Both betweenness centrality and the density of daily WiFi usage significantly and positively contributed to explaining the patterns of pedestrian flows. Only variables of functional density and weighted betweenness were captured as the critical factors accounting for the variation of pedestrian flows in the second model. The explanatory power of model 1 with the actual distribution of activities was only 2.2% higher than that of model 2, which illustrated the effectiveness of applying functional density to modeling pedestrian wayfinding behaviors.

Table 20 Multiple regressions of pedestrian flows on network and functional centrality

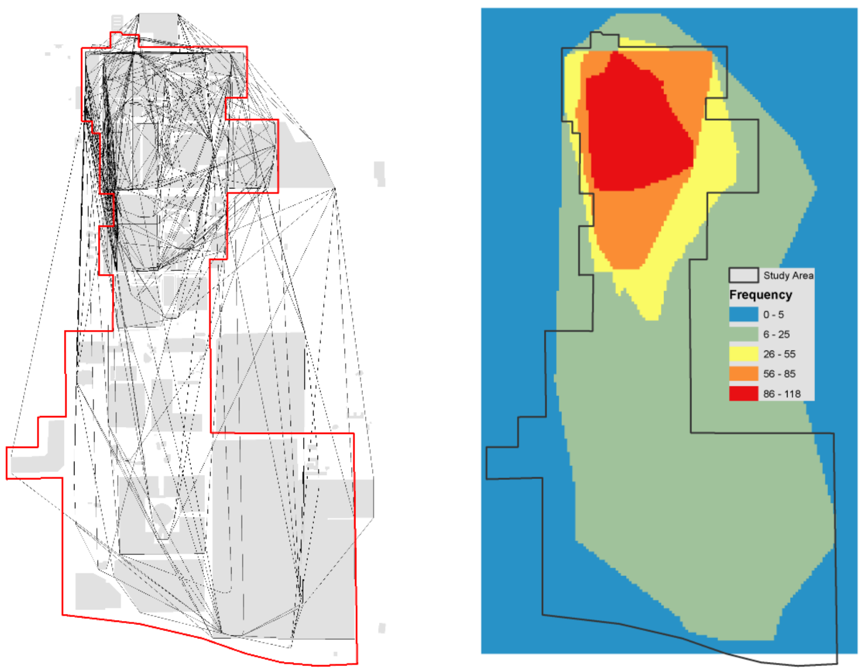
	Variables	Coefficients	AIC	Adjusted R^2
Model 1	Betweenness	987,900***	529.43	53.22%
	WiFi density	0.001***		
Model 2	Betweenness	1,325,000***	532.87	51.08%
	Density	2.17**		
	Diversity	3.12		

Significance: *** = 0.001, ** = 0.01,* = 0.05

4.3 The image of OU campus

4.3.1 Perception of campus boundaries

The study first estimated perceived campus areas by applying the method of convex hull to landmarks drawn in sketch maps. The identification of core area on campus is crucial as modeling spatial configuration is sensitive to boundary effects. The raw-data convex polygons in Figure **31**(a) made it evident that campus area was perceived differently by each survey participant. Within a set of overlapping polygons, the smaller was mostly contained within the larger ones. In terms of frequency, the larger degree of overlap suggested the central core of campus areas. Therefore, the perception of campus area could be interpreted as with a continual surface with the diminishing probability of membership around the core area rather than a single precise boundary. The resulting map in Figure **31**(b) apparently communicated the perceived boundaries effectively, although this method produced some redundant areas near the periphery due to the calculation of convex hull. The core area of OU campus was located in the academic area between South Oval and North Oval. The more distance away from the core area, the less likely it would be captured in sketch maps of campus area. Half of survey participants included residential areas while only 10% of them mentioned research campus in the sketch maps. Figure **32** displayed a histogram of perceived campus area using the convex hull method. The entire study area was 3.8 km^2 while the academic area was 0.8 km^2. Most of survey respondents (76%, 98) delimited the campus area less than 1 km^2.



(a) (b)

Figure 31 Perception of campus areas
(a) Raw-data convex polygons for each participant's concept of campus area (b) perceived campus areas in terms of frequency

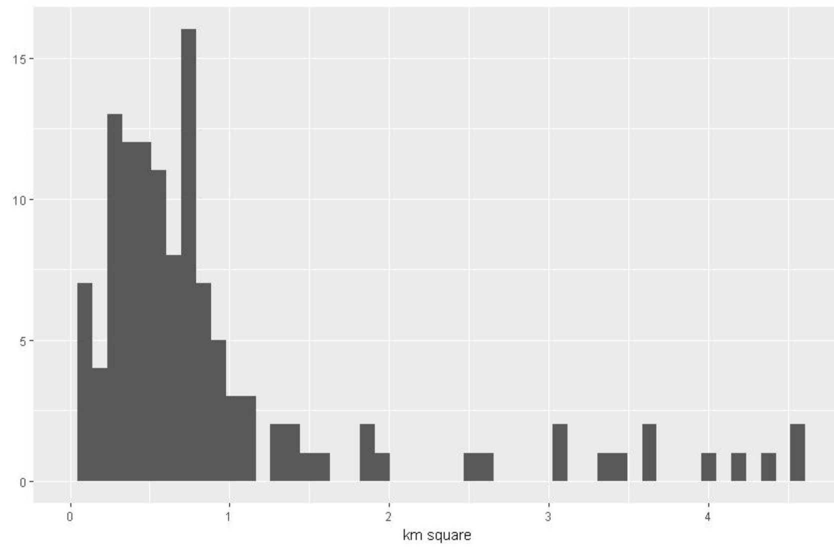


Figure 32 Distribution of frequency of perceived campus areas

4.3.2 Landmarks in sketch maps

In order to construct the image of OU Norman campus, the study calculated the frequency of appearance for landmarks in sketch maps. The composite image of all 126 sketch maps was drawn in Figure **33**. Specifically, buildings that were most frequently captured were Bizzell Library (91%, 115), Oklahoma Memorial Union (80%, 101), Gaylord Stadium (78%, 98), Dall Hall (75%, 95), and Gaylord Hall (71%, 90). As for paths, over 85% of survey participants mentioned Lindsey St. and Asp Ave.. When considering general areas captured in sketch maps, South Oval and North Oval appeared most often in 85% (107) and 70% (84) of the sketch maps. In terms of frequency, buildings and paths were two dominant features captured in sketch maps. Most of survey participants mentioned no more than 30 buildings and no more than 10 paths (Figure **34**).

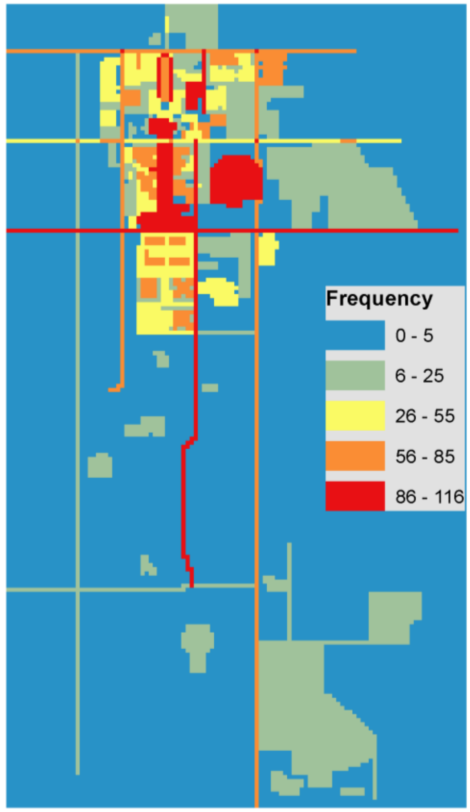
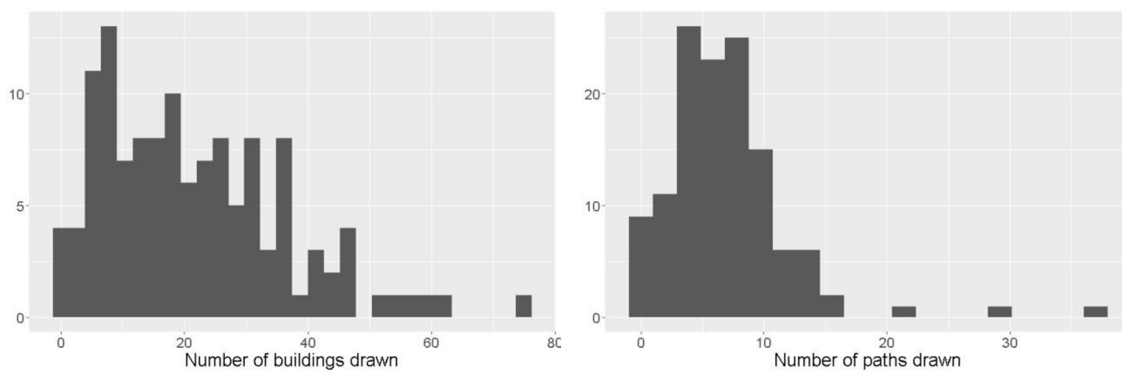


Figure 33 Frequency of landmarks identified in sketch maps



(a) (b)

Figure 34 Distribution of frequency of buildings and paths drawn in sketch maps (a) buildings (b)paths

An analysis of variance (ANOVA) was used to evaluate the effects of spatial familiarity on completeness of spatial knowledge in terms of number of landmarks captured in sketch maps. Table **21** demonstrated the mean of the number of landmarks drawn by survey groups with different levels of spatial familiarity. A one-way ANOVA was carried out with self-assessment of familiarity and number of years at OU on the average number of landmarks captured by sketch maps. Both self-assessment of familiarity ($F(3,126)=8.338$, $p<0.001$) and number of years ($F(4,126)=2.56$, $p<0.05$) resulted in significant effects. As the level of familiarity increased, respondents' sketch maps were more complete with more landmarks captured. Tukey post-hoc tests further showed that the very familiar draw more landmarks than the other three groups of familiar ($p<0.01$), average ($p<0.001$), and unfamiliar ($p<0.01$). Respondents living or being in the study area for more than four years drew more landmarks than respondents being in the area for less than one year. All the other post-hoc tests were non-significant ($p>0.05$) (Table **22**).

Table 21 Average number of landmarks drawn by survey groups with different levels of spatial familiarity

		Buildings	Paths	Intersections	All landmarks
Self-assessment of familiarity	Unfamiliar	19.6	6	5.2	30.8
	Average	14.9	4.9	3.4	23.2
	Familiar	22.1	6.3	5.3	33.6
	Very familiar	30.8	9.5	10.5	50.8
Number of years at OU	< 1	15.3	5.3	4	24.6
	1-2	22.8	5.3	4.6	32.8
	2-3	22.9	7.1	5.9	35.7
	3-4	22.5	6.33	6.1	35
	> 4	26.8	8.13	8.7	43.6

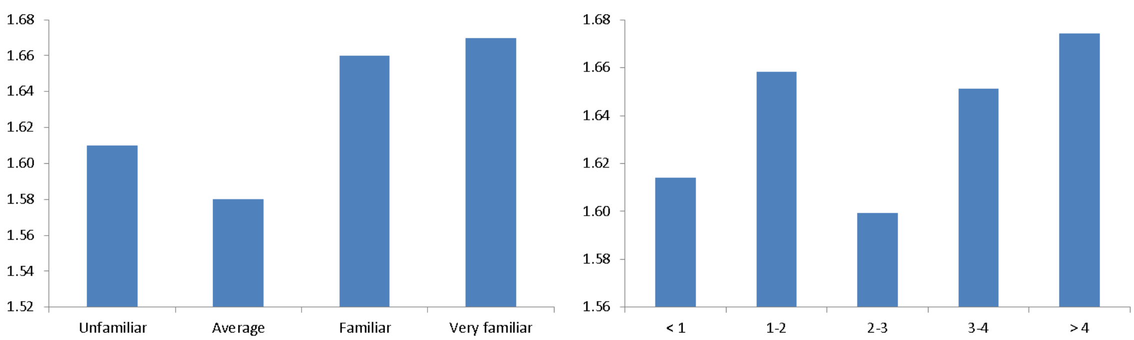
Table 22 Tukey pairwise comparisons of mean number of landmarks for groups with different levels of familiarity

		Difference
Self-assessment of familiarity	Unfamiliar - Average	-7.6
	Unfamiliar - Familiar	2.8
	Unfamiliar - Very familiar	20**
	Average - Familiar	10.4
	Average - Very familiar	27.6***
	Familiar - Very familiar	17.2**
Number of years at OU	<1 - 1-2 years	8.2
	<1 - 2-3 years	11
	<1 - 3-4 years	10.4
	<1 - >4 years	19**
	1-2 - 2-3 years	2.9
	1-2 - 3-4 years	2.2
	1-2 - >4 years	10.8
	2-3 - 3-4 years	-0.7
	2-3 - >4 years	7.9
	3-4 - >4 years	8.6

Significance: *** = 0.001, ** = 0.01,* = 0.05

4.3.3 Topological accuracy in sketch maps

Sketch map does not only illustrate the identification of landmarks but also the spatial relations between them. Since fragmentation and systematic distortion were common characteristics of cognitive map (Tversky, 1992), parts of sketch maps contain accurate information while other parts may contain inaccurate or missing information. This study continued to examine the accuracy in sketch maps and how it was influenced by spatial familiarity. Although people did not often require Euclidean accuracy in their representation of an environment, topological accuracy was found to be a vital factor that influenced wayfinding performances (Rovine & Weisman, 1989). Thus, the following analysis focused on topological accuracy which was determined by how landmarks were located with each other on sketch maps. As described in 3.4.3.3, matched description of relative direction between landmarks obtained a score of 2 while the partial matched obtained a score of 1. The mean score of accuracy for all survey respondents resulted in 1.65. Figure **35** showed that sketch maps drawn by the familiar group with over 4 years staying at OU produced the highest score of topological accuracy. ANOVA was then applied to examine whether spatial familiarity was a significant factor that contributed to topological accuracy in sketch maps. According to results, accuracy differences were found to be significant among groups by self-assessment of familiarity ($F(3,126)=128$, $p<0.001$) and among groups by number of years ($F(4,126)=76.13$, $p<0.001$). When Tukey post-hoc tests were conducted in Table **23**, the familiar ($p<0.001$) and the very familiar ($p<0.001$) groups produced sketch maps with better topological accuracy than the average. With the increase of years staying at OU, respondents resulted in more topologically accurate sketch maps.



