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Examining the impact of urban morphology on bicycle mode choice

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Abstract. Nonmotorized transport modes such as bicycling are becoming important components to urban transportation systems in the United States, in particular with the recent emphases on sustainable urban development. Recent bicycle forecasting methods have included urban design elements to help explain bicycle behavior but most measures lack accountability of microscale built form attributes that address bicyclist perception. This study developed a discrete choice model to examine the impact of urban morphological factors on people's utilitarian bicycle mode choice decisions. In the model, traditional factors considered include personal, household, and environmental variables. Urban morphology variables from space syntax were also incorporated in the model to test for the marginal influence of microscale design and space characteristics in the decision to bicycle. Results indicate that microscale built form factors that enhance visibility and contain well connected street networks significantly affected bicycle mode choice decisions at the trip origin. The finding that built form variables by and large influence the probability that someone will commute via bicycle suggests that policies and planning efforts aimed at increasing bicycle mode share should include human-scaled built form metrics that address urban space and cognition.

Keywords: urban form, bicycling, GIS, visibility analysis, discrete choice model

1 Introduction

The relationship between neighborhood design, land use, and transportation has been studied extensively and across many disciplines. As a result, there is now a general consensus that an undeniable connection exists between transportation decisions and the built form. An example of this notion can be found in the principles of 'new urbanism' where it is postulated that proper urban design may increase levels of nonmotorized transportation (Saelens et al, 2003). Policies that incorporate this belief have been implemented throughout many US cities with varying degrees of success in reducing automobile usage or increasing nonmotorized transportation (Crane and Crepeau, 1998; Frank et al, 2003). The connection between built form and physical activity is also found throughout the public health, and more recently, transportation planning arenas. Researchers in these fields have begun to systematically address chronic health diseases, such as obesity, by investigating how the built environment affects nonmotorized transportation modes such as walking and bicycling. As a result, there is a burgeoning field of research attempting to increase nonmotorized transportation modes such as bicycling, by determining how the built environment influences mode choice.

The literature suggests that there is a link between the built environment and nonmotorized travel behavior. This finding has traditionally been investigated from a global viewpoint. There is now an extensive effort to include microscale urban design factors to promote and implement alternative transportation modes (Cervero and Kockelman, 1997; Frank and Pivo, 1995; Moudon et al, 2005). Built form elements that have been correlated to bicycling include directness (Aultman-Hall et al, 1997; McDonald and Burns, 2001), connectivity (Dill, 2004), density (Cervero and Kockelman, 1997), and general neighborhood and transportation network design (Cervero and Kockelman, 1997; Noël and Lee-Gosselin, 2004). The relationship between bicyclist and environment is also supported by Rapoport (1987) who posited that pedestrians and bicyclists are very engaged and responsive to the environment in contrast to motorists. The intimate connection between the environment and traveler was also noted and popularized by Jane Jacob's (1961) seminal text. The body of work surrounding the connection between the built form and nonmotorized transportation modes supports further inquiry into methods than can assimilate human-scaled information to drive successful bicycle policy and planning initiatives.

Despite several studies that have found positive associations between the built environment and bicycle mode choice, few have been able to disentangle the link between urban form and bicycling at a microscale (Frank and Engelke, 2001). The reasons for this may be due to minimal consideration of disaggregated objective built form factors, no accountability of bicyclist's perception, lack of a common theoretical urban form–nonmotorized model, underreporting of short trips due to bicycling and walking, problems associated with variable aggregation, or subjective personal assessments of the built form (Frank and Engelke, 2001; Hess et al, 2001; Moudon et al, 2005; Van der Waerden et al, 2004). Considering the lack of research pertaining to the detailed relationship between the built environment and bicycling, this study sets out to provide a sharper focus into the role urban morphology holds in daily bicycle commute decisions. Furthermore, it is hypothesized that microscaled variations in spatial visibility, regulated by the built form, can affect bicycle mode choice decisions. This hypothesis will be tested by invoking a hierarchical discrete choice model to ascertain the relative importance of built form factors and their relations to bicycle mode choice decisions. The anticipated outcomes of this research will contribute to an understanding of an functional aspects of urban morphology and utilitarian bicycle mode choice decisions so that stakeholders involved in retrofitting neighborhoods or implementing planning initiatives to elevate utilitarian bicycling can incorporate spatial topologies into the larger decision support system.

In order to accomplish the goals set out above, this paper is organized as follows. The next section details the underpinnings of urban morphological assessments, highlighting bicycling applications. Section 3 describes the study area and dataset employed in this study. Research methodology and results are reported in sections 4 and 5, respectively, and finally, section 6 concludes this paper.

2 Urban morphology and bicycling

An area of research that focuses on the interaction between society and space is space syntax. Space syntax operationalizes the built form by examining the configuration of areas and networks using graph theory (Hillier and Hanson, 1984). This theory posits that the spatial configuration of objects in the environment is not an ancillary component of human activity, but is shaped by and intrinsically linked to human perception. Space syntax has served as a basis for associated cognition–built form theories such as: natural movement (Hillier et al, 1993), optic flows (Gibson, 1979), and movement economy (Hillier and Penn, 1996). Modeling techniques within the paradigm of space syntax include axial map analysis (Hillier and Hanson, 1984), visibility graph analysis (Turner, 2003), and segment-angular analysis (Hillier and Iida, 2005). To better understand how the built environment is quantified using space syntax, consider the arrangement of roads, buildings, and potential visual fields depicted in figure 1(a). The initial step in most space syntax research is the derivation of

