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Physiological responses to urban design during bicycling: A naturalistic investigation

Abstract: The current research set out to measure the moderating effect that urban design may have on bicyclist physiology while in transition. Focusing on the hilly City of Wuppertal, Germany, we harnessed bicyclists with mobile sensors to measure their responses to urban design metrics obtained from space syntax, while also adjusting for known traffic, terrain, and contextual factors. The empirical strategy consisted of exploratory data analysis (EDA), ordinary least squares (OLS), and a local regression model to account for spatial autocorrelation. The latter model was robust (R^2 = 68%), and showed that two statistically significant ($p < 0.05$) urban design factors influenced bicyclist physiology. Controllability, a measure of how spatially dominated a space is, increased bicyclist responses (i.e., decreased comfortability); while integration, which is related to accessibility and connectivity, had the opposite effect. Other noteworthy covariates included one-way streets and density of parked automobiles: these exerted a negative influence on bicyclist physiology. The results of this research ultimately showed that nuanced urban designs have a moderate influence on bicycling comfort. These outcomes could be utilized by practitioners focused on implementing appropriate interventions to increase bicyclist comfort levels and this mode share.

Keywords: bicycling, space syntax, naturalistic data, urban design, GIS, heart rate, wearable biosensors

1. Introduction

Active transportation modes such as bicycling continue to be studied in the hopes of increasing this mode share. Past works have indicated that bicycling may help with alleviating congestion, air pollution, greenhouse gas emissions, physical inactivity, and chronic disease (Mertens et al., 2017; Rupi & Schweizer, 2018). Cities have made concerted efforts to implement policies and planning initiatives to promote this mode, especially in regards to increasing bicycling safety and comfort. The U.S. Safe Routes to School program is a clear example of a national program focused on increasing traffic safety by implementing active transportation infrastructure (Geraghty et al., 2009). Policies such as this have undoubtedly helped elevate bicycling in the United States (U.S.) and Europe (Dozza & Werneke, 2014; Tribby & Tharp, 2019). Unfortunately, bicycling injuries continue to rise (Beck et al., 2017). This is an unfortunate trend considering that active commuting, such as bicycling, has been shown to increase physical and subjective well-being of people (Gatersleben & Uzzell, 2007; Humphreys, Goodman, & Ogilvie, 2013).

Reducing bicycling stress (and increasing comfortability) has been the focus of researchers and policy-makers for decades as it's one of the most important factors affecting this mode choice (Dill & Voros, 2007). The comfort level of bicyclists are associated with objective and perceived environmental conditions (Ma & Cao, 2019; Mertens et al., 2017). Iwinska et al., (2018) found that bicyclists in Warsaw, Poland were sensitive to the perceived dangers of bicycling and Harkey et al.,(1998) found that the provision of a wide bicycle lane and the presence of on-street parking increased the perceived comfort level of cyclists. Others have found that increasing comfortability also increases perceived safety, Monsere et al., (2012) discovered that more comfortable bicycle facilities (i.e., buffered bike lanes and cycle tracks) largely elevated feelings of safety among a sample of bicyclists in Portland, Oregon. Of the objective factors that affect bicycling, past research has indicated that traffic conditions, roadway surface quality, and surface material type are important (Ayachi, Dorey, & Guastavino, 2015). Previous research also suggests that residents from

communities with increased density, greater connectivity, and a healthy mix of land-uses reported higher rates of bicycling for utilitarian purposes than low-density, poorly connected, and single land use neighborhoods (B. Saelens, J. F. Sallis, & L. D. Frank, 2003; Winters, Brauer, Setton, & Teschke, 2010). Linkages between the built environment and non-motorized transportation behavior have been well established (Cervero, 2002). A popular means to assess this has been connectivity. This can be measured several ways, including: street density (Cervero et al., 2009) block size (Berrigan, Pickle, & Dill, 2010) intersection density (Carlson et al., 2015), connected node ratio[1] (Dill & Voros, 2007), as well as more advanced methods which consider distance and built environment features along routes (Broach & Dill, 2016) and the use of graph theory summary metrics (i.e. number of edges and vertices) to explain bicycle commuting (Schoner & Levinson, 2014). Investigations such as these describe the average properties of street networks but fail to systematically evaluate the structural qualities of street systems or urban design elements. The design of the street networks can be defined as the alignment of streets and street connections to create a hierarchy of connectivity evidenced through urban design which may influence mobility. The significance of urban design and resulting behaviors has been addressed through the framework of space syntax.

For more than 30 years, space syntax has been used to investigate the relationship between the built environment, social interactions, and movement (Singleton, Spielman, & Folch, 2017). Space syntax is built on the architectural theory that space can explain human movement potentials and has become a tool of many planners and designers. It has been used studies ranging from human wayfinding to examining urban and suburban neighborhoods (Baran, 2008; M. Batty, 1997). In terms of bicycling, a few notable studies exist. Raford (2007) discovered that the radius of the road angle corresponded to bicyclist usage rates in London, UK, and McCahill (2008) found that on average "choice", i.e., the potential for travel along road segments was positively correlated to actual bicycling volumes. More recently, Koohsari et al., (2019) conducted an experiment to measure how the built environment, including integration obtained from space syntax, influenced bicycle usage. The authors discovered that the odds of bicycle use would increase 10% within neighborhoods that were highly integrated. Despite this research, there remains a need for applying space syntax to bicycling; and more importantly, assessing the intricate relationship between bicyclist, urban design, and physiology. The use of naturalistic data sources from mobile sensors to investigate this should be considered.

Investigating the relationship between urban design and bicycling is complicated, but may provide valuable insight into how the built environment moderates bicyclist physiology (i.e., comfortability). Up until recently, the strategies used most-often consisted of non-naturalistic methods where the bicyclist is analyzed in an unnatural setting and data is collected either objectively or after-the-fact based on hypothetical scenarios. Two examples of this are the bicycle level of service (BLOS) index (Landis, Vattikuti, & Brannick, 1997) and the recent level of traffic stress (LTS) index (Mekuria, 2012). These tools are useful, but do not provide any means for intelligent mapping or monitoring real-time perceptions (Joo & Oh, 2013). Surveys are another common way to measure bicyclist comfort. Sener et al., (2008) designed a web-based survey to elicit preferred bicyclist route choices based on bicyclist characteristics, parking, and bicycle facility characteristics. This method is concerning because it doesn't capture the "in the moment" experience, and can be biased, untimely, and costly (Hunt & Abraham, 2007). A naturalistic investigation should be considered as it has the ability to collect bicyclist data *in-situ* without significant interference. Moreover, this tactic can capture the transitory experience of the bicyclist in real-time with the added benefit of capturing perception, comfort, and stress (Dozza, Werneke, & Fernandez, 2012). Of the studies which have implemented this approach, most have focused on risk assessment using videos and GPS. Dozza et al., (2014) used data from several sensors to assess interactions between bicyclists and their

[1] The connected Node Ratio (CNR) measures the number of street intersections divided by the number of intersections along with cul-de-sacs (Dill 2004). A lower CNR designates lower connectivity, with fewer direct routes between origin and destination.

environment and Johnson et al., (2010) utilized data from helmet-mounted video cameras to investigate automobile-bicyclist conflicts along roadways. Clearly, this approach has shown