(a) (b)

Figure 35 Average score of topological accuracy drawn by groups of familiarity
(a) self-assessment familiarity (b) number of staying years

Table 23 Tukey pairwise comparisons of topological accuracy for groups with different levels of familiarity

		Difference
Self-assessment of familiarity	Unfamiliar - Average	-0.08***
	Unfamiliar - Familiar	0
	Unfamiliar - Very familiar	0.01
	Average - Familiar	0.08***

	Average - Very familiar	0.09***
	Familiar - Very familiar	0.01
Number of years at OU	<1 - 1-2 years	0.04***
	<1 - 2-3 years	-0.01
	<1 - 3-4 years	0.04***
	<1 - >4 years	0.06***
	1-2 - 2-3 years	-0.05***
	1-2 - 3-4 years	-0.01
	1-2 - >4 years	0.01***
	2-3 - 3-4 years	0.05***
	2-3 - >4 years	0.07***
	3-4 - >4 years	0.02***

Significance: *** = 0.001, ** = 0.01,* = 0.05

4.3.4 Modeling the presence of landmarks

Logistic regression established a functional relationship between the binary coded landmarks (i.e., present or absent) and factors that were recognized as playing a role in the forming of cognitive map. Specifically, four factors were considered in the analysis: syntactical prominence in terms of betweenness centrality, semantic significance in terms of functional density, spatial familiarity in terms of self-assessment of familiar levels and number of years, and personal experience in terms of distance to anchor points. The KDE with a 400-feet bandwidth was used to derive the distributions of betweenness centrality and functional density (see calculation in 4.1 and 4.2). Self-assessment of familiar levels and number of years were considered as ordinal variables.

As for landmarks used in logistic regression analyses, there were 226 buildings, 95 paths, and 208 street intersections. Results of logistic regression analyses were presented in Table **24**. These odd ratios indicated the relative likelihood of a landmark present in the sketch map. For all landmarks, all four variables of betweenness centrality, functional density, familiarity, and distance to anchors significant contributed to the likelihood of presence in sketch maps. For a one-unit increase in betweenness, we expected to see 104% increase in the odds of being present in sketch maps. For a one-unit increase in functional density, only 0.1% increase was expected. For self-assessment of familiarity, the odds of being familiar or very familiar were 13% and 54% higher respectively than the odds of being unfamiliar. Compared with the group staying at OU for less than one year, the odds for the group for more than four years were 110% higher. With the distance to anchors increased, the odd of landmark presence decreased. When types of landmarks were considered, four variables significantly and positively influenced the likelihood of presence for buildings. However, self-assessment of familiarity was not a significant factor for the presence of paths. There were evidences of increased odds of buildings' presence and decreased odds of paths' presence with increasing betweenness. Only stay years significantly contributed to modeling the probability of presence for street intersections. McFadden R^2 (Table **24**) and ROC curves (Figure **36**) suggested that the logistic regression models resulted in better performance for predicting the presence of paths than the presence of buildings and intersections.

Table 24 Odd ratios for a landmark present in cognitive map

	All landmarks		Buildings		Paths		Intersections	
	OR	P	OR	P	OR	P	OR	P
Betweenness	2.04	<0.001	2.09	<0.001	0.001	<0.001	0.001	-
Functional density	1.001	<0.001	1.001	<0.001	1.04	<0.001	1.11	-
Self-assessment of familiarity								
Unfamiliar [b]	1	-	1	-	1	-	1	-
Average	0.90	-	0.9	-	0.82	-	0.89	-
Familiar	1.13	<0.05	1.17	<0.05	1.16	-	1.12	-
Very familiar	1.54	<0.001	1.74	<0.001	1.42	-	1.35	<0.01
Number of years at OU								
<1 year [b]	1	-	1	-	1	-	1	-
1-2 years	1.47	<0.001	1.57	<0.001	1.55	<0.01	1.24	<0.05
2-3 years	1.55	<0.001	1.61	<0.001	1.37	-	1.39	<0.05
3-4 years	1.72	<0.001	1.66	<0.001	1.39	-	1.96	<0.001
>4 years	2.10	<0.001	1.79	<0.001	2.42	<0.001	2.49	<0.001
Distance to anchors	0.99	<0.001	0.99	<0.001	0.99	<0.001	0.99	<0.001
McFadden R^2	0.20		0.13		0.49		0.23	

[b] Baseline category

OR: Odd ratio; P: p-value

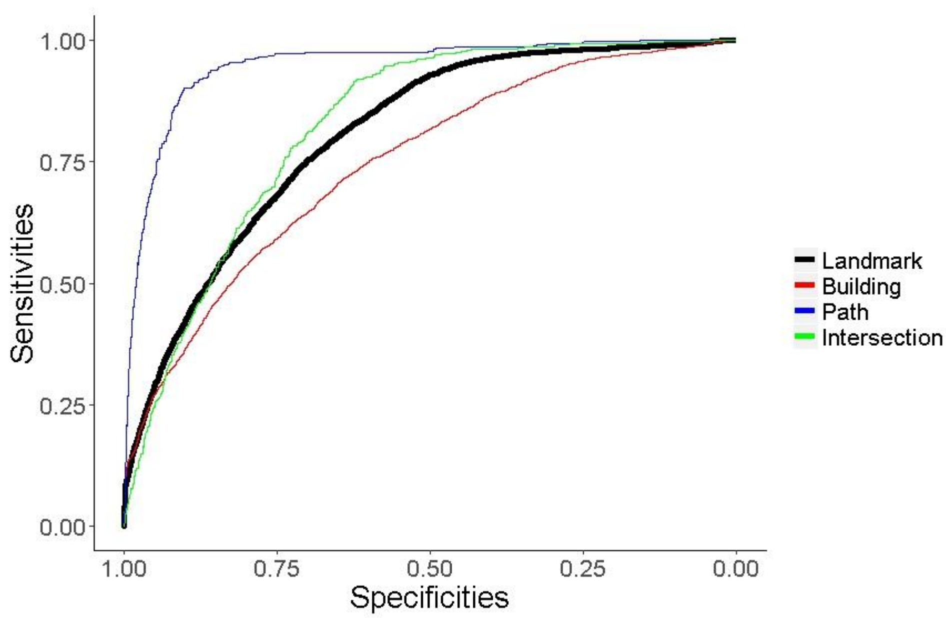


Figure 36 ROC curve of logistic regression models

4.4 Individual wayfinding behaviors

4.4.1 Perceived distances in route selection

The previous correlation analysis between network centrality and pedestrian flows in 4.1 implies that people on OU campus prefer the paths with the shortest length. However, the aggregated patterns of pedestrian traffic are not able to explain how individual pedestrian behaves in changing situations. Therefore, the study continued to examine individual route choices.

The analysis first applied the method of Frechet distance to comparing preferred routes with the target routes calculated by three different concepts of distance. Specifically, for the route between Bizzeell Memorial Library and Sarkeys Energy Center, the average discrete Frechet distances between the chosen routes and the target routes of the shortest length, the fewest number of turns and the least angle change were 510.31, 843.29, and 832.90 respectively (Table **25** below). For the route between Sarkeys Energy Center and Dale Hall, the average discrete Frechet distances were 777.60, 813.27, and 1314.65 for the metrically, topologically, geometrically shortest paths (Table **25** below). The smallest Frechet distance indicates the smallest shape difference between the route drawn and routes of the shortest length. Thus, the routes of shortest length resulted in a better fit of the chosen routes. However, when the origin and the destination were father away, differences between the route of shortest length and the route of the fewest number of turns were smaller while differences between the route of shortest length and the route of the least angle change were larger.

The study then examined the best criteria describing individual route choices. For each survey participant, the shortest Frechet distance determined the best criteria of perceived distance describing the route choice. For the route between Library and Sarkeys Energy Center, of 126 survey participants, 67% (84) chose the route closer to the shortest path by length while 22% (28) preferred the route closer to the path by the fewest turns (Table **26** below). No route choices resemblance to the geometrically shortest route. The other 11% (14) were not able to find the route. The route selection between Sarkeys Energy Center and Dale Hall (Table **26** below) provided a consistent picture that the survey respondents were able to capture the route closer to the one of the shortest length.

Table 25 Average Frechet distance between the chosen routes and the target routes

	Library - Sarkeys Energy Center	Sarkeys Energy Center - Dale Hall
Metric (Shortest length)	510.31	777.60
Topological (Fewest turns)	843.29	813.27
Geometric (Least angle change)	842.91	1314.65

Table 26 Best criteria of distance describing individual route choices with the smallest Frechet distance

Best criteria	Library - Sarkeys Energy Center	Sarkeys Energy Center - Dale Hall
Shortest length	67%	44%
Fewest turns	22%	36%
Least angle change	0%	5%
Don't know	11%	15%

4.4.2 Spatial familiarity and perceived distances

The perception of distance is dynamic and changes with the increasing exposure to the environment. This study continues to evaluate the influence of familiarity on route choices. Familiarity was measured by years of work/study and self-reported familiarity. Both route selection tasks resulted in consistent findings. As for years of work/study shown in Table **27** below, the average Frechet distance decreased as the number of years at OU increased. The Frechet distances were smallest for the group staying at OU for over 4 years. As for self-reported familiarity shown in Table **28** below, the Frechet distances were smallest when survey participants reported that they were very familiar with the campus layout. With the increase of familiarity levels, the routes drawn by survey participants more closely resembled to the shortest path. A one-way ANOVA was then applied to analyzing the significance of difference of perceived distance among groups of different levels of familiarity. The analysis results suggested that significant differences were found neither among groups of self-reported familiarity ($F(3,126)=1.76$, $p=0.16$) nor among groups of number of years ($F(4,126)=2.11$, $p=0.11$). In other words, most of survey respondents chose the routes closer to the shortest path by length regardless of their familiarity levels. Using the method of Frechet distance was also able to identify individuals who relied on more one type of distances than the others. In other words, the survey respondent depended more on the specific concept of distance which was associated with the smallest Frechet distance. We then looked into the percentage of survey respondents whose chosen routes were best described by the shortest length. As the level of familiarity increased, more survey participants were able to capture the shortest path by length while fewer ones reported that they did not know the route (Table **29** below).

Table 27 Average Frechet distance between the chosen routes and the target routes among survey groups by number of years

	Metric (Shortest length)	Topological (Fewest turns)	Geometric (Least angle change)
Years	Bizzeell Memorial Library - Sarkeys Energy Center		
<1	555.98	805.10	805.10
1-2	525.12	849.36	849.36
2-3	521.57	910.08	910.08
3-4	493.98	854.31	854.31
>=4	471.88	847.98	847.98

	Sarkeys Energy Center - Dale Hall		
<1	793.86	801.51	1345.62
1-2	756.90	805.95	1305.24
2-3	862.57	875.64	1274.38
3-4	760.76	835.11	1304.04
>=4	739.47	804.48	1304.02

Table 28 Average Frechet distance between the chosen routes and the target routes among survey groups by self-reported familiarity

	Metric (Shortest length)	Topological (Fewest turns)	Geometric (Least angle change)
	Bizzeell Memorial Library - Sarkeys Energy Center		
Unfamiliar	441.65	867.30	867.30
Average	584.76	828.68	828.68
Familiar	529.42	815.70	815.70
Very familiar	453.89	877.46	877.46
	Sarkeys Energy Center - Dale Hall		
Unfamiliar	679.88	743.29	1354.75
Average	870.52	848.96	1275.52
Familiar	772.10	827.10	1334.12
Very familiar	708.72	797.20	1311.08

Table 29 Best criteria of distance describing individual route choices with the smallest Frechet distance among survey groups by self-reported familiarity

	Perception of distance	Library - Sarkeys Energy Center		Sarkeys Energy Center - Dale Hall	
		Count	Percentage	Count	Percentage
Unfamiliar (20)	Shortest length	14	70%	9	45%
	Fewest turns	2	10%	5	25%
	Least angle change	0	0	0	0%
	Don't know	4	20%	6	30%
Average (40)	Shortest length	24	60%	13	33%
	Fewest turns	12	30%	15	38%
	Least angle change	0	0%	5	13%
	Don't know	4	10%	7	18%
Familiar (35)	Shortest length	21	60%	17	49%
	Fewest turns	10	29%	15	43%
	Least angle change	0	0%	1	3%
	Don't know	4	11%	2	6%

Very familiar (31)	Shortest length	25	81%	17	55%
	Fewest turns	4	13%	10	32%
	Least angle change	0	0%	0	0%
	Don't know	2	6%	4	13%

4.4.3 Criteria for route selections

Efficiency in terms of perceived distance is related to the shortest route. However, the shortest route is not necessarily the preferred route. In route selection tasks, survey respondents were asked to not only identify the route but also report why they chose the specific route. Based on previous studies (Golledge, 1995), this study focused on the following criteria of route selection: least crowded, shortest length, least time, fewest number of turns, most direct, most familiar, and most pleasant. When asked about reason for choosing the specific route, survey respondents tended to rely on two or more criteria. As shown in Table **30**, over 50% of survey participants reported that they followed the most familiar path, which suggested that people would take the advantage of places they knew. Choosing the shortest distance was preferred by 40% of survey respondents. It was surprising that 39% of respondents thought that they chose the most direct route (i.e., geometrically shortest route) while only 18% of them reported the preference of the route with the fewest number of turns (i.e., topologically shortest route). Some other survey respondents considered the situations of crowdedness and the sense of aesthetics.