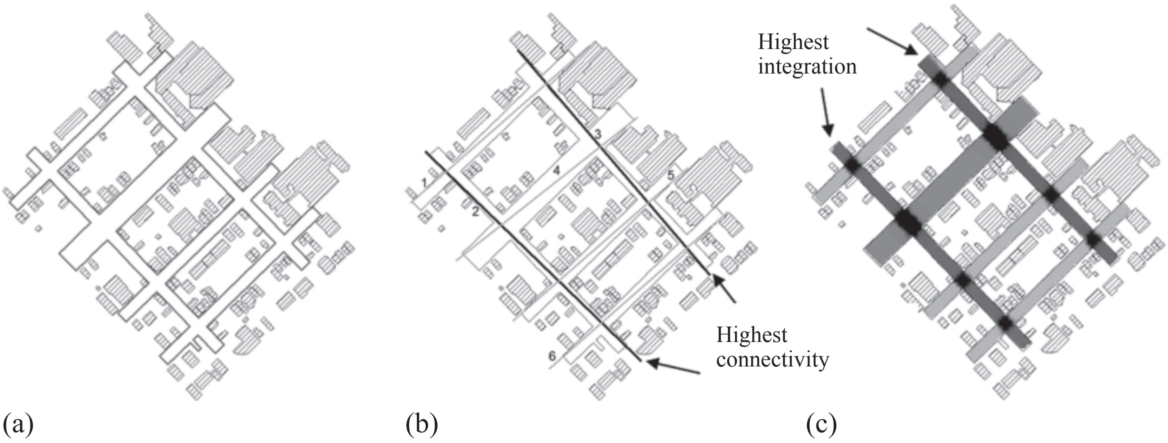

Figure 1. Built form topologies and space syntax: (a) transportation right-of-way and buildings, (b) fewest line axial map indicating connectivity, and (c) visibility graph analysis depicting integration.

an axial map which depicts the fewest and longest lines of site among all visible spaces [figure 1(b)]. A graph is then constructed where the lines of sight (axial lines) are depicted as nodes and the intersections between axial lines as vertices. Common axial map analyses includes: connectivity, control, and integration (Baran, 2008). The connectivity metric is displayed in figure 1(b) and clearly shows that streets 2 and 3 contain increased connections to neighboring streets, indicating that these roadways have greater movement potential, compared with adjacent and less connected streets. A space syntax measure that is not limited by a single graph representing spatial relationships and is a bottom-up approach is visibility graph analysis (VGA) (Franz and Wiener, 2008). VGA is premised on isovists that represent mutually visible nodes in space (Turner et al, 2001). According to Turner et al (2001), isovists in a visibility graph G can be denoted by a pair of sets containing vertices V and edges E, represented by:

$$V = \{v_1, v_2, ..., v_n\} .$$

The edges E between mutually visible vertices take the form:

$$e_{12} = \text{mutually visible vertices}, \{v_1, v_2\} ,$$

and

$$E = \{e_{12}, e_{23}, ..., e_{ij}\}, \qquad \text{where } e_{ij} \leftrightarrow e_{ji} .$$

Figure 1(c) demonstrates how the VGA output, integration, varies in a typical urban street network. It is observed in this figure that street intersections and arterial roadways that offer elevated visual accessibility lend themselves to potential areas of human congregation or roadways that are likely to be more traversable.

Space syntax has made investigations into the relationship between society and space achievable, and as a result, shed light into several human–space interactions such as: pedestrian flow patterns, human wayfinding mechanisms, crime rates, and vehicle movement patterns (Crucitti et al, 2006; Hillier and Hanson, 1984). More specifically, space syntax research has discovered that potential movement of pedestrians, and to a lesser degree bicyclists, are strongly correlated to the configuration of the environment (McCahill and Garrick, 2008; Raford and Ragland, 2003; 2004; Turner, 2003). A study conducted by Raford et al (2005) found that low mean angular depth, or the least number of turns per traversable segment, corresponded with high bicyclist flow, and Raford et al (2007) also found strong correlations between road angularity and actual bicyclist volumes, resulting in the finding that bicyclists attempt to minimize angles when traversing the network. The ability of space syntax to assign spatial and visibility measurements to traversable space may provide an important contribution to understanding bicycle mobility and mode choice decisions.

3 Study area and data

The study area of this research is the City of Madison, Wisconsin (figure 2). Madison is a medium-sized city with a population of approximately 223 000 covering approximately 7.2 square miles and containing 796 miles of roadways. Madison is also home to the University of Wisconsin—the state's largest university. The university-orientated city contains 129 miles of off-street trails, and 147 miles of on-street facilities, all of which contribute to an elevated bicycle mode share of approximately 3.2% for work trips and 2.4% for all trips (Schaefer, 2008). Despite these promising statistics, there is still a high percentage of single-occupant car commuters (65%) and congestion remains a problem (Schaefer, 2008).

The 2001 National Household Travel Survey (NHTS) was used in this study and this data-collection effort spanned 1 May 2001 to 6 May 2002 via telephone. The Dane County, Wisconsin 2001 NHTS add-on sample is comprised of 2841 households, 6210 persons interviewed, 26 351 trips, and 6601 long-distance trips reported. The data are comprised of six categories: household, person, auto, daily travel, long-distance travel, and most recent long-distance travel (Proussaloglou et al, 2004). The categorical variables were recoded using a simple coding function in the SPSS 16.0 statistical software program (SPSS Inc. Chicago, IL). Residential, renter, and housing densities per 2000 US Census block group were incorporated into this research as well. Infrastructure and physical data such as topography, land use, road centerlines, right-of-way (ROW), transportation network (ie, traffic volume, bicycle facility, off-street trails), and traffic generators were obtained from the Dane County Land Information Office and the City of Madison's Engineering Department. Bicycle facilities used in this analysis included all present on-street bicycle routes, trails, on-street bicycle lanes, and marked pathways. Climate data were obtained from the National Climatic Data Center. Climate factors used in this study include daily minimum temperature, daily maximum temperature, dew point, precipitation (inches), and wind speed in miles per hour (mph). Travel day weather conditions spanned a period of one year and were included here to determine possible relationships between varying weather conditions and the decision to bicycle.