Table 30 Criteria of choosing the route

Criteria of choosing the route	Percentage
Most familiar	58%
Shortest distance	40%
Most direct	39%
Least time	27%
Most pleasant	27%
Least crowded	18%
Fewest number of turns	18%
Other	1%

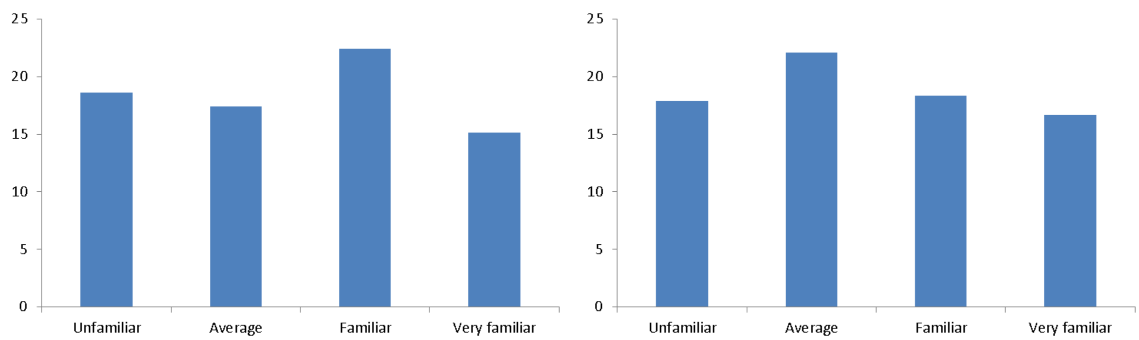
4.4.4 Landmark-based pathfinding

As shown in the self-reported criteria of route selections, familiarity plays an important role in pedestrian navigation and probably explains why the preferred route that pedestrians take is not necessarily the shortest one. Familiarity is closely related to landmarks which serve as the organizing concept of cognitive map. Landmarks in cognitive map describe the activity space where pedestrians are familiar with. The landmark-based pathfinding approach in this chapter is grounded on the idea that people prefer a path not only of short length but also familiar to them.

Landmark-based approaches were implemented using personal landmarks captured in sketch maps. The landmark-based path was then compared to the path of the shortest length in terms of Frechet distance to the chosen routes. Frechet distance refers to the geometrical similarity between two routes. As shown in Table **31**, the mean Frechet distance of landmark-based path was smaller than the path of the shortest length, which suggested that the landmark-based approach resulted in a better description of the routes selected. For all groups of different familiarity, the landmark-based approach outperformed the method of the shortest length. Figure **37** and Figure **38** illustrated the difference of Frechet distance between landmark-based approach and the shortest length method by groups of familiarity. These differences of Frechet distance were used to describe how much explanative power increased by adding landmarks to pathfinding. No significant differences were observed among groups of self-assessment familiarity. Compared with the other groups based on years being at OU, landmark-based pathfinding significantly improved the explanative power for the group staying at OU for less than one year.

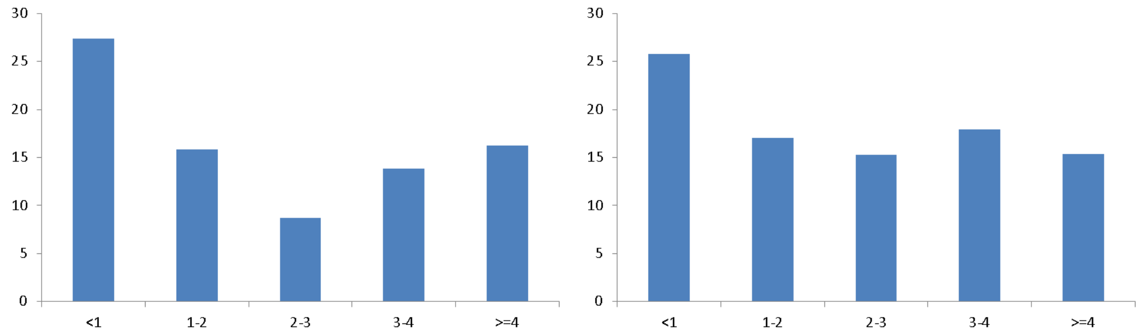
Table 31 Average Frechet distance between the chosen routes and the target routes of the shortest length and the landmark-based approach

	Library - Sarkeys Energy Center	Sarkeys Energy Center - Dale Hall
Shortest length	510.31	777.6
All landmarks	496.99	755.4



(a) Library-Sarkeys Energy Center (b) Sarkeys Energy Center-Dale Hall

Figure 37 Difference of Frechet distance between landmark-based approach and the shortest length method by groups of self-assessed familiarity
[Frechet distance (shortest length) - Frechet distance (landmark)]



(a) Library-Sarkeys Energy Center (b) Sarkeys Energy Center-Dale Hall

Figure 38 Difference of Frechet distance between landmark-based approach and the shortest length method by groups of number of years staying at OU
[Frechet distance (shortest length) - Frechet distance (landmark)]

4.5 Summary

This chapter used the proposed interdisciplinary framework of space, cognition, and movement to guide an empirical study conducted at OU Norman campus. The study started with the space syntax analysis and focused on network effects on pedestrian movement. Network centrality measures were used to determine how important a street segment was based on its network position. Positions relative to rest of network were described from four aspects: being connected (degree), being near (closeness), being between (betweenness), and being clustered (PageRank). Besides global and local measures used in previous studies (Hillier et al., 1993; Penn et al., 1998), this study further improved the measures of network centrality by considering spatial heterogeneity of activities and distance decay effects. Betweenness centrality calculated by the shortest length and weighted by distance decay effects resulted in the best description of observed pedestrian flows. The following space semantics analysis provided evidence that pedestrian movement depended on the spatio-functional interactions. The distribution of activities not only took the location advantage provided by spatial configuration but also reinforced network effects on pedestrian movement. The functional centrality of a place was characterized by two aspects of density and diversity. The study found that only functional density significantly contributed to modeling pedestrian flows. In sum, the aggregated pattern of pedestrian flows suggested that betweenness centrality and functional density were significant factors for modeling pedestrian movement.

In order to examine individual variations of pedestrian movement, the analysis continued with investigation of personal cognitive map and wayfinding behaviors. The sketch map analysis suggested that as people became more familiar with the environment, the increase of completeness and accuracy was observed in their cognitive map. Completeness was described by number of landmarks in sketch maps while accuracy concentrated on the relative positions between pairs of landmarks. Landmark served as the organizing concept of cognitive map. Betweenness centrality, functional density, and familiarity significantly contributed to modeling the presence of landmarks. When landmarks were used in navigation, this study developed a landmark-based pathfinding method. Landmark-based pathfinding resulted in a better description of routes selected by survey participants. In sum, individual cognitive maps, particularly the organization of landmarks, serve as the core in determining where pedestrians choose to hold activities and how to get there.

Chapter 5: Discussion and conclusions

This chapter begins with a summary of the research done in this study. It describes the three components of space syntax, space semantics, and spatial cognition that we analyzed for modeling pedestrian movement. We then present the results and major findings of our work. After that, we propose a conceptual model for agent-based pedestrian wayfinding simulation that is grounded in human perception and cognition. Finally, we outline the limitations and various directions for future research.

5.1 Space and pedestrian movement

Space was characterized by syntactical and semantic aspects. In Chapter 4.1, the network effect on pedestrian movement was examined. This study focused on network centrality which described the to-movement and through-movement when shortest routes were made between every segment on the network. Although global measures of network centrality had been widely used in space syntax studies, it was also criticized for "edge effect" problems. The choice of study boundary will influence the interpretation of internal structure of the environment (Park, 2009; Ratti, 2004). Empirical studies suggested using local measures of centrality and truncating analysis within neighboring space of a specific radius. Besides global and local measures used in previous studies (Hillier et al., 1993; Penn et al., 1998), the measure of network centrality in this study was further improved by considering uneven spatial distribution of origin-destination pairs and distance decay effects.

Correlation analysis between network centrality and pedestrian flows suggests that the chance that a pedestrian visited a street segment can be determined by the connectivity of the segment. The connectivity between segments contributes to the aggregated pattern of pedestrian movement and demonstrates some level of correlation to pedestrian flows. Global and local measures of centrality provide a consistent picture about network effects on pedestrian movement on campus. First of all, betweenness centrality serves as the best candidate of network centrality to describe observed pedestrian flows. Significant correlations were observed between pedestrian flows and measures of closeness and betweenness. Closeness and betweenness essentially describe two aspects of pedestrian movement: to-movement and through-movement. To-movement and through-movement are relevant to two major tasks in pedestrian navigation: the selection of the destination and the route choices respectively. When both closeness and betweenness were included in multiple regression models, only betweenness significantly explained the variation in pedestrian flows. Network effect of through-movement was more obvious than to-movement. Additionally, the concept of distances is best captured by the metric description. Three types of distances were test in the calculation of centrality measures: metric distance of the shortest length, topological distance of the fewest number of turns, and geometrical distance of the least angle change. Closeness and betweenness outperformed the others in correlation analysis when distances were calculated by the shortest length. In local analysis, radiuses of neighbors were also the metric distance by length when the best significant correlation was obtained. This radius of neighbors is related to the size of activity territory. Correlation results imply that pedestrians on campus are able to read the network in metric terms.

Due to unsatisfactory correlation coefficients with pedestrian flows, the study continued to examine the three assumptions made in betweenness centrality: equal probabilities of traveling, homogeneous distribution of OD pairs, and identical criteria for route selections. The best syntactical measure in explaining pedestrian movement is the betweenness centrality weighted by distance decay effects. First of all, adding distance decay functions to network centrality measures resulted in significantly better prediction of pedestrian patterns. Power law functions were used to describe the probability of traveling from one node to another. The distance decay effects for campus pedestrian movement were best described by the power law function with an exponent of 2.0. Additionally, weighting spatial heterogeneity of campus activities did not contribute to explaining more variation in pedestrian flows. The reason why the spatial heterogeneity of campus activities is redundant in explaining pedestrian flows lies in two aspects. On one hand, the application of WiFi traffic to describing the distribution of campus activities is reasonable, that is, the travel demands and WiFi traffic are positively correlated. However, biases do exist and these introduce errors to network analysis. On the other hand, it is possible that the spatial heterogeneity of campus activities has already been captured by the network structures. Network structure is the underlying generator of campus activities while the distribution of activities reinforces the network effects on pedestrian movement.

Syntactical analysis suggests that spatial configuration contributes to the pedestrian flows. However, whether the network independently influences pedestrian movement has not been empirically tested by controlling the land use variations. Pedestrians do not randomly walk over a physical network but plan a sequence of purposive actions based on interpreted meaning of place. In Chapter 4.2, the prominence of a place was characterized from two aspects: functional density and functional diversity. On one hand, density refers to the quantities of activities that occupy a place. On the other hand, diversity refers to mixed patterns of land use that support dense and varied population. Jacobs (1961) emphasized the importance of diversity for a vital street life. The analysis started with the spatial distribution of WiFi usage which was used to represent the density patterns of campus activities. Kernel density estimation (KDE) was used to interpolate the proximity of a place to central streets and to activities centers. Significant correlation between KDE of WiFi usage and pedestrian flows confirmed the effectiveness of activity densities in modeling pedestrian movement. The best bandwidth in describing the relationships between WiFi density and pedestrian flows resulted in 400 feet. The radius of 100 meters (328 feet) was widely used in urban planning to model street-level pedestrian catfchment area (Porta et al., 2009).

The second part of semantic analysis lies in identifying the spatio-function interactions. Urban planners and geographers have developed models to capture relationships between transportation network and land use patterns (Getis & Getis, 1966). In this study, the significant and positive correlation was observed between KDE of betweenness centrality and WiFi densities, which implied that network structure served as the driving force in shaping urban form in terms of land uses, specifically in this study the patterns of campus activities. The significant correlation also explained why adding spatial heterogeneity of activities did not contribute to better descriptions of network effects on pedestrian movement in Chapter 4.1. Network centrality captures location advantage, which contributes to shaping the variation of campus activities. Despite the fact that the patterns of campus activities are more complex than possible activities that can occupy a specific location, the perceived affordance is the primary factor of determining the underlying probability of wayfinding destinations. The semantic analysis in Chapter 4.2 did not only examine the patterns of campus activities but also investigate perceived use of space identified by survey participants. The correlation between KDE of centrality measures and functional density of perceived affordances not only confirmed the finding that space semantics was an important component in modeling pedestrian movement but also made it more specific. Flexible activities (such as entertainment, exercises and dining) showed higher correlations with street centrality than fixed activities (i.e., work and class), which implied that network structure significantly influenced destination selections for flexible activities. This observation can be explained by the fact that fixed activities are attractive enough by their function to drive pedestrian to the destinations. When pedestrians obtain more freedom in deciding time and locations for flexible activities, the destination selection is attracted by the perception of pass-by locations over the network. Therefore, the spatial layout of campus areas and how the campus performed functionally or socially are interlinked.

Finally, the study provided evidence about effectiveness of the perceived functional centrality in modeling pedestrian movement. Multiple regression models indicated that pedestrian movement depends on the interactions of form and function. The pedestrian movement is constrained by the spatial configuration of the walking network and is attracted by the spatial distribution of campus activities. Betweenness centrality weighted by distance decay and functional density were the best candidates to model syntactical and semantic effects on pedestrian movement. However, functional diversity was not a significant factor that contributed to predicting pedestrian flows, which implied that the majority of pedestrian traffic on campus was not attracted by the variety of activities. The size of attractions plays a more important role in determining where pedestrians choose to go than the co-existence of functions. The reasons for low contribution of functional diversity lie in the patterns and distributions of campus activities. On one hand, work and classes determine the basic pattern of campus life. Flexible activities that fill in between work and classes are constrained by spatiotemporal affordances. The destination selection depends on a feasible set of activities within the potential path area. Places located in areas of higher pass-by rate are more likely to be perceived and selected as the destination. On the other hand, the frequency distribution of functional diversity was right-skewed, which suggested that most of segments over the network were accessible to areas with a good mixture of activities. In other words, areas with higher segment density gained more activity mixture than less dense areas. The influence of functional diversity on pedestrian wayfinding has been captured in the network structure.

5.2 Spatial cognition and wayfinding behaviors

Although syntactical and semantic analysis resulted in significant explanations of pedestrian flows, the aggregated pattern of pedestrian activities discards individual variations and therefore is not able to adapt to the dynamic environment. In order to examine pedestrian navigation at a finer resolution, we continue to analyze personal cognitive maps and individual wayfinding behaviors.

Understanding cognitive maps (i.e., mental maps) held by pedestrians is important because they can be used to identify desirable locations and also reveal pedestrians' travel patterns. The analysis of space and spatial cognition is grounded on the hypothesis that individuals' cognitive maps of the environment (i.e., spatial cognition) serve as the core in determining where they choose to hold activities and how to get there. In Chapter 4.3, psychological effect on pedestrian movement was investigated. The first part of analysis is to examine completeness and accuracy of cognitive map which is externally represented by sketch maps. In order to identify the impacts of spatial familiarity, sketch maps were analyzed by groups with different levels of familiarity. Completeness was described by the number of landmarks captured in sketch maps while accuracy refers to the topological correctness of relative positions between pairs of landmarks. The concept of landmarks in this study included all salient features. Groups by self-assessment familiarity and groups by number of staying years provide a consistent outcome that as people became familiar with the environment, they would be able to memorize and recall more landmarks in the sketch map task, and their sketch maps produced higher scores of accuracy. The ANOVA analysis further suggested that these performance differences in sketch map task were significant among groups of different familiarity. If we looked into the difference of each group pair, the very familiar group staying at OU for over four years was significantly different from the other groups. In sum, spatial familiarity significantly influenced the completeness and accuracy of cognitive map. With the increasing exposure to an environment, pedestrians gradually update their cognitive maps and will be able to draw better maps of the familiar areas in terms of completeness and accuracy. Familiarity is an important factor in predicting the presence of landmarks in cognitive map.

The second part of analysis is to model the presence of landmarks in cognitive map. Cognitive map consists of the layout of salient features as well as the prominent utilities afforded by these features. Landmarks serve as the important organizing concept of cognitive map. In Chapter 4.3, logistic regression models were used to assess the impacts of network and functional centrality on the presence of landmarks in cognitive map. Spatial familiarity and distance to anchor locations were covariate variables. The sketch map analysis suggested that syntactically and semantically salient features were expressed as landmarks in human knowledge of space. The regression models can be used to predict the probability that a landmark was captured in cognitive map.

Landmarks are useful wayfinding aids for pedestrian navigation as they support fast reasoning and efficient communication. Chapter 4.4 looked into the individual wayfinding behaviors and developed a landmark-based approach of pedestrian pathfinding. The analysis of individual wayfinding behaviors started with the reexamination of the concept of distances. The correlation analysis in Chapter 4.1 between network centrality and pedestrian flows implied that pedestrians on campus were able to perceive and follow the path of the shortest length. Instead of aggregated patterns of moving flows, Chapter 4.4 examined the individual choices in route selection tasks. The routes selected by survey participants were compared to target routes calculated by different concepts of distances. Comparison outcomes confirmed the correlation analysis results that the perception of distance was shaped by the metric properties of network. The reason for better explanation of distances using metric terms is attributed to the nature of campus areas. Most of pedestrians are familiar with campus areas with repeated exposure to the environment. Pedestrians are able to choose the metrically shortest paths if they have perfect spatial knowledge of the environment. Meanwhile, the route selection tasks occurred in academic area on campus which was a small neighborhood size. The small and simple navigation environment makes it easy for pedestrians to perceive the route of the shortest length. Compared to the route from Library to Sarkeys Energy Center, the route from Sarkeys Energy Center to Dale Hall was more complex with a longer distance. The percentage of pedestrians choosing routes closer to the topologically shortest path was higher in the latter route selection task, which implied that it was harder for pedestrians to follow the shortest path by length in large and complex navigation environment. High cognitive demand in finding the route of the shortest length also explains why previous space syntax studies found that the concept of distance was shaped more by topological properties than metric properties in urban areas (Hillier & Iida, 2005). Therefore, although the connected structures between segments govern underlying network effects on pedestrian movement, cognitive choices of distance interpretation determine how individual pedestrians choose the route differently.

Since familiarity significantly influences the forming of personal cognitive maps, the study continues to examine whether impacts of familiarity on spatial knowledge leads to difference in individual wayfinding behaviors. When survey participants were asked about the reason for choosing the specific routes, over 50% of respondents preferred the most familiar route while 40% chose the route of the shortest length. It is no doubt that familiarity is crucial in modeling individual pathfinding. The influences of familiarity on individual wayfinding were examined from two aspects: the concept of distance and landmark. Surprising, although the completeness and accuracy of cognitive map are significantly different among groups of familiarity levels, wayfinding performances in terms of Frechet distance to target routes is not significantly different from each other. As the familiarity level increased, a larger percentage of survey participants chose the route closer to the one with the shortest length. However, differences among groups of familiarity were not significant. In other words, familiarity does not significantly influence how pedestrians perceive or define the distance. Meanwhile, the reason why people choose the familiar path lies in the fact that less cognitive energy is required to navigate through the known space. Landmarks play an important role in reorientation at intersections and confirming the right way to be followed. The more landmarks visible along the route, the less cognitive load it gives to pedestrians. The study added the number of visible landmarks to the weight of segments. Compared to the route of the shortest length, the landmark-based pathfinding resulted in smaller average Frechet distance from the routes chosen by survey respondents, which implied that adding landmarks to pathfinding resulted in a better prediction of route selections. If we looked into groups of familiarity, the explanative power significantly increased for groups staying at OU for less than one year, which implied that the influences of landmarks on route selections were more significant for people with limited experience in the environment. However, most of navigation systems focus on the organization of network elements but ignore the availability of landmarks. This study provides evidence that landmark-based pedestrian navigation significantly benefits the route selection.

5.3 Conceptual model of agent-based model for pedestrian movement

Previous analysis on space, cognition and wayfinding behaviors serves as a foundation for the conceptual agent-based model (ABM) for pedestrian movement. In this chapter, we aim to describe the factors that influence the complexity of pedestrian navigation situation and develop the conceptual agent-based process model for pedestrian movement in familiar environment. The proposed conceptual model is grounded on significant factors identified in previous analysis: betweenness centrality, functional density, familiarity, concept of distance and use of landmarks.

The ABM for pedestrian movement consists of agent and environment. The simulated environment includes syntactical and semantical components. Syntactically and semantically salient features are captured and stored as landmarks in cognitive map of the agent. The core of this ABM lies in a cognizing agent that is able to solve pathfinding tasks based on perceptual information and knowledge of cognitive map. As shown in Figure **39**, the wayfinding agent consists of five elements: agent's states, activity pattern, perception, cognitive map, and wayfinding behaviors. Agent's states refer to familiarity, role, gender, and age of pedestrians which determine the personal activity patterns and levels of knowledge about the environment in cognitive map. The activity pattern includes three types of activities: fixed/scheduled activities, flexible/opportunities activities, and reactive activities. Fixed activities, such as taking classes and work, consist of goal-directed behaviors corresponding to scheduled start and end time. Fixed activities usually obtain a higher priority of need than flexible activities. Choices of flexible activities are selected from a feasible set of activities within the area that a pedestrian can reach between fixed activities. For example, a student goes to a nearby cafe for lunch between classes. For fixed and flexible activities, cognitive maps (i.e., mental maps) are useful in modeling where pedestrian want to go and what they want to do. Navigating to fixed and flexible activities is executed by a sequence of purposive actions. Meanwhile, reactive activities refer to simple reactions in response to perception of the environment. A sequence of reactive actions is guided and implemented by rule-based model of perceived information. The execution of reactive behaviors is not purposive and does not rely on knowledge of the environment in cognitive map.

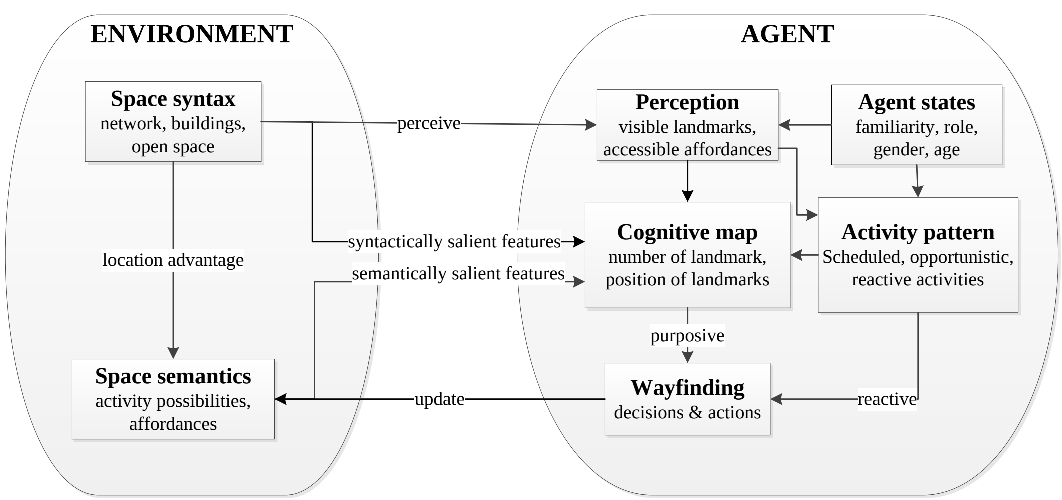


Figure 39 Conceptual model of ABM for pedestrian movement

5.4 Major findings

The major finding of this study is to fill in the interdisciplinary gaps of pedestrian studies and develop a methodological framework of space, cognition and movement. This framework is different from ones in previous studies for pedestrian movement because it is extendable and scalable to guide studies from aggregated patterns of movement to individual behaviors of wayfinding. The core of this framework lies in the assumption that people become familiar with the environment over time and construct personal cognitive maps. Our empirical studies utilized this framework and provided evidences that syntactically and semantically salient features were captured and stored as personal landmarks in cognitive map which were further used to guide the pathfinding. This framework can also be used by architects and urban planners to assess how new design of spatial layouts would influence the pedestrians' perception of the environment, and how new construction of attractions would change the route choices. This framework can also be used by cognitive scientist and psychologist to analyze how people find the route based on different perceptual and cognitive capabilities.

From a methodological point of view, the main results of this study are the landmark-based pathfinding approach and integrated centrality measures from two aspects of syntax and semantics. First, the landmark-based pathfinding approach depends on the idea that pedestrians prefer routes that are not only of shortest distance but also with landmarks familiar to them. The landmark-based approach allows analysis about the influence of landmarks on pedestrian movement, and simulation of wayfinding process using personal landmarks. Comparison analysis from this study provided evidences that use of landmarks and the concept of distance were two major factors that contributed to route selections. Second, the calculation of centrality measures depends on the idea that the salient meaning of a place is determined not only by its position on network but also by its accessibility to activities possibilities. Network centrality measures in this study improve the predictive power of previous syntactical measures by varying the concept of distance and adding distance decay effects. Functional centrality measures are able to characterize spatial distribution of activities in terms of density and diversity. Integrated measures of centrality make it possible to quantitatively describe space and allow analyzing spatio-functional interactions. Our empirical study used integrated measures of centrality to examine impacts of spatio-functional interactions on pedestrian movement and found that the position on the network generated the location advantage while the distribution of activity possibilities reinforced these network effects on pedestrian movement.

The study further demonstrates a conceptual model of ABM for pedestrian movement. This model is grounded on the theoretical framework and significant factors identified in empirical studies. Such a conceptual model is useful for computer scientists to simulate cognizing agent learning the environment and adapting to dynamic environments and for GIS developers to design and implement landmark based navigation system.

5.5 Limitations and future research

Understanding pedestrian movement remains the core challenge for psychology, geography, computer science, and urban planning studies. First, this study was able to collect information to support a comprehensive understanding of pedestrian navigation, from what pedestrians think of the environment, where they choose to go for an activity, and how their knowledge of the environment guides wayfinding behaviors. However, lack of data availability remains an issue. This study obtained an appropriate sample size for sketch map analysis compared with previous studies. But more observations would produce a higher predictive power in logistic regression model for the presence of landmarks, and further benefit the construction and validation of ABM for pedestrian movement.

Additionally, the study area at the University of Oklahoma Norman campus demonstrates unique characteristics that will influence pedestrian navigation. For example, most of people on campus are familiar with the study area with repeated exposure to the environment. Work and classes determine the underlying pattern of campus activities. Although the campus area can be used to represent a miniature version of an urban neighborhood, it is valuable to ask and test whether the significant impacts of spatio-functional interactions on pedestrian movement are still observed in other types of neighborhood and in other regions of urban areas. Larger test cases also need to be carried out to see whether the theoretical framework is applied to guide the analysis of pedestrian movement for varied purposes of studies under different scenario and whether the proposed ABM can be implemented into an efficient testing tool that can be used to simulate agents with different perceptual and cognitive capabilities. Meanwhile, the survey interview in this study was conducted through a convenient sampling. The study confirmed that no systematical bias was observed by participant types, gender or race between the sample frame of OU facts and the sample of participants. However, whether a convenient sample is representative of the entire population is still open to question.

Furthermore, analysis in this empirical study depended on the sketch maps and perceived use of space for one period of time. However, the image of a neighborhood is a dynamic object and change over time. Considering the changing status of cognitive maps in future studies would contribute to better understanding how people visually and semantically connect salient features to landmark knowledge and better explaining impacts of a new city construction before and after the project.

Finally, this study provides evidences that route selections are determined by the shortest distance of length and number of visible landmarks. But it is not clear how the concept of distances and use of landmarks interact with each other. Specifically, when people will choose the shortest length over the cues of landmarks or choose guidance of landmarks over the shortest path under different scenario? Future empirical studies by urban planner or agent based simulation by computer scientists might provide the answers to this question. Meanwhile, this study concentrated on the influences of perceived distance and use of landmarks on pedestrian pathfinding. Although they are reported as the most important reasons for pedestrians' pathfinding on campus, criteria of route selection are not limited by distances and landmarks. Additional consideration such as aesthetic scenes and road signs should be addressed in the future research. Landmark-based pathfinding method could be extended by explicitly integrating all relevant elements that influenced pedestrian wayfinding decisions.

References

Alt, H., & Godau, M. (1995). Computing the Fréchet distance between two polygonal curves. *International Journal of Computational Geometry & Applications, 5*(01n02), 75-91.

Amedeo, D., & Golledge, R. G. (1975). *An introduction to scientific reasoning in geography*: Wiley New York.

Appleyard, D. (1970). Styles and methods of structuring a city. *Environment and behavior*.

Asami, Y., Kubat, A. S., Kitagawa, K., & Iida, S.-i. (2003). *Introducing the third dimension on Space Syntax: application on the historical Istanbul.* Paper presented at the Proceedings of the Fourth International Symposium on Space Syntax, University College London, London.

Bafna, S. (2003). Space syntax: A brief introduction to its logic and analytical techniques. *Environment and behavior, 35*(1), 17-29.

Banai, R. (1999). A methodology for The Image of the City. *Environment and Planning B: Planning and Design, 26*(1), 133-144.

Baran, P. K., Rodríguez, D. A., & Khattak, A. J. (2008). Space syntax and walking in a new urbanist and suburban neighbourhoods. *Journal of Urban Design, 13*(1), 5-28.

Batty, M. (2001). Exploring isovist fields: space and shape in architectural and urban morphology. *Environment and Planning B, 28*(1), 123-150.