For all the environmental and space syntax variables, the average value within a 3 km airline (straight-line) buffer around each individual's home location was employed using ESRI ArcGIS 9.2 (figure 3). Previous research indicates that persons are more apt to bicycle

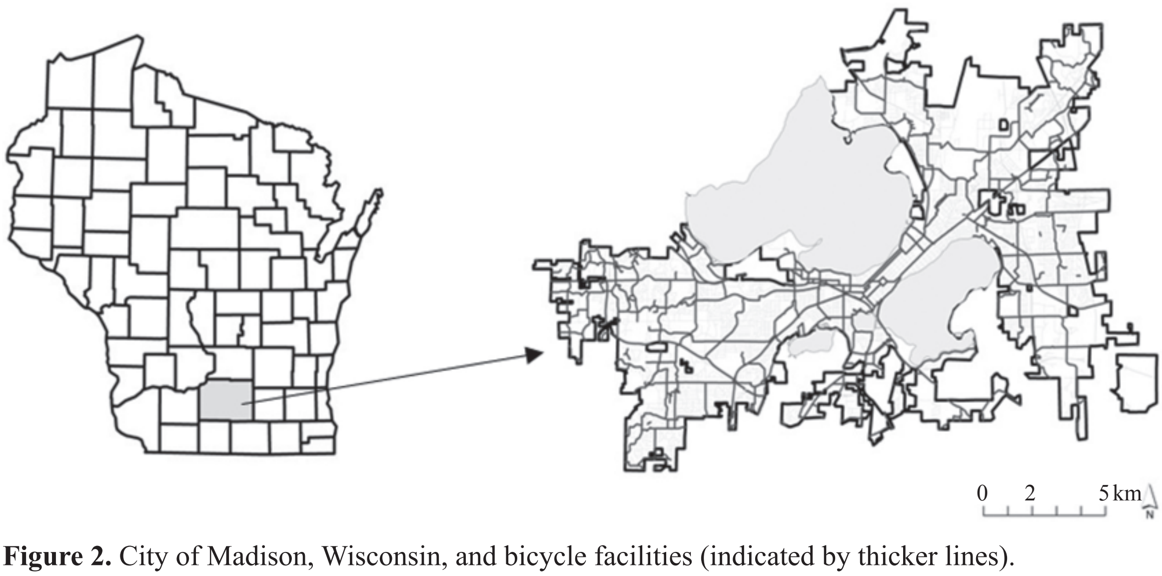

Figure 2. City of Madison, Wisconsin, and bicycle facilities (indicated by thicker lines).

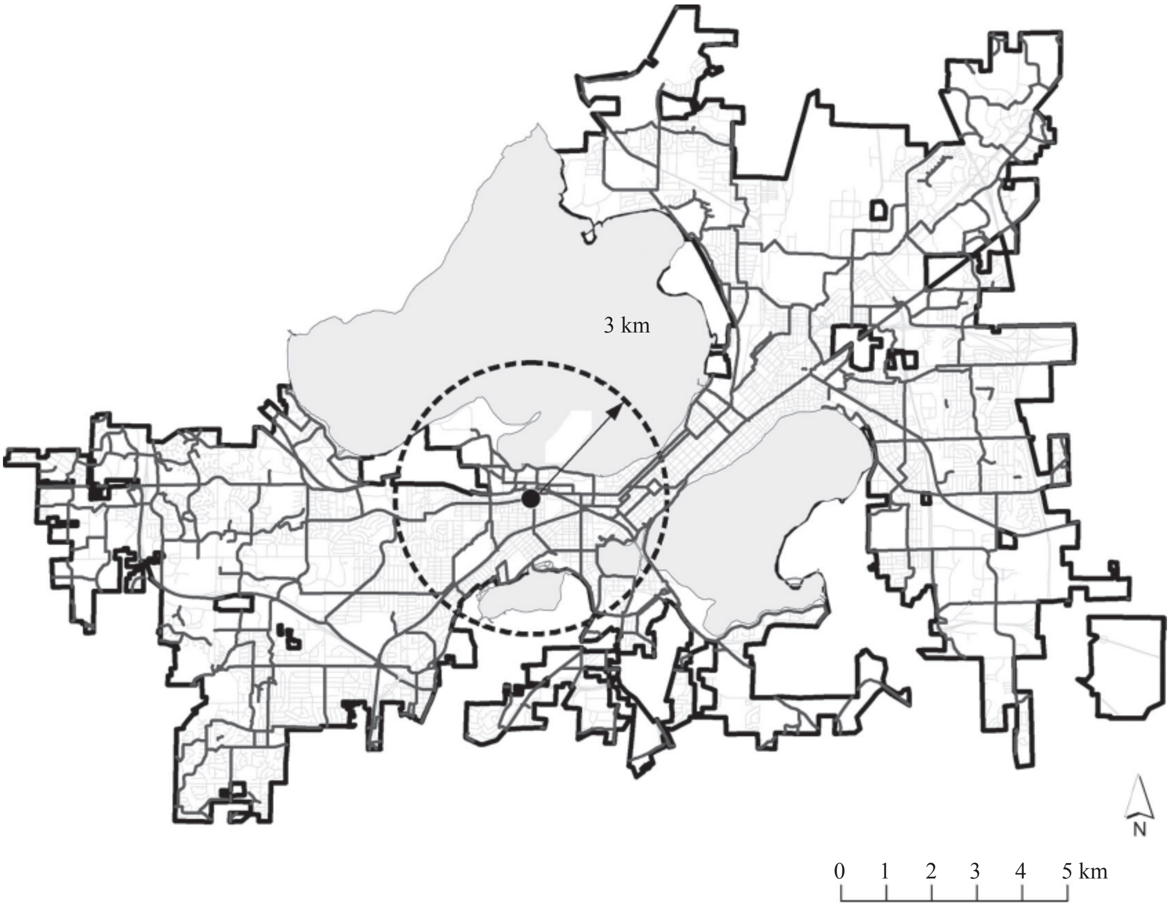

Figure 3. Example of a 3 km buffer encircling National Household Travel Survey home location.

or engage in physical activity within approximately 3 km of their home (Cervero and Duncan, 2003; McGinn et al, 2007). A symmetric area was utilized in this study to allow for standard assessment of response variables that are not reliant on the network itself due to the subsequent treatment of network configurational attributes in this study using space syntax.

4 Methodology

4.1 Binomial logit discrete choice model

In order to examine how personal, household, and environmental attributes affect the decision to bicycle, a sequence of binary logit choice models was constructed. A binary logit model is similar to an ordinary least squares regression model in that it predicts a choice among many alternatives, but differs because the dependent variable is dichotomous and is skewed in one direction. The binary logit model is commonly used in studies of this kind due to the nonnormal dependent variable: that is, a large segment of bicyclists is comprised of a small portion of the population.

The logit model predicts the logit of Y from X independent variables. The logit is defined as the natural logarithm (ln) of the odds of Y, the outcome variable. According to Peng et al (2002), the general logit model takes the form:

$$\ln\left(\frac{\pi}{1-\pi}\right) = \ln(\text{odds}) = \text{logit} = \alpha + \beta x \,, \tag{1}$$

$$\pi = \text{probability} \; (Y = \text{outcome of interest} \mid X = \text{set of response variables})$$

$$= \frac{\exp(\alpha + \beta x)}{1 + \exp(\alpha + \beta x)} \,,$$

where π is the probability of the outcome of interest (event), α is the intercept, and β is the slope. The X response variables can be continuous or categorical in logit regression and represent the utility of any particular vector. In order to capture the decision to commute to work via bicycle, the binary logit function takes the form of equation (2). Equation (2) is associated with the odds of a bicycle work commute:
where

$$\mathrm{prob}(Y_i) = \frac{1}{1 + \exp(U_i \mid Y_i = k)} , \quad (2)$$

where

$$U_i = b_0 + b_1 X_1 + b_2 X_2 + \ldots + b_j X_j ,$$

Y_i is the bicycle commute to work for NHTS survey respondent i,
k is bicycle commute 'yes' in binary form.

Previous studies postulate that there is a tendency for personal, household, and environmental factors to be collinear (Cervero, 1996). Therefore, to minimize this effect multicollinearity measures were calculated in SPSS 16.0. All independent factors with nonlinear relations and a variance inflation factor (VIF) less than 5 were included in the initial model. The VIF threshold index utilized here was established as a cut-off value based on prior statistical literature (Kutner et al, 2004). From this pool of independent variable candidates, careful selection and elimination of outcome variables were conducted so that model performance was maximized without sacrificing theoretical value. The final best fit model therefore included independent variables that showed strong signs of probability and influence on the likelihood of bicycling: for example, age, education, and family composition. The dependent variable was obtained from the NHTS dataset and was based on residential trip origin, trip purpose, and bicycle mode choice. To differentiate between the importance of personal, household, environmental, and urban morphological characteristics in bicycle mode choice decisions, four sequential models were constructed:
Model 1: personal characteristics only,
Model 2: personal + household characteristics,
Model 3: personal + household + environmental characteristics,
Model 4: personal + household + environmental + urban morphological characteristics.

4.2 Traditional factors influencing bicycle mode choice

The transportation mode choice literature suggests that personal, household, and environmental characteristics influence travel behavior. As a result, this study utilized several datasets and partitions them based on four categories: individual (personal)-level, household-level, environment-level variables, and urban morphology. Personal-scale attributes such as income, gender, physical activity level, ethnicity, employment status, age, and automobile access have been shown to affect bicycle mode choice (Dill and Voros, 2007; Handy et al, 2010; Parkin et al, 2008; Pucher et al, 1999; Sener et al, 2009; Xing et al, 2008). This research takes this body of work into consideration by including personal characteristics such as age, gender, ethnicity, education, and income (see table 1). It should be noted that various research has posited that individuals 'self-select' their home locations based on personal and environmental features; however, a stronger argument can be made that a significant segment of society does not have the means to do so (Frank et al, 2003). Therefore, to control for the potential biases of 'residential self-selection', several personal and household socioeconomic variables were included in this analysis. The descriptive statistics for the personal attributes indicate that most residents are auto-centric, nonwhite, professionals, active, and educated (table 1).

Table 1. Individual-level variables.