Batty, M. (2004). A new theory of space syntax.

Batty, M. (2017). Space Syntax and Spatial Interaction: Comparisons, Integrations, Applications.

Batty, M., & Rana, S. (2004). The automatic definition and generation of axial lines and axial maps. *Environment and Planning B: Planning and Design, 31*(4), 615-640.

Beeharee, A. K., & Steed, A. (2006). *A natural wayfinding exploiting photos in pedestrian navigation systems.* Paper presented at the Proceedings of the 8th conference on Human-computer interaction with mobile devices and services.

Benedikt, M. L. (1979). To take hold of space: isovists and isovist fields. *Environment and Planning B, 6*(1), 47-65.

Bessho, M., Kobayashi, S., Koshizuka, N., & Sakamura, K. (2008). *uNavi: Implementation and deployment of a place-based pedestrian navigation system.* Paper presented at the Computer Software and Applications, 2008. COMPSAC'08. 32nd Annual IEEE International.

Blades, M. (1990). The reliability of data collected from sketch maps. *Journal of Environmental Psychology, 10*(4), 327-339.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences, 99*(suppl 3), 7280-7287.

Brin, S., & Page, L. (1998). The anatomy of a large-scale hypertextual web search engine. *Computer networks and ISDN systems, 30*(1-7), 107-117.

Brockmann, D., Hufnagel, L., & Geisel, T. (2006). The scaling laws of human travel. *nature, 439*(7075), 462.

Brooks, R. A. (1986). A robust layered control system for a mobile robot. *Robotics and Automation, IEEE Journal of, 2*(1), 14-23.

Brown, L. N., Lahar, C. J., & Mosley, J. L. (1998). Age and gender-related differences in strategy use for route information: A" map-present" direction-giving paradigm. *Environment and behavior, 30*(2), 123-143.

Chai, X. J., & Jacobs, L. F. (2010). Effects of cue types on sex differences in human spatial memory. *Behavioural brain research, 208*(2), 336-342.

Choi, Y. K. (1999). The morphology of exploration and encounter in museum layouts. *Environment and Planning B: Planning and Design, 26*(2), 241-250.
Claramunt, C., & Winter, S. (2007). Structural salience of elements of the city. *Environment and Planning B: Planning and Design, 34*(6), 1030-1050.
Conroy-Dalton, R., & Bafna, S. (2003). The syntactical image of the city: a reciprocal definition of spatial elements and spatial syntaxes.
Couclelis, H., Golledge, R. G., Gale, N., & Tobler, W. (1987). Exploring the anchor-point hypothesis of spatial cognition. *Journal of Environmental Psychology, 7*(2), 99-122.
Crucitti, P., Latora, V., & Porta, S. (2006). Centrality in networks of urban streets. *Chaos: an interdisciplinary journal of nonlinear science, 16*(1), 015113.
Dalton, N. (2001). *Fractional configurational analysis and a solution to the Manhattan problem.* Paper presented at the Space Syntax 3rd International Symposium, Atlanta.
Dayan, P. (1999). Unsupervised learning. *Wilson, R. A. and Keil, F., editors. The MIT Encyclopedia of the Cognitive Sciences*.
De Jonge, D. (1962). Images of urban areas their structure and psychological foundations. *Journal of the American Institute of Planners, 28*(4), 266-276.
de Smith, M. J., Goodchild, M. F., & Longley, P. A. (2009). Geospatial analysis. *Matador*.
Desyllas, J., & Duxbury, E. (2001). *Axial maps and visibility graph analysis.* Paper presented at the Proceedings, 3rd International Space Syntax Symposium.
Dijst, M., & Kwan, M.-P. (2005). Accessibility and quality of life: time-geographic perspectives. *Social Dimensions of Sustainable Transport: Transatlantic Perspectives*, 109-126.
Eiter, T., & Mannila, H. (1994). *Computing discrete Fréchet distance*. Tech. Report CD-TR 94/64, Christian Doppler Lab. Expert Sys., TU Vienna, Austria, 1994.
Epanechnikov, V. A. (1969). Non-parametric estimation of a multivariate probability density. *Theory of Probability & Its Applications, 14*(1), 153-158.
Fisher-Gewirtzman, D., Shach Pinsly, D., Wagner, I. A., & Burt, M. (2005). View-oriented three-dimensional visual analysis models for the urban environment. *Urban Design International, 10*(1), 23-37.
Frank, A. U. (1998). *Formal models for cognition—taxonomy of spatial location description and frames of reference.* Paper presented at the Spatial Cognition.
Frank, L. D., & Pivo, G. (1994). Impacts of mixed use and density on utilization of three modes of travel: single-occupant vehicle, transit, and walking. *Transportation research record, 1466*, 44-52.
Franklin, S., & Graesser, A. (1997). Is it an Agent, or just a Program?: A Taxonomy for Autonomous Agents *Intelligent agents III agent theories, architectures, and languages* (pp. 21-35): Springer.
Freeman, J. (1975). The modelling of spatial relations. *Computer graphics and image processing, 4*(2), 156-171.
Freksa, C. (1992). *Using orientation information for qualitative spatial reasoning*: Springer.
Gao, S., Wang, Y., Gao, Y., & Liu, Y. (2013). Understanding urban traffic-flow characteristics: a rethinking of betweenness centrality. *Environment and Planning B: Planning and Design, 40*(1), 135-153.
Getis, A., & Getis, J. (1966). Christaller's central place theory. *Journal of Geography, 65*(5), 220-226.
Gibson, J. J. (1977). The theory of affordances. *Hilldale, USA*.
Gibson, J. J. (2013). *The ecological approach to visual perception*: Psychology Press.
Glicksohn, J. (1994). Rotation, orientation, and cognitive mapping. *The American journal of psychology*, 39-51.

Golledge, R. G. (1995). Defining the criteria used in path selection. *University of California Transportation Center*, 1995.

Golledge, R. G. (1997). *Spatial behavior: A geographic perspective*: Guilford Press.

Goodchild, M. F., Yuan, M., & Cova, T. J. (2007). Towards a general theory of geographic representation in GIS. *International Journal of Geographical Information Science, 21*(3), 239-260.

Goodman, J., Gray, P., Khammampad, K., & Brewster, S. (2004). Using landmarks to support older people in navigation. *Mobile Human-Computer Interaction–MobileHCI 2004*, 37-57.

Gulick, J. (1963). Images of an Arab city. *Journal of the American Institute of Planners, 29*(3), 179-198.

Gwynne, S., Galea, E., Lawrence, P. J., & Filippidis, L. (2001). Modelling occupant interaction with fire conditions using the buildingEXODUS evacuation model. *Fire Safety Journal, 36*(4), 327-357.

Hägerstraand, T. (1970). What about people in regional science? *Papers in regional science, 24*(1), 7-24.

Hansen, W. G. (1959). How accessibility shapes land use. *Journal of the American Institute of Planners, 25*(2), 73-76.

Haq, S., & Girotto, S. (2003). *Ability and intelligibility: Wayfinding and environmental cognition in the designed.* Paper presented at the 4th international space syntax symposium, London.

Heft, H. (1996). The ecological approach to navigation: A Gibsonian perspective. *The construction of cognitive maps*, 105-132.

Hillier, B. (1999). The hidden geometry of deformed grids: or, why space syntax works, when it looks as though it shouldn't. *Environment and Planning B: Planning and Design, 26*, 169-191.

Hillier, B., & Hanson, J. (1989). *The social logic of space*: Cambridge university press.

Hillier, B., & Iida, S. (2005). *Network and psychological effects in urban movement.* Paper presented at the International Conference on Spatial Information Theory.

Hillier, B., Penn, A., Hanson, J., Grajewski, T., & Xu, J. (1993). Natural movement-or, configuration and attraction in urban pedestrian movement. *Environ Plann B, 20*(1), 29-66.

Hochmair, H. (2004). *Decision support for bicycle route planning in urban environments.* Paper presented at the Proceedings of the 7th AGILE Conference on Geographic Information Science.

Hölscher, C., Meilinger, T., Vrachliotis, G., Brösamle, M., & Knauff, M. (2006). Up the down staircase: Wayfinding strategies in multi-level buildings. *Journal of Environmental Psychology, 26*(4), 284-299.

Horton, F. E., & Reynolds, D. R. (1971). Effects of urban spatial structure on individual behavior. *Economic geography, 47*(1), 36-48.

Hu, Z., & Lo, C. (2007). Modeling urban growth in Atlanta using logistic regression. *Computers, Environment and Urban Systems, 31*(6), 667-688.

Jacobs, J. (1961). *The death and life of great American cities*: Vintage.

Jiang, B. (2007). A topological pattern of urban street networks: universality and peculiarity. *Physica A: Statistical Mechanics and its Applications, 384*(2), 647-655.

Jiang, B. (2009). Ranking spaces for predicting human movement in an urban environment. *International Journal of Geographical Information Science, 23*(7), 823-837.

Jiang, B., & Claramunt, C. (2002). Integration of space syntax into GIS: new perspectives for urban morphology. *Transactions in GIS, 6*(3), 295-309.

Jiang, B., & Claramunt, C. (2004). Topological analysis of urban street networks. *Environment and Planning B: Planning and Design, 31*(1), 151-162.

Jiang, B., & Jia, T. (2011). Agent-based simulation of human movement shaped by the underlying street structure. *International Journal of Geographical Information Science, 25*(1), 51-64.

Jiang, B., & Liu, C. (2009). Street‐based topological representations and analyses for predicting traffic flow in GIS. *International Journal of Geographical Information Science, 23*(9), 1119-1137.

Jiang, B., & Liu, X. (2010). Automatic generation of the axial lines of urban environments to capture what we perceive. *International Journal of Geographical Information Science, 24*(4), 545-558.

Jiang, B., & Sun, X. (2008). Tutorial for Automatically Generating Axial Lines. *Department of Technology and Built Environment, Division of Geomatics, University of Gävle, 801*, 76.

Jordan, T., Raubal, M., Gartrell, B., & Egenhofer, M. (1998). *An affordance-based model of place in GIS.* Paper presented at the 8th Int. Symposium on Spatial Data Handling, SDH.

Kim, Y. O. (2001). *The role of spatial configuration in spatial cognition.* Paper presented at the Proceedings of the Third International Space Syntax Symposium, Ann Arbor, University of Michigan.

Kim, Y. O., & Penn, A. (2004). Linking the spatial syntax of cognitive maps to the spatial syntax of the environment. *Environment and behavior, 36*(4), 483-504.

Kitchin, R. M., Blades, M., & Golledge, R. G. (1997). Understanding spatial concepts at the geographic scale without the use of vision. *Progress in Human Geography, 21*(2), 225-242.

Klippel, A. (2003). Wayfinding choremes *Spatial Information Theory. Foundations of Geographic Information Science* (pp. 301-315): Springer.

Klippel, A., & Winter, S. (2005). *Structural salience of landmarks for route directions.* Paper presented at the COSIT.

Kuipers, B. (1978). Modeling Spatial Knowledge*. *Cognitive science, 2*(2), 129-153.

Kuipers, B. (2000). The spatial semantic hierarchy. *Artificial Intelligence, 119*(1), 191-233.

Kuipers, B., Tecuci, D. G., & Stankiewicz, B. J. (2003). The Skeleton In The Cognitive Map A Computational and Empirical Exploration. *Environment and behavior, 35*(1), 81-106.

Kurashima, T., Iwata, T., Irie, G., & Fujimura, K. (2010). *Travel route recommendation using geotags in photo sharing sites.* Paper presented at the Proceedings of the 19th ACM international conference on Information and knowledge management.

Kwan, M. P. (1998). Space‐time and integral measures of individual accessibility: a comparative analysis using a point‐based framework. *Geographical analysis, 30*(3), 191-216.

Lee, P. U., & Tversky, B. (2005). Interplay between visual and spatial: The effect of landmark descriptions on comprehension of route/survey spatial descriptions. *Spatial Cognition & Computation, 5*(2-3), 163-185.

Lerman, Y., Rofè, Y., & Omer, I. (2014). Using space syntax to model pedestrian movement in urban transportation planning. *Geographical analysis, 46*(4), 392-410.

Levine, N. (2006). Crime mapping and the Crimestat program. *Geographical analysis, 38*(1), 41-56.

Li, Y., Xiao, L., Ye, Y., Xu, W., & Law, A. (2016). Understanding tourist space at a historic site through space syntax analysis: The case of Gulangyu, China. *Tourism Management, 52*, 30-43.

Liu, Y., Wang, X., Jin, X., & Wu, L. (2005). *On internal cardinal direction relations.* Paper presented at the International Conference on Spatial Information Theory.

Llobera, M. (2003). Extending GIS-based visual analysis: the concept of visualscapes. *International Journal of Geographical Information Science, 17*(1), 25-48.
Long, Y., Baran, P. K., & Moore, R. (2007). *The Role of Space Syntax in Spatial Cognition.* Paper presented at the Proceedings of the Sixth International Space Syntax Symposium, Istanbul, Turkey.
Lovelace, K. L., Hegarty, M., & Montello, D. R. (1999). *Elements of good route directions in familiar and unfamiliar environments.* Paper presented at the International conference on spatial information theory.
Lynch, K. (1960). *The image of the city* (Vol. 11): MIT press.
Macal, C. M., & North, M. J. (2005). *Tutorial on agent-based modeling and simulation.* Paper presented at the Simulation Conference, 2005 Proceedings of the Winter.
Mark, D. M. (1993). Human spatial cognition. *Human factors in geographical information systems*, 51-60.
McNamara, T. P. (1986). Mental representations of spatial relations. *Cognitive psychology, 18*(1), 87-121.
Meilinger, T., Franz, G., & Bülthoff, H. H. (2012). From isovists via mental representations to behaviour: first steps toward closing the causal chain. *Environment and Planning-Part B, 39*(1), 48.
Miller, H. J. (1999). Measuring space - time accessibility benefits within transportation networks: basic theory and computational procedures. *Geographical analysis, 31*(1), 1-26.
Miller, H. J. (2004). Activities in space and time. In: Stopher P, B K, Haynes K, Hensher D, editors. *Handbook of Transport 5: Transport Geography and Spatial Systems*. Pergamon/Elsevier Science
Millonig, A., & Schechtner, K. (2007). Developing landmark-based pedestrian-navigation systems. *IEEE Transactions on Intelligent Transportation Systems, 8*(1), 43-49.
Montello, D. R. (1997). *The perception and cognition of environmental distance: Direct sources of information.* Paper presented at the International Conference on Spatial Information Theory.
Montello, D. R. (1998). A new framework for understanding the acquisition of spatial knowledge in large-scale environments. *Spatial and temporal reasoning in geographic information systems*, 143-154.
Montello, D. R. (2007). *The contribution of space syntax to a comprehensive theory of environmental psychology.* Paper presented at the Proceedings of the 6th International Space Syntax Symposium, _Istanbul, iv-1–12.
Montello, D. R., Goodchild, M. F., Gottsegen, J., & Fohl, P. (2003). Where's downtown?: Behavioral methods for determining referents of vague spatial queries. *Spatial Cognition & Computation, 3*(2-3), 185-204.
Montello, D. R., & Pick, H. L. (1993). Integrating knowledge of vertically aligned large-scale spaces. *Environment and behavior, 25*(3), 457-484.
Montello, D. R., & Sas, C. (2006). Human factors of wayfinding in navigation. In W. Karwowski(Ed.) *International encyclopedia of ergonomics and human factors*. London: CRC Press: Taylor and Francis, Ltd.
Morello, E., & Ratti, C. (2009). A digital image of the city: 3D isovists in Lynch's urban analysis.
Norman, D. A. (2002). *The design of everyday things*. Sydney: Currency, 1990.
Nothegger, C., Winter, S., & Raubal, M. (2004). Selection of salient features for route directions. *Spatial cognition and computation, 4*(2), 113-136.
O'Neill, M. J. (1991). Evaluation of a conceptual model of architectural legibility. *Environment and behavior, 23*(3), 259-284.

O'Neill, M. J. (1992). Effects of familiarity and plan complexity on wayfinding in simulated buildings. *Journal of Environmental Psychology, 12*(4), 319-327.
Openshaw, S. (1983). *The modifiable areal unit problem* (Vol. 38): Geo Books Norwich.
Pelechano, N., Allbeck, J. M., & Badler, N. I. (2008). Virtual crowds: Methods, simulation, and control. *Synthesis Lectures on Computer Graphics and Animation, 3*(1), 1-176.
Penn, A. (2003). Space syntax and spatial cognition: or why the axial line? *Environment and behavior, 35*(1), 30-65.
Penn, A., Hillier, B., Banister, D., & Xu, J. (1998). Configurational modelling of urban movement networks. *Environment and Planning B-Planning & Design, 25*(1), 59-84.
Penn, A., & Turner, A. (2001). Space syntax based agent simulation.
Poppinga, B., Magnusson, C., Pielot, M., & Rassmus-Gröhn, K. (2011). *TouchOver map: audio-tactile exploration of interactive maps.* Paper presented at the Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services.
Porta, S., Latora, V., Wang, F., Strano, E., Cardillo, A., Scellato, S., Messora, R. (2009). Street centrality and densities of retail and services in Bologna, Italy. *Environment and Planning B: Planning and design, 36*(3), 450-465.
Portugali, J. (1996). Inter-representation networks and cognitive maps. *The construction of cognitive maps* (pp. 11-43): Springer.
Rasmussen, J., & Pejtersen, A. M. (1995). Virtual ecology of work. *Flach et al, 219*, 121-156.
Ratti, C. (2004). Urban texture and space syntax: some inconsistencies. *Environment and Planning B: Planning and Design, 31*(4), 487-499.
Ratti, C. (2005). The lineage of the line: space syntax parameters from the analysis of urban DEMs. *Environment and Planning B: Planning and Design, 32*(4), 547-566.
Raubal, M. (2001). *Agent-based simulation of human wayfinding: A perceptual model for unfamiliar buildings*. Ph.D. thesis, Technical University of Vienna.
Raubal, M. (2008). Wayfinding: Affordances and agent simulation. *Encyclopedia of GIS* (pp. 1243-1246): Springer.
Raubal, M., Miller, H. J., & Bridwell, S. (2004). User ‐ centred time geography for location ‐ based services. *Geografiska Annaler: Series B, Human Geography, 86*(4), 245-265.
Raubal, M., & Moratz, R. (2008). A functional model for affordance-based agents. *Towards affordance-based robot control* (pp. 91-105): Springer.
Raubal, M., & Winter, S. (2002a). Enriching wayfinding instructions with local landmarks. In *Geographic Information Science. Lecture Notes in Computer Science*, Vol. 2478, M.-J. Egenhofer, D. M. Mark, Eds., Heidelberg: Springer, 2002, pp. 243-259.
Raubal, M., & Winter, S. (2002b). *Enriching wayfinding instructions with local landmarks.* Paper presented at the International Conference on Geographic Information Science.
Raubal, M., & Worboys, M. (1999). A formal model of the process of wayfinding in built environments. *Spatial information theory. Cognitive and computational foundations of geographic information science*, 748-748.
Read, S. (1999). Space syntax and the Dutch city. *Environment and Planning B: Planning and Design, 26*(2), 251-264.
Rehrl, K., Häusler, E., & Leitinger, S. (2010). Comparing the effectiveness of GPS-enhanced voice guidance for pedestrians with metric-and landmark-based instruction sets. *Geographic information science*, 189-203.
Reynolds, C. W. (1987). Flocks, herds and schools: A distributed behavioral model. *ACM SIGGRAPH Computer Graphics, 21*(4), 25-34.

Richter, K.-F. (2007). *A uniform handling of different landmark types in route directions.* Paper presented at the International Conference on Spatial Information Theory.
Rovine, M. J., & Weisman, G. D. (1989). Sketch-map variables as predictors of way-finding performance. *Journal of Environmental Psychology, 9*(3), 217-232.
Sabidussi, G. (1966). The centrality index of a graph. *Psychometrika, 31*(4), 581-603.
Samson, R., Frank, M., & Fellous, J.-M. (2010). Computational models of reinforcement learning: the role of dopamine as a reward signal. *Cognitive neurodynamics, 4*(2), 91-105.
Sevtsuk, A. (2009). Mapping the MIT campus in real time using WiFi *Handbook of Research on Urban Informatics: The Practice and Promise of the Real-Time City* (pp. 326-338): IGI Global.
Sevtsuk, A., & Mekonnen, M. (2012). Urban network analysis. A new toolbox for ArcGIS. *Revue Internationale de Géomatique, 22*(2), 287-305.
Shaw, S.-L., & Yu, H. (2009). A GIS-based time-geographic approach of studying individual activities and interactions in a hybrid physical–virtual space. *Journal of Transport Geography, 17*(2), 141-149.
Shi, Y., Serdyukov, P., Hanjalic, A., & Larson, M. (2011). Personalized Landmark Recommendation Based on Geotags from Photo Sharing Sites. *ICWSM, 11*, 622-625.
Siegel, A. W., & White, S. H. (1975). The development of spatial representations of large-scale environments. *Advances in child development and behavior, 10*, 9-55.
Silverman, B. W. (2018). *Density estimation for statistics and data analysis*: Routledge.
Sokhansefat, G., Delavar, M., & Banedj-Schafii, M. (2012). *Multi-agent simulation of wayfinding for rescue operation during building fire.* Paper presented at the Proceedings of World Academy of Science, Engineering and Technology.
Sorrows, M. E., & Hirtle, S. C. (1999a). *The nature of landmarks for real and electronic spaces.* Paper presented at the International Conference on Spatial Information Theory.
Sorrows, M. E., & Hirtle, S. C. (1999b). The nature of landmarks for real and electronic spaces *Spatial information theory. Cognitive and computational foundations of geographic information science* (pp. 37-50): Springer.
Spector, L., Klein, J., Perry, C., & Feinstein, M. (2003). *Emergence of collective behavior in evolving populations of flying agents.* Paper presented at the Genetic and Evolutionary Computation—GECCO 2003.
Stead, D., & Marshall, S. (2001). The relationships between urban form and travel patterns. An international review and evaluation. *European Journal of Transport and Infrastructure Research, 1*(2), 113-141.
Stevens, A., & Coupe, P. (1978). Distortions in judged spatial relations. *Cognitive psychology, 10*(4), 422-437.
Summers, L., & Johnson, S. D. (2017). Does the configuration of the street network influence where outdoor serious violence takes place? Using space syntax to test crime pattern theory. *Journal of Quantitative Criminology, 33*(2), 397-420.
Takes, F. W., & Kosters, W. A. (2014). *Adaptive landmark selection strategies for fast shortest path computation in large real-world graphs.* Paper presented at the Web Intelligence (WI) and Intelligent Agent Technologies (IAT), 2014 IEEE/WIC/ACM International Joint Conferences on.
Thomson, R. C. (2004). *Bending the axial line: Smoothly continuous road centre-line segments as.* Paper presented at the Proceedings 4th International Space Syntax Symposium, London, UK.

Timothée, P., Nicolas, L.-B., Emanuele, S., Sergio, P., & Stéphane, J. (2010). *A network based kernel density estimator applied to Barcelona economic activities.* Paper presented at the International conference on computational science and its applications.

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic geography, 46*(sup1), 234-240.

Tolman, E. C. (1948). Cognitive maps in rats and men. *Psychological review, 55*(4), 189.

Tu Huynh, N., & Doherty, S. T. (2007). Digital sketch-map drawing as an instrument to collect data about spatial cognition. *Cartographica: The International Journal for Geographic Information and Geovisualization, 42*(4), 285-296.

Tuan, Y.-F. (1977). *Space and place: The perspective of experience*: U of Minnesota Press.

Turner, A. (2001a). *Angular analysis.* Paper presented at the Proceedings of the 3rd international symposium on space syntax.

Turner, A. (2001b). *Depthmap: a program to perform visibility graph analysis.* Paper presented at the Proceedings of the 3rd International Symposium on Space Syntax.

Turner, A. (2007a). From axial to road-centre lines: a new representation for space syntax and a new model of route choice for transport network analysis. *Environment and Planning B: Planning and Design, 34*(3), 539-555.

Turner, A. (2007b). The ingredients of an exosomatic cognitive map: Isovists, agents and axial lines? In: Hölscher, C., Conroy Dalton, R., Turner, A. (Eds.), Space Syntax and Spatial Cognition. Universität Bremen, Bremen, Germany.

Turner, A., Doxa, M., O'sullivan, D., & Penn, A. (2001). From isovists to visibility graphs: a methodology for the analysis of architectural space. *Environ Plann B, 28*(1), 103-121.

Turner, A., Penn, A., & Hillier, B. (2005). An algorithmic definition of the axial map. *Environment and Planning B: Planning and Design, 32*(3), 425-444.

Tversky, B. (1981). Distortions in memory for maps. *Cognitive psychology, 13*(3), 407-433.

Tversky, B. (1992). Distortions in cognitive maps. *Geoforum, 23*(2), 131-138.

Tversky, B. (1993). Cognitive maps, cognitive collages, and spatial mental models *Spatial Information Theory A Theoretical Basis for GIS* (pp. 14-24): Springer.

Vilar, E., Rebelo, F., & Noriega, P. (2014). Indoor human wayfinding performance using vertical and horizontal signage in virtual reality. *Human Factors and Ergonomics in Manufacturing & Service Industries, 24*(6), 601-615.

Vragović, I., Louis, E., & Díaz-Guilera, A. (2005). Efficiency of informational transfer in regular and complex networks. *Physical Review E, 71*(3), 036122.

Walmsley, D., & Jenkins, J. M. (1993). Appraisive images of tourist areas: application of personal constructs. *The Australian Geographer, 24*(2), 1-13.

Ward, S. L., Newcombe, N., & Overton, W. F. (1986). Turn left at the church, or three miles north: A study of direction giving and sex differences. *Environment and behavior, 18*(2), 192-213.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications* (Vol. 8): Cambridge university press.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world'networks. *nature, 393*(6684), 440-442.

Wells, A. J. (2002). Gibson's affordances and Turing's theory of computation. *Ecological Psychology, 14*(3), 140-180.

Wooldridge, M., & Jennings, N. R. (1995). Intelligent agents: Theory and practice. *The knowledge engineering review, 10*(02), 115-152.

Wrigley, N., Holt, T., Steel, D., & Tranmer, M. (1996). Analysing, modelling, and resolving the ecological fallacy. *Spatial analysis: Modelling in a GIS environment*, 23-40.

Xing, W., & Ghorbani, A. (2004). *Weighted pagerank algorithm.* Proceedings. Second Annual Conference on Communication Networks and Services Research, 2004.. IEEE, 2004..

Yan, X. (1990). *Human impacts of changing city form: A case study of Beijing.* Dissertation. The University of Ann Arbor, Michigan.

Yeung, H. W.-c., & Savage, V. R. (1996). Urban imagery and the Main Street of the nation: The legibility of Orchard Road in the eyes of Singaporeans. *Urban Studies, 33*(3), 473-494.

Yun, Y. W., & Kim, Y. O. (2007). *The effect of depth and distance in spatial cognition.* Paper presented at the Proceedings. 6th International Space Syntax Symposium, Istanbul.

Zaff, B. S. (1995). Designing with affordances in mind. *Global perspectives on the ecology of human-machine systems*. CRC Press, 2018. 238-272.

Appendix A: Survey design

Space, cognition and human movement - How do people interpret, understand and use the space?

Task I:

1. Do you have any experience of reading or drawing maps?
    - A lot of experience
    - Some experience
    - Little experience
    - No experience

2. How are your map-drawing skills?
    - Good
    - Above average
    - Average
    - Below average
    - Poor

3. Thinking of OU Norman campus, please list 3 locations/areas on campus that you have visited most frequently.

4. What location/area on campus do you like the most? And why do you like this location/area?
    - Please describe your favorite location on campus or specify the name of the building:
    - Please specify the reason why you like it:

5. Suppose a/other visitor asks for your help about navigating on OU Norman campus, please sketch a map of campus areas from memory to help him/her.
    (1) Please sketch this graph as detailed as possible and include **all buildings, streets, and regions that you remember**. You may label the buildings, streets, and regions if you know.
    (2) Keep in mind that there is no right or wrong drawing. So please draw the map from memory and **don't refer to other map products** (e.g., online/hard maps or GPS).

1

(3) Although **time for this drawing task** is not restricted, you are expected to draw this graph **within 15 minutes**. Please finish this drawing before starting the task II.

2

You have finished the task I. Please review and confirm your sketch graph from memory of the campus layout before continuing with task II. After starting the task II, you are NOT expected to go back and revise your sketch map.