Variable	Coding	Data type	Mean or mode*	Standard deviation
Average miles driven/month	count	cont	655.00	893.57
No. of walk trips/month	count	cont	5.22	7.21
No. of bicycle trips/month	count	cont	0.930	3.55
Distance to work	miles	cont	4.43	7.98
Age	21: 18–24, 30: 25–34, 40: 35–44, 50: 45–54, 60: 55–64, 70: 65–74, 80: 75+	cat	30*	na
Occupation	categories: 0: not ascertained, 1: sales or service, 2: clerical or administrative, 3: manufacturing, 4: professional, 91: other	cat	4*	na
Driver status	1 if primary driver, 0 otherwise	cat	1*	na
Public transit	1 if uses public transit, 0 otherwise	cat	0*	na
Gender	1 if male, 0 female	cat	0*	na
Employment	1 if employed, 0 otherwise	cat	1*	na
Ethnicity	1 if white, 0 otherwise	cat	1*	na
Education	1 = post high school degree, 0 = not	cat	1*	na
Income	1 ⩾ \$40 000/year, 0 ⩽ \$40 000/year	cat	0*	na

Note. cat = category variable; cont = continuous variable; na = not applicable.

Numerous nonmotorized transportation studies have highlighted various household attributes that influence travel, including household income (Dill and Voros, 2007; Parkin et al, 2008), housing type (Plaut, 2005), and household vehicles (Dill and Voros, 2007). To be consistent with this research, several household characteristics were included during model development (table 2). The variables selected consist of household income, homeownership status, household size, ratio of workers to adults, and family lifestyle. The largest variation among these predictors occurs within household size, family composition, and household bicycles (table 2).

Several environmental attributes have long been investigated to gauge their effects on bicycling. Distance to destinations, topography, population density, and weather appear in the literature as influential factors of bicycle transportation (Cervero and Duncan, 2003; Handy et al, 2010; Nankervis, 1999; Plaut, 2005). In terms of built environment influences towards bicycle mode choice, Handy et al, (2005) discovered that travel mode choice was significantly correlated to the built environment and Frank (1994) found that land-use mix and density affected trip generation levels. The quantities and types of bicycle infrastructures present have also been shown to affect bicycle mode choice decisions (Landis et al, 1997; Tilahun et al, 2007). For example, Handy et al (2010) found that separated bicycle paths are positively associated with bicycling. With these studies in mind, population density, bicycle facility density, transportation infrastructure, land-use, park, traffic conditions, and daily climatic conditions are included in this study (see table 3). Table 3 indicates that moderate variation exists among most explanatory factors, with the largest occurring within housing and population density.

Table 2. Household-level variables.

Variable	Coding	Data type	Mean or mode*	Standard deviation
Vehicle count	count	cont	1.38	0.793
Household size	count	cont	1.57	0.776
Percent worker	percentage of workers per household size	cont	0.626	0.560
Percent vehicle	percentage of vehicles per household size	cont	0.932	0.478
Driver per house	percentage of household drivers per household size	cont	0.890	0.267
Per adult driver	percentage of drivers per adults	cont	1.35	0.688
Ratio16V	ratio of household members (age 16+) to vehicles	cont	0.973	0.499
Ratio16W	ratio of household adults (age 16+) to workers	cont	0.838	0.550
RatioWV	ratio of household workers to vehicles	cont	0.697	0.578
No. of adults	number of adults per household size	cont	1.48	0.790
No. of bikes	number of bicycles per household	cont	1.07	1.36
HH children	1 = children present, 0 = no children present in household	cat	1*	na
Home-owned	1 if owned, 0 otherwise	cat	1*	na
Household income	1 $\geqslant$ \$40 000, 0 $\leqslant$ \$40 000	cat	0*	na
Home type	1 = detached single house, 2 = duplex, 3 = rowhouse or townhouse, 4 = apartment, condominium, 5 = mobile home or trailer, 6 = dorm room, fraternity or sorority house, 91 = other	cat	1*	na

Note. cat = category variable; cont = continuous variable; na = not applicable.

4.3 Urban morphological variables

In addition to the individual, household, and environmental level variables, this paper includes urban morphological variables obtained from the space syntax software, Depthmap, developed at University College London. VGA was selected as the method to obtain visibility measurands that may elicit a bicycle transportation behavioral response due to its strict bottom-up approach and precise determinations of intervisibilities throughout the environment (Franz and Wiener, 2008). Several global and local vision-based factors produced by VGA were initially considered for model consideration and are depicted in table 4. The means and standard deviations of the VGA factors indicate that there is moderate variation between these variables, pointing to discernible differences in urban morphology throughout the study area (table 4). The final VGA factors selected for model development are based on theoretical backing and association with bicycle mode choice and include: mean depth, integration, entropy, and clustering coefficient.

Mean depth is a global measure that quantifies the fewest number of turns: ie, shortest path, from each node within the traversable space. It analyzes routes for angle minimization, which is relevant to bicycle mobility as directness, distance, and angular minimization have been shown to influence bicyclist route choices (Raford et al, 2005). Integration is a global VGA measure that assists in understanding the relationship between transportation links within the system. In other words, integration is a measure of how easily reachable a space is based on the number of turns needed to reach any other traversable space. For example, integrated travel corridors are those that possess the fewest number of turns. Longest lines of

Table 3. Environment-level variables.