Task II:

6. Are you a student/faculty/staff/visitor?
   - Student
   - Faculty
   - Staff
   - Visitor: Resident in Norman
   - Visitor: Resident outside Norman

7. How familiar are you with the layout of OU Norman campus?
   - Very unfamiliar
   - Unfamiliar
   - Average
   - Familiar
   - Very familiar

8. Where do you live on campus?

☐ I do not live on campus.

If you do, please specify the name of building or describe its location below:

If you are a **Visitor**, please Skip Question 9-14.

9. How long have you been at OU either working or studying?
   - < 1 year
   - 1-2 years
   - 2-3 years
   - 3-4 years
   - >= 4 years

10. What building on campus is your work office or cubicle located?

☐ I do not have a work office or cubicle on campus.

If you do, please specify the name of building or describe its location below:

3

11. What is your field of study? Or what was your college major? (Please check all that apply.)

- ☐ Social Science (e.g., History, Linguistics, Arts, Economics, Political Science, Psychology, Sociology)
- ☐ Physical Science (e.g., Biology, Chemistry, Physics, Earth Science)
- ☐ Engineering
- ☐ Other:____

12. What buildings on campus are your classes scheduled for this semester?

- ☐ I do not have any classes on Norman campus this semester.

If you do, please specify the names of buildings below:

13. What days of the week do you visit the campus? (Please check all that apply.)

- ☐ Monday
- ☐ Tuesday
- ☐ Wednesday
- ☐ Thursday
- ☐ Friday
- ☐ Weekend

14. How do you often get to campus? (Please check all that apply.)

- ☐ On foot
- ☐ By bus
- ☐ By bicycle
- ☐ By car
- ☐ Other____________________________.

If you are a **Visitor**, please **continue** to answer questions from here.

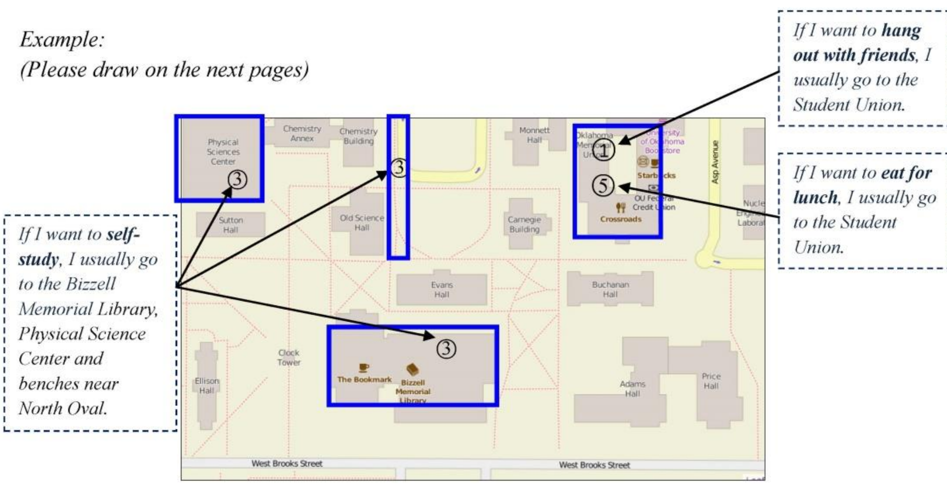
15. If you have free time between/after classes, work or scheduled visits, what activities on campus would you likely participate in? (Please check all that apply.)

- ☐ Having lunch, dinner or snacks
- ☐ Hanging out with friends or colleagues
- ☐ Self-studying/Self-reading
- ☐ Group studying/Group meeting
- ☐ Attending open lectures or seminars
- ☐ Looking for something to do for fun (e.g. movies, billiards, watch TV)
- ☐ Doing physical exercises or physical activities (e.g. Frisbee, walking, weight-lifting)
- ☐ Practicing musical instruments or dancing
- ☐ Taking a nap
- ☐ Wandering around
- ☐ Other: ____

16. What locations or general areas (e.g., Bizzel Library, South Oval or the bench in front of Student Union) will you go for the following activities? Please draw **all/the top 3 areas** for each activity on the map and also mark the area by the **activity ID to specify the type of activity**.

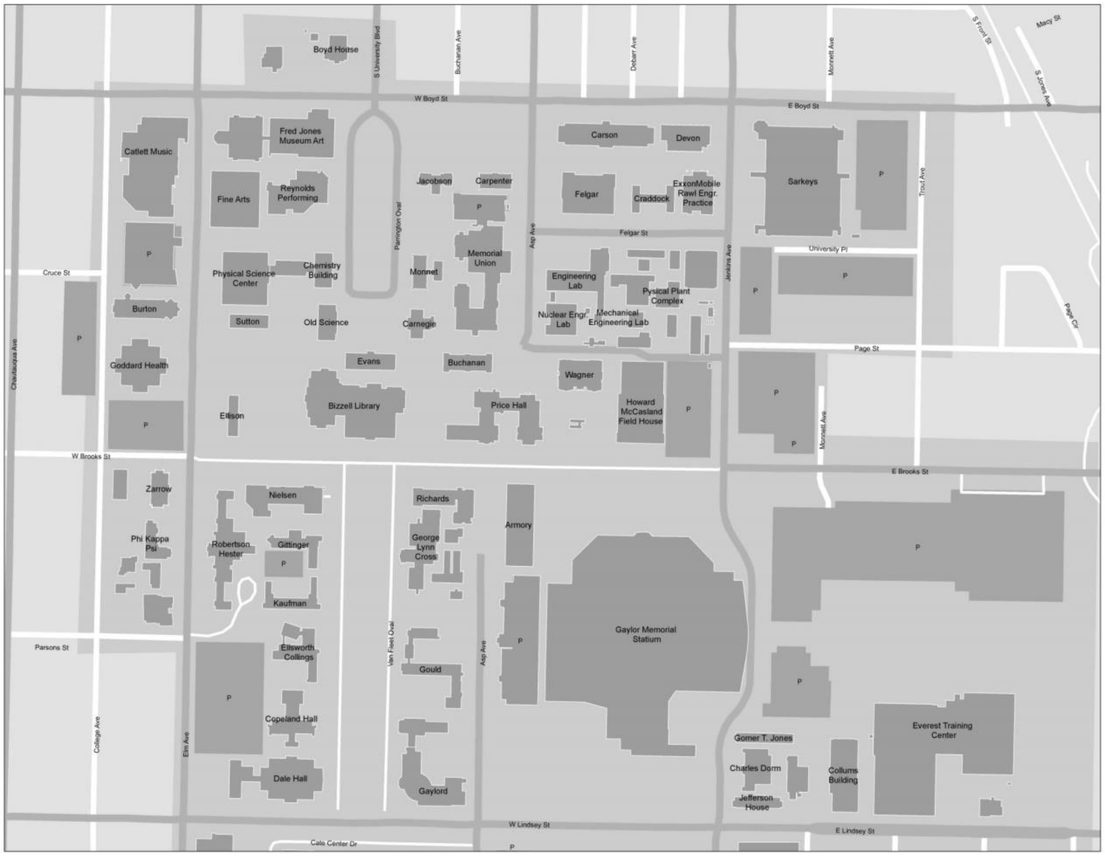
① **Hanging out** with friends or colleagues ☐ I don't know any location for ①	⑥ **Eating** lunch, dinner or snacks ☐ I don't know any location for ⑥.
② Looking for something for **fun or entertainment** (e.g. movies, billiards, watch TV) ☐ I don't know any location for ②.	⑦ Doing **physical exercises or physical activities** (e.g., Frisbee, walking, weight-lifting) ☐ I don't know any location for ⑦.
③ **Self-studying** ☐ I don't know any location for ③.	⑧ **Parking/taking public transit** ☐ I don't know any location for ⑧.
④ Organizing **group study or group meeting** ☐ I don't know any location for ④.	⑨ Taking a **nap/break** ☐ I don't know any location for ⑨.
⑤ Looking for open **lectures or seminars** ☐ I don't know any location for ⑤.	

Example:
(Please draw on the next pages)



Main Campus I

Note: Research campus is on page 7.



Campus map of activities (1/2)

17. Campus daily activity diary:

What locations or general areas on campus did you stop for an activity yesterday or on your last day on campus? Please describe locations, stay time, and activities (e.g. parking, classes, or meeting) that you participated. If you have visited in over 9 locations on campus, you may ask the interviewer for additional pages of the activities diary.

Example:

I had a group discussion in Bizzell Library scheduled at 11:00 AM. The discussion continued in North Oval. After the meeting, our group members went for a lunch together in Union.

Stay time	*Locations visited*	*Activities*	
From: *11:00 AM* *To:* *11:45 AM*	*Bizzell Memorial Library & North Oval*	☐ *Take the class* ☐ *Work* ☐ *Self-study* ✓ *Group study/meeting* ☐ *Lecture/seminar* ☐ *Practice instrument/dancing* ☐ *Eat for meals or snacks* ☐ *Other:* ____	☐ *Parking* ☐ *Entertainment* ☐ *Physical exercises* ☐ *Hang out with friends* ☐ *Student organization* ☐ *Take a nap* ☐ *Wander around* ☐ *Rest in dorm/apartment*
From: *12:00 PM* *To:* *12:30 PM*	*Memorial Union*	☐ *Take the class* ☐ *Work* ☐ *Self-study* ☐ *Group study/meeting* ☐ *Lecture/seminar* ☐ *Practice instrument/dancing* ✓ *Eat for meals or snacks* ☐ *Other:* ____	☐ *Parking* ☐ *Entertainment* ☐ *Physical exercises* ✓ *Hang out with friends* ☐ *Student organization* ☐ *Take a nap* ☐ *Wander around* ☐ *Rest in dorm/apartment*

Your daily activity diary on campus:

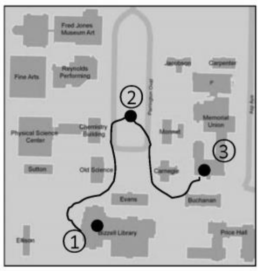
Stay time	Locations visited	Activity	
From: ____ To: ____		☐ Take the class ☐ Work ☐ Self-study ☐ Group study/meeting ☐ Lecture/seminar ☐ Practice instrument/dancing ☐ Eat for meals or snacks ☐ Other: ____	☐ Parking ☐ Entertainment ☐ Physical exercises ☐ Hang out with friends ☐ Student organization ☐ Take a nap ☐ Wander around ☐ Rest in dorm/apartment

Stay time	Location visited	Activity
From: ______________ To: ______________		☐ Take the class ☐ Parking ☐ Work ☐ Entertainment ☐ Self-study ☐ Physical exercises ☐ Group study/meeting ☐ Hang out with friends ☐ Lecture/seminar ☐ Student organization ☐ Practice instrument/dancing ☐ Take a nap ☐ Wander around ☐ Eat for meals or snacks ☐ Rest in dorm/apartment ☐ Other: ____________________
From: ______________ To: ______________		☐ Take the class ☐ Parking ☐ Work ☐ Entertainment ☐ Self-study ☐ Physical exercises ☐ Group study/meeting ☐ Hang out with friends ☐ Lecture/seminar ☐ Student organization ☐ Practice instrument/dancing ☐ Take a nap ☐ Wander around ☐ Eat for meals or snacks ☐ Rest in dorm/apartment ☐ Other: ____________________
From: ______________ To: ______________		☐ Take the class ☐ Parking ☐ Work ☐ Entertainment ☐ Self-study ☐ Physical exercises ☐ Group study/meeting ☐ Hang out with friends ☐ Lecture/seminar ☐ Student organization ☐ Practice instrument/dancing ☐ Take a nap ☐ Wander around ☐ Eat for meals or snacks ☐ Rest in dorm/apartment ☐ Other: ____________________
From: ______________ To: ______________		☐ Take the class ☐ Parking ☐ Work ☐ Entertainment ☐ Self-study ☐ Physical exercises ☐ Group study/meeting ☐ Hang out with friends ☐ Lecture/seminar ☐ Student organization ☐ Practice instrument/dancing ☐ Take a nap ☐ Wander around ☐ Eat for meals or snacks ☐ Rest in dorm/apartment ☐ Other: ____________________

Stay time	Location visited	Activity
From: ________ To: ________		☐ Take the class ☐ Work ☐ Self-study ☐ Group study/meeting ☐ Lecture/seminar ☐ Practice instrument/dancing ☐ Eat for meals or snacks ☐ Parking ☐ Entertainment ☐ Physical exercises ☐ Hang out with friends ☐ Student organization ☐ Take a nap ☐ Wander around ☐ Rest in dorm/apartment ☐ Other: ________
From: ________ To: ________		☐ Take the class ☐ Work ☐ Self-study ☐ Group study/meeting ☐ Lecture/seminar ☐ Practice instrument/dancing ☐ Eat for meals or snacks ☐ Parking ☐ Entertainment ☐ Physical exercises ☐ Hang out with friends ☐ Student organization ☐ Take a nap ☐ Wander around ☐ Rest in dorm/apartment ☐ Other: ________
From: ________ To: ________		☐ Take the class ☐ Work ☐ Self-study ☐ Group study/meeting ☐ Lecture/seminar ☐ Practice instrument/dancing ☐ Eat for meals or snacks ☐ Parking ☐ Entertainment ☐ Physical exercises ☐ Hang out with friends ☐ Student organization ☐ Take a nap ☐ Wander around ☐ Rest in dorm/apartment ☐ Other: ________
From: ________ To: ________		☐ Take the class ☐ Work ☐ Self-study ☐ Group study/meeting ☐ Lecture/seminar ☐ Practice instrument/dancing ☐ Eat for meals or snacks ☐ Parking ☐ Entertainment ☐ Physical exercises ☐ Hang out with friends ☐ Student organization ☐ Take a nap ☐ Wander around ☐ Rest in dorm/apartment ☐ Other: ________

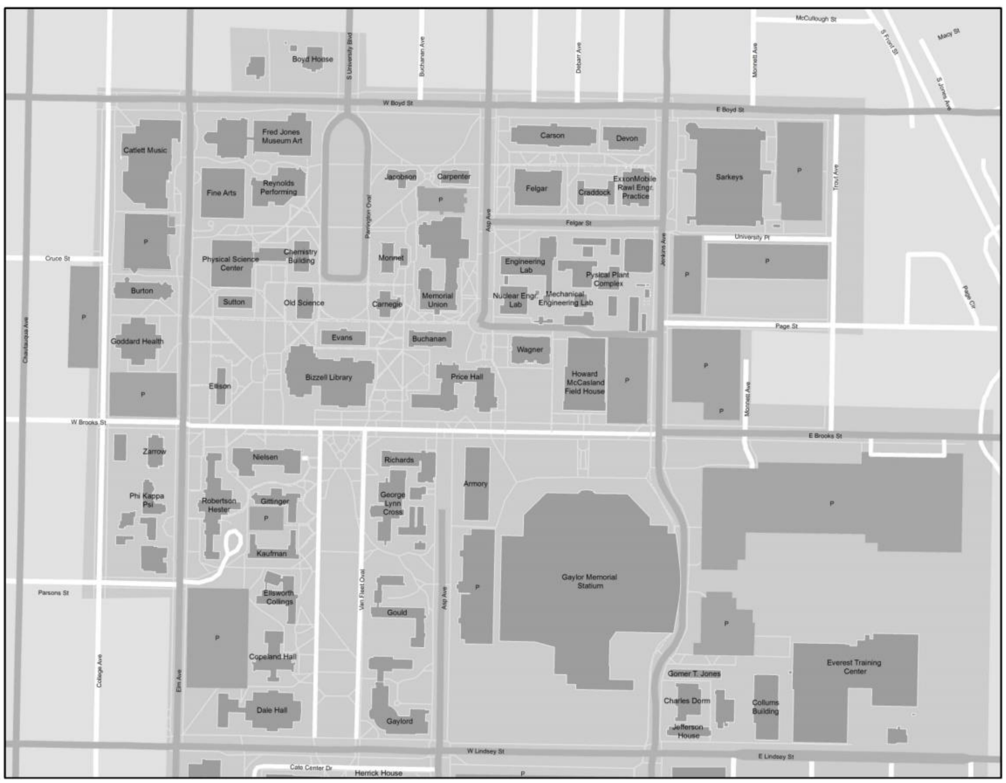
18. On-campus moving path of one day

Please draw your on-campus walking/driving path of yesterday or your last day on campus on maps below and use the number to specify the order of your destinations.

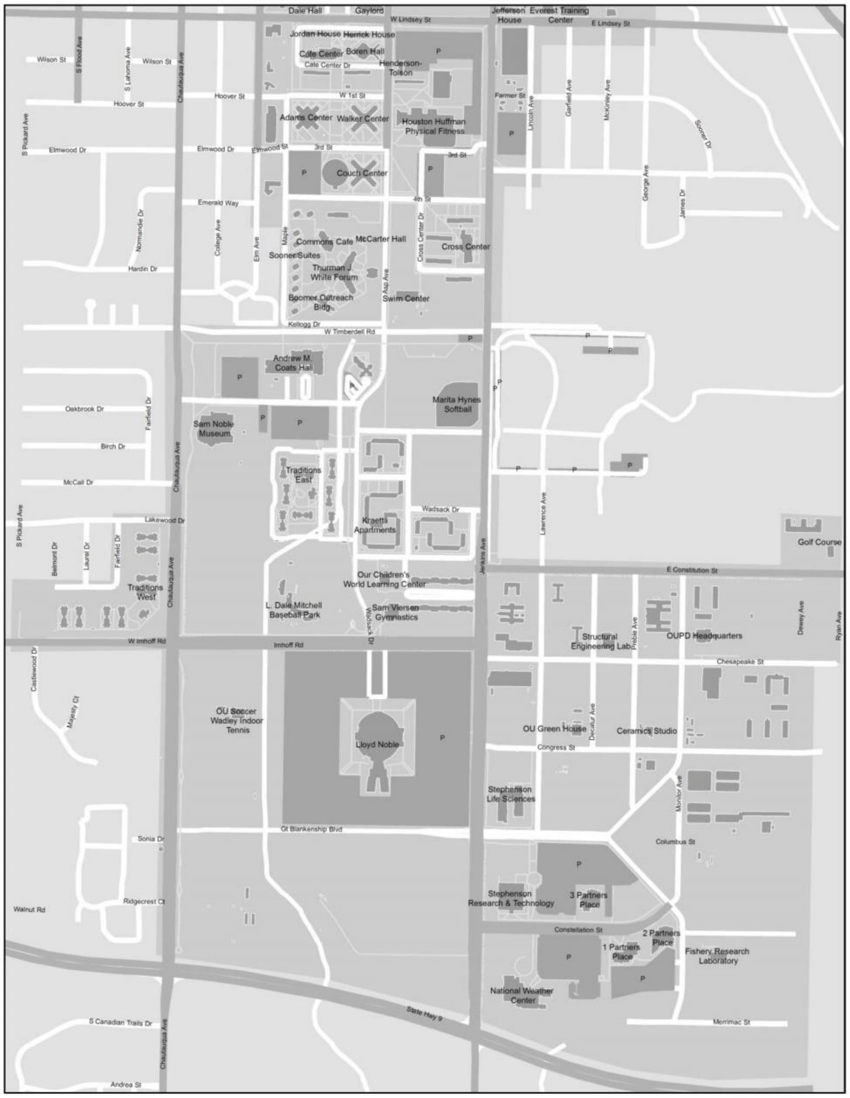


Example:

*I had a group discussion in **Bizzell Library** scheduled at 11:00 AM. The discussion continued in **North Oval**. After the meeting, our group members went for a lunch together in **Union**.*



Campus map of moving path (1/2)



Campus map of moving path (2/2)

19. Looking at the campus maps of moving path above again, where are locations/areas that you have never visited? Please circle them on map above.

☐ I am confident that I have visited all places on campus.

12

20. How do you or how may you get from the **main campus** (e.g., student union) to the **research campus** (e.g., National Weather Center/Stephenson Centers)?

- ☐ On foot
- ☐ By bus
- ☐ By bicycle
- ☐ By car
- ☐ I do not know where research campus (e.g., National Weather Center) is
- ☐ Other______________________________.

21. Please give a route instruction from **Memorial Union** to the **National Weather Center (NWC)** by drawing or describing the route in the box below. Please provide important clues along the route so a visitor can follow this route from Union to NWC.

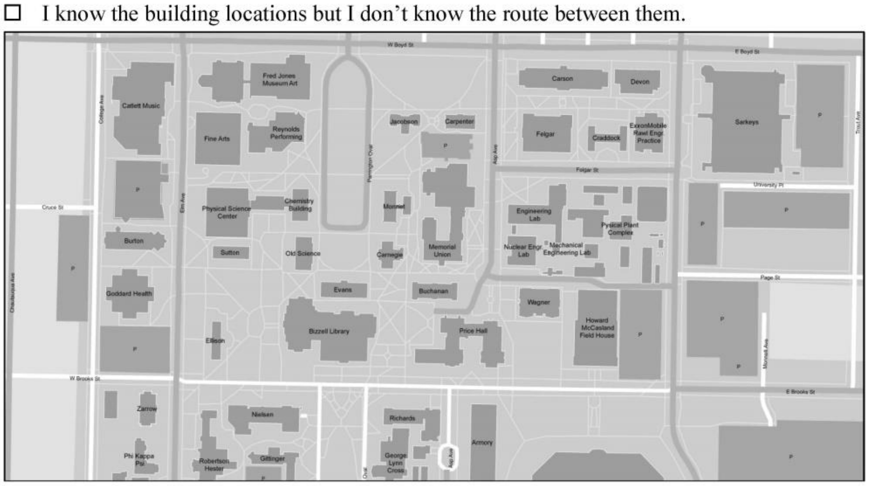
Example: Turn left->Elm Ave.->See art museum->Turn right at the 2nd intersection

☐ I don't know the route from Union to NWC.

22. Please draw the route that you may take from **Bizzell Memorial Library** to **Sarkeys Energy Center** on the map below and specify the reason why you choose this route.

☐ I don't know where the buildings are located.

☐ I know the building locations but I don't know the route between them.



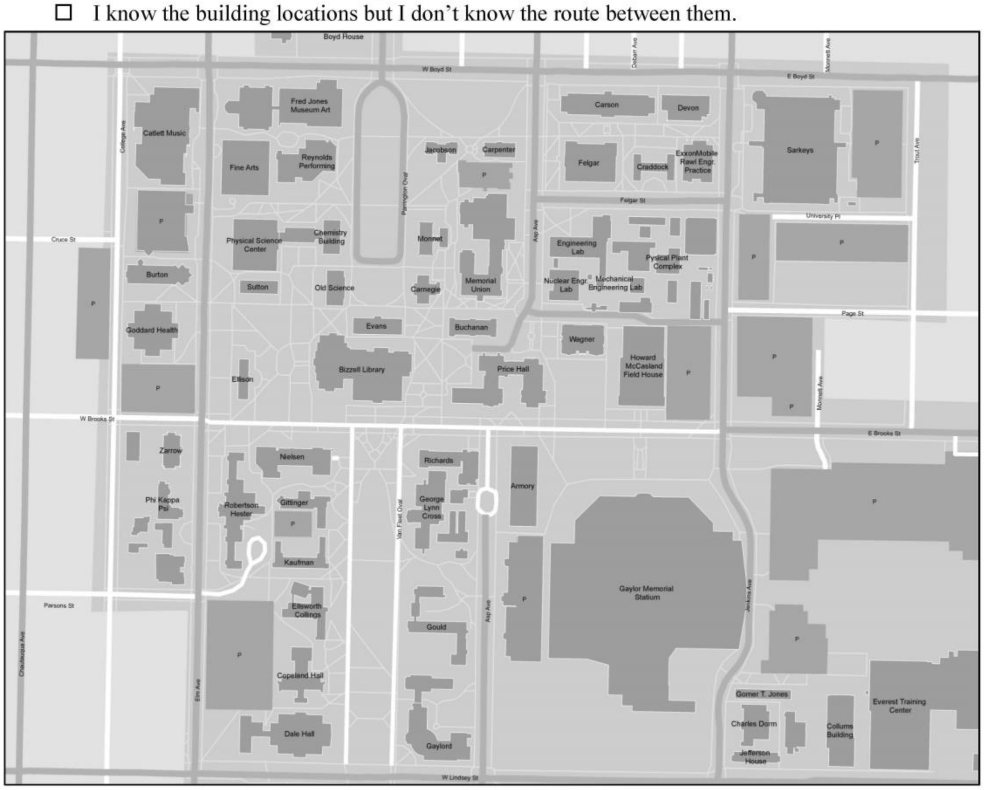
13

- Why do you choose this route from **Bizzell Library** to **Sarkeys Energy Center**? (Check all that apply)
  - ☐ Least crowded
  - ☐ Shortest distance
  - ☐ Least time
  - ☐ Fewest number of turns
  - ☐ Most direct
  - ☐ Most familiar
  - ☐ Most pleasant
  - ☐ Other_________________________________.

23. Please draw the route that you may take from **Sarkeys Energy Center** to **Dale Hall** near South Oval on the map below and specify the reason why you choose this route

☐ I don't know where the buildings are located.

☐ I know the building locations but I don't know the route between them.



14

IRB NUMBER: 5980
IRB APPROVAL DATE: 09/30/2015

- Why do you choose this route from **Sarkeys Energy Center** to **Dale Hall**? (Check all that apply)
  ☐ Least crowded
  ☐ Shortest distance
  ☐ Least time
  ☐ Fewest number of turns
  ☐ Most direct
  ☐ Most familiar
  ☐ Most pleasant
  ☐ Other_________________________________.

24. Gender:
    - Male
    - Female
    - Other:______________

25. Race:
    - White
    - Black
    - Hispanic
    - Native American
    - Asian
    - Other:____________

Thank you for your participation.

There is a **follow-up study** of this survey with GPS tracking of your daily path on campus. If you are interested in this GPS study, please leave your email address below and you will be further contacted.

Date: _____________ Time: _____________ Location: _____________

Appendix B: Consent to participate in research

701-A-2

Unsigned Consent to Participate in Research

Would you like to be involved in research at the University of Oklahoma?

I am Ying Zhang from the Center of Spatial Analysis and I invite you to participate in my research project entitled "Space, Cognition and Human Movement". This research is being conducted at the University of Oklahoma. You are selected as a possible participant because you currently study, work and/or visit at the University of Oklahoma Norman Campus. You must be at least 18 years of age to participate in this study.

Please read this document and contact me to ask any questions that you may have BEFORE agreeing to take part in my research.

What is the purpose of this research? The purpose of this study is to understand how students, faculty, staff, and visitors interpret, understand and use space on campus. Specifically, what is your image of the spatial layout of the campus? What activities are you participating in campus buildings or general areas? And how do you select a route to a destination when you navigate through the campus?

How many participants will be in this research? About 150 people will take part in this research.

What will I be asked to do? If you agree to be in this research, you will be asked to (1) draw a sketch map about the physical layout of OU Norman campus from memory; (2) response to questions about your spatial experience at OU, your perception of use of campus space, and your route selection to specific destinations.

How long will this take? Your participation will take 30-50 minutes, varied depending on your response rate.

What are the risks and/or benefits if I participate? There are no risks and no benefits from being in this research.

Will I be compensated for participating? You will be reimbursed for your time and participation in this research. If you choose to participate in this study, free pizza will be offered at the survey location.

Who will see my information? In research reports, there will be no information that will make it possible to identify you. Research records will be stored securely and only approved researchers and the OU Institution Review Board will have access to the records.

Do I have to participate? No. If you do not participate, you will not be penalized or lose benefits or services unrelated to the research. If you decide to participate, you don't have to answer any question and can stop participating at any time.

Who do I contact with questions, concerns or complaints? If you have questions, concerns or complaints about the research or have experienced a research-related injury, contact me at

Ying Zhang	yingzhangcsa@ou.edu	405-512-4595
Scott Gronlund	sgronlund@ou.edu	405-325-4553

You can also contact the University of Oklahoma – Norman Campus Institutional Review Board (OU-NC IRB) at 405-325-8110 or irb@ou.edu if you have questions about your rights as a research participant, concerns, or complaints about the research and wish to talk to someone other than the researcher(s) or if you cannot reach the researcher(s).

Please keep this document for your records. By providing information to the researcher(s), I am agreeing to participate in this research.

Revised 03/01/15
Page 1 of 1

IRB APPROVED
IRB NUMBER: 5980
IRB APPROVAL DATE: 06/21/2017
IRB EXPIRATION DATE: 05/31/2018