Variable	Coding/definition	Data type	Mean	Standard deviation
HBG_PopDensity	population per square mile, block group	cont	5 531.58	2 105.29
HBG_ResiDensity	housing units per square mile, block group	cont	2 091.22	890.72
HBG_RenterDensity	percentage renter-occupied block group	cont	1 164.43	901.88
BikeFacDensity	percentage of bicycle facilities within 3 km buffer	cont	2.92	2.97
PerBike	percentage of bicycle facilities within 3 km buffer	cont	1.71	2.14
RdDensity	road length sum in km within 3 km buffer	cont	683 220	147 277
LU_density	number of land uses within 3km of household	cont	55.62	5.74
Urban	1 if urban, 0 otherwise, block group	cont	0.98	0.127
TripGenDensity	trip generators (schools, employers, parks, recreation facilities) within 3 km of household	cont	41.96	19.35
ParkDensity	park density within 3 km of household	cont	1.17	1.62
MedianRent	median census 2000 land rent	cont	437.9	68.72
BusStopDensity	percentage of bus stops within 3 km of household	cont	3.06	2.36
DistoBikeFac	distance to nearest on-street bike facility, km	cont	0.162	0.148
DistoAct	distance to nearest activity centers, km	cont	0.088	0.090
DistoTrl	distance to nearest off-street bike trail, km	cont	0.162	0.148
TrVolCap	mean traffic volume per capita within 3km	cont	0.270	0.199
MnSlope	average slope (%) in 3 km household buffer	cont	0.150	0.720
Maxtemp	maximum reported daily temperature	cont	56.64	19.34
Precip	reported daily precipitation	cont	0.070	0.290

Note. cont = continuous variable.

sight and ample open-areas, therefore, may weigh heavily in bicycle mode choice decisions [see figure 1(c)] (Hillier et al, 1993). Entropy was selected for model inclusion because it describes the global spatial distribution of locations from any node in the traversable space, and relates to how ordered the spatial environment is. Moreover, the more symmetric spaces are in relation to any other space, the lower the entropy value, and the higher the likelihood that bicycling may be chosen. The clustering coefficient represents the number of vertices that are connected to each vertex in the neighborhood, compared to the quantity of vertices that could be connected (Turner, 2004). Increased coefficients reach a maximum of one when every point in the convex polygon is mutually visible. Conversely, reduced coefficients represent areas where the potential for visual change and human interaction is greatest, and, correspondingly, may provide insight into human responses to urban form and were therefore selected for model inclusion (Turner, 2003; 2004; Turner et al, 2001). The descriptive statistics for these metrics indicate that there is moderate variability throughout the study area.

Table 4. Urban morphological variables derived from space syntax model.

Variable	Definition	Data type	Mean	Standard deviation
Connectivity	average number of immediate neighbors that are directly connected	cont	137.35	137.69
IsoComp	average compactness defined by a circle whose radius is equivalent to the isovist's mean radial length	cont	0.085	0.009
IsoOcclus	average length of the nonvisible radial components separating the visible space from the space one cannot see from a point	cont	6327.26	2942.06
ClusterCoef	average calculation of the number of junction points in the environment	cont	0.817	0.025
VisControl	average visually dominated areas	cont	0.995	0.013
VisControllability	average number of areas that can be visually dominated	cont	0.218	0.034
VisEntropy	average measure of the distributions of locations in terms of visual depth	cont	3.81	0.184
VisInthh	average integration value proposed by Hillier and Hanson (1984), normalized version of mean depth	cont	1.52	0.160
VisIntPVal	average integration value, normalized by *p*-value	cont	0.131	0.037
VisInttek	average integration value proposed by Teklenburg (1993) normalized on log scale	cont	0.417	0.003
VisMnDepth	average index, similar to a shortest path via turn minimization algorithm	cont	9.78	0.679
AngMnDepth	average segment analysis of cumulative shortest angular paths divided by the node count	cont	4.58	0.439
AngTotDepth	average segment analysis of cumulative shortest angular paths	cont	206202.5	19932.0

Note. cont = continuous variable.

5 Results and discussion

5.1 Regression modeling results

5.1.1 *Binary logit model*

On the basis of the statistical tests referenced above and methodical response variable selection, a summary of the best-fitting binary logit model is shown in tables 5 and 6. For each model in these tables, the −2 log-likelihood, Nagelkerke R^2, and Hosmer and Lemeshow test (HL) results are illustrated in table 5. Each of these model fitting tests indicates how well the model performed at each stage. The −2 log-likelihood is a preferred measure of model fitness and is used to determine the predictive power where a lower value equates to a stronger predictive ability (Trexler and Travis, 1993). As evidenced in table 5, the −2 log-likelihood ratio starts with a value of 279.26 for the first model, and then proceeds to increase in robustness towards a final ratio of 185.32 (model 4). Model 4 is 33.64% more efficient than the base model and 5.62% stronger than model 3. The Nagelkerke R^2 statistic in this model ranges from 0 to 1 making it akin to OLS regression (Peng et al, 2002). The largest increase in predictive power is observed between model 1 and model 2 where the pseudo-R^2 increases by approximately 42%. The Nagelkerke R^2 reaches 0.56 in model 4 and represents an approximately 52% increase in predictability from the base model and a 4.23% increase from model 3. Although the increase in the Nagelkerke R^2 from model 3 to model 4

Table 5. Binary logit model summary.

Model	−2 log-likelihood		Nagelkerke R^2		Hosmer and Lemeshow test, p-value
	value	percentage change	value	percentage change	
1	279.258	0.00	0.27	0.00	0.358
2	219.263	21.48	0.46	41.67	0.655
3	201.042	28.01	0.51	47.84	0.716
4	185.328	33.64	0.56	52.07	0.469

Table 6. Classification table.

Model	Bicycle trip?	Percentage correct
1	no	99.0
	yes	1.9
2	no	98.2
	yes	31.5
3	no	98.4
	yes	44.4
4	no	98.8
	yes	50.0

is marginal, it provides a strong argument for the importance of visibility when deciding to commute via bicycle. The last test for overall model fit is the Hosmer and Lemeshow χ^2 goodness of fit test (table 5). The HL statistic for each step in table 5 exceeds 0.05 indicating that that the overall model is well fitted and variable selection is appropriate. The classification table corroborates the HL statistics and displays the degree that the predicted probabilities for each model agree with the actual outcomes (table 6). The first two rows for each model present in table 6 indicate the possible bicycle mode choice outcomes, 1 (yes) and 0 (no) and the percentage of correctly classified events, as evidenced in the 'percentage correct' column. Table 6 indicates that model 1 correctly classifies 1.9% bicycle commute decisions, whereas model 4 correctly classifies 50% or 27 of the 54 bicycling commute decisions. This increase in predictive ability equates to a 5.6% increase from model 3 when built form variables are included. The goodness-of-fit tests and classification table presented in tables 5 and 6 validate the utility of the final model and variable selection. Moreover, the success of the overall model is evidenced by the improvement in −2 log-likelihood, Nagelkerke R^2, and HL statistics, and proportion of correctly classified events at 50%, pointing to the importance of spatial configuration in bicycle commute decisions at the trip origin.

5.1.2 *Personal, household, and environmental factors*

Tables 7, 8, and 9 display final binary logit model coefficients grouped by personal, household, and environmental variables, respectively. The tables also represent the final model selection after removal of insignificant independent variables. The significance column (p-value) is represented by the two-tailed test at the 0.05 significance level. The odds ratio measures the strength of association, directionality, and predicted log odds of bicycle commute decisions. Moreover, the relationships presented in these tables provide useful insights into the interrelationships between personal, household, environmental, and urban form factors when deciding to commute via bicycle. The personal characteristics that exert the most

Table 7. Individual variables and the odds of bicycling.

Name	Standard error	p-value	Odds ratio
Gender, 1 = male	0.437	0.020	2.901
Miles traveled per month	0.000	0.000	0.999
Education, 1 = post high school degree	0.562	0.710	0.814
Occupation		0.040	
sales or service	0.692	0.020	0.203
clerical or administrative	0.899	0.020	0.113
manufacturing, construction, or farming	1.192	0.250	0.250
professional, managerial or technical, reference category	1.230	0.140	0.162
Distance to work (miles)	0.048	0.170	0.936
Age		0.070	
18–24	1.435	0.450	0.341
25–34	1.203	0.300	3.455
35–44	1.301	0.790	0.705
45–54	1.256	0.910	1.15
55–64	1.259	0.500	2.359
65–74 (reference category)	4485.46	1.000	0.000

Table 8. Household variables and the odds of bicycling

Name	Standard error	p-value	Odds ratio
Vehicle count	0.259	0.010	1.952
RatioWV (workers to vehicles)	0.484	0.039	2.715
No. of bikes	0.165	0.000	2.069
No. of adults	0.413	0.277	0.638
No. of children	0.869	0.008	0.101

Table 9. Environmental variables and the odds of bicycling.

Name	Standard error	p-value	Odds ratio
Maxtemp	0.012	0.001	1.040
Precip	1.319	0.079	0.098
MedianRent	0.004	0.075	0.993
BusStopDensity	0.097	0.141	1.154
HBG_PopDensity	0.000	0.004	1.001
HBG_RenterDensity	0.000	0.036	0.999
ParkDensity	0.189	0.026	0.656
PerBike	0.127	0.207	1.173

influence on the decision to bicycle to work—gender, and miles driven per month—are highly significant (table 7). In this study, males are nearly three times more likely than females to bicycle to work and this finding is supported by previous studies (Cervero and Duncan, 2003; Wendel-Vos et al, 2004). Age and education also exhibit a positive relationship to bicycle commute decisions (odds ratio > 1). Specifically, respondents without a post high school degree, between the ages of 25–35 and 45–64 years, who live close to their employer are more inclined to bicycle to work. This result was found in previous work (specifically, Dill and Voros, 2007). The number of miles driven can be construed as an economic indicator and positively relates to bicycle usage and is verified by previous research (Frank et al, 2003).

Among the household response variables, the number of vehicles, bicycles, children, and the ratio of workers to vehicles in the household are significant in the model (table 8). Of these independent variables the number of bicycles in the household is most significant (0.000), as a respondent owning a bicycle is twice as likely to bicycle to work when a bicycle is available. This outcome confirms that bicycle access enables bicycle mode choice. The number of household vehicles is also positively associated with bicycling controlling for personal factors. This finding contradicts previous work that stipulates the increase in household vehicles is negatively associated with the likelihood of bicycling (Cervero and Duncan, 2003; Plaut, 2005). However, we can infer that this variable is a proxy for income and the directionality corresponds to previous work conducted by Dieleman et al (2002). The last significant independent variable is the ratio of workers to vehicles (0.039). As the ratio of workers to vehicles increases, the likelihood of bicycling increases nearly threefold. This finding points to the latent demand for bicycling as household workers increase relative to available transportation options. The numbers of adults and children per household do not have significant influences on bicycle mode choice in this study

Several environmental predictors were found significant in model 3 and displayed in table 9. The significant environmental predictors include: weather, population density, proportion of renter-occupied housing, and density of parks as they all exhibited a p-value less than 0.05. Starting with weather predictors, the maximum daily temperature is significant at 0.001 and to a lesser degree; precipitation is significant with a p-value of 0.079. Furthermore, the odds ratios for these climate factors approach 1, indicating that weather factors have a negligible influence on the decision to bicycle. Population density is significant in the model (0.004), but displays a minimal influence towards bicycle mode choice. The marginal influence of population density on the bicycle mode choice decision follows other studies that have come to this conclusion (Newman and Kenworthy, 1991; Saelens et al, 2003). Median rent displays no statistical significance; however, renter-occupied housing is significant and displays marginal influence on bicycle mode choice. Together these two predictors relate to rental housing condition and neighborhood composition, suggesting that the decision to commute via bicycle is inelastic to the quality and density of rental housing near one’s residence. The density of parks near the trip origin is significant in the model (0.036) and displays an inverse relationship to bicycle commute choice. This result may reflect the perception that parks are unsafe and therefore decrease levels of walking and bicycling (Frank et al, 2003).

5.1.3 *Urban morphological variables*

The syntactical properties surrounding each resident’s home location and their influence on bicycle commute decisions are shown in table 10. The final VGA outputs from space syntax display important and varied relationships to bicycle mode choice. Integration was found to be marginally influential in bicycle commute choice (0.089) but displays the highest influence (12.74) in bicycling decisions. The large odds ratio indicates that respondents are nearly thirteen times more likely to select the bicycle when nearby traversable areas are well connected and provide strategic visual properties relative to other spaces in the system.

Table 10. Urban morphological variables and the odds of bicycling.

Name	Standard error	p-value	Odds ratio
VisEntropy	2.573	0.006	0.001
VisInthh	1.496	0.089	12.739
VisMnDepth	0.510	0.320	1.662
ClusterCoef	17.804	0.015	0.000

Moreover, the strong relationship exhibited here points to the fact that areas that are highly ‘integrated’ influence bicyclists in a similar manner as pedestrians. For example, Conroy (2000) discovered that well-integrated streets, and areas that included junctions, were correlated to pedestrian activity. The result provides further evidence that the decision to bicycle is linked to perceptions of the spatial configuration and apparent need for traversable areas that are connected visually. The VGA measurand, mean depth, is also positively associated with the odds of bicycling to work (1.66) though this factor is minimally important in the model (0.320). Mean depth is the average number of syntactic steps needed to reach the next closest space in the graph, and, according to Turner (2003), may represent the journey’s ‘experience’. We can conclude from the result observed here that utilitarian bicycle mode choice is positively linked to the perceived ease of reaching the closest traversable space. Table 10 shows that mean visual entropy is highly significant (0.006) and strongly deters bicycle mode choice (0.001). The odds ratio indicates that an increase in the visual distribution of objects produces a negative effect on bicycle mode choice. Moreover, increased disorder near the trip origin produces a downward effect on the probability of bicycling. This result provides insight into how the spatial configuration, and potential difficulty with traveling via bicycle in the environment, influence bicycle mode choice. Of the VGA factors tested, the clustering coefficient had the greatest downward effect on utilitarian bicycle mode choice. This metric displays a p-value of 0.015 and odds ratio of 0.0 (table 10), demonstrating that for each one unit increase in the clustering coefficient there is an equal decrease in the odds of bicycling. The clustering coefficient characterizes the spatial complexity and degree of visual change in the environment: therefore, it is apparent that bicycle mode choice decreases when the potential for visual change and presence of junction points in the convex area decreases. This outcome further suggests that residents located in neighborhoods that offer multidirectional fields and locations to interact with the environment and people, are more likely to utilize a bicycle and perhaps efficiently find their way to the destination. Note that this relationship parallels findings in pedestrian wayfinding studies that demonstrate the importance of visibility (Turner et al, 2001) and junctions (Conroy, 2000) for human movement. In summary, it is clear that urban morphology and spatial qualities (such as complexity, arrangement, connectivity, and visibility) influence bicycle mode choice both positively and negatively.

6 Conclusions

In this paper we have argued for the incorporation of microscale built environment variables offered from space syntax as a means to address the ambiguity surrounding the built form–utilitarian bicycle mode choice selection. The causal relationship between space syntax metrics and utilitarian bicycle mode choice at the trip origin was evidenced through a series of binary logistic regression models. We estimated the importance of individual, household, environmental, and urban morphological variables in the decision to commute via bicycle. Specifically, the assimilation of 2001 NHTS, infrastructural, physical, climate, and VGA metrics were partitioned into individual, household, environmental, and urban morphology metrics to ascertain the marginal importance of each predictor group in bicycle mode choice decisions. Microscaled urban morphology metrics included: integration, entropy, mean depth, and clustering coefficient. These measurands displayed reasonable influences and directionality towards bicycle mode choice while controlling for personal, household, and environmental variables. This outcome was evidenced by a hierarchical binary logit model that displayed a substantial increase in predictive power when urban form variables are included. In particular, the inclusion of urban form variables in model 4 increased the −2 log-likelihood and pseudo-R^2 from model 3 by approximately 6% and 4%, respectively. The increase in predictive power offered by model 4 and the discovery of significant causal urban morphology factors suggest that the design of the built environment holds an important role in utilitarian bicycle mode choice. Furthermore, the research confirms the hypothesis that visibility and perception as regulated by the urban form affect the probability of utilitarian bicycling, and, more importantly, provide a basis for further inquiry.

The results of this research have offered a unique and positive outlook into the role of urban morphology and bicycle commuting decisions. In order to solidify this viewpoint and understand how to harness the encouraging results demonstrated in this study, further research is warranted. For example, a cross-sectional analysis with two varied study areas and associated spatial configurations would validate the results shown in this research by uncovering similarities in how space is perceived amongst residents in differing built environments. The outcomes of this duel cross-sectional analysis may provide additional evidence regarding the importance of visibility and urban form in bicycle mode choice decisions. The results of this study lend themselves towards the development of a disaggregated rule-based agent based model (ABM). An ABM based on specific VGA metrics, such as the ones presented in this research, would extend this study by displaying how bicyclists perceive the built environment and learn from it in real time. This bottom-up cognitive approach would allow for an understanding of bicyclist wayfinding mechanisms within a virtual environment, regardless of the consideration of household or personal socioeconomic attributes. The patterns observed in this modeling approach would add value to the results found in this study, and assist stakeholders in the proper design of sustainable transportation systems that encourage the use of alternative transportation modes such as bicycling.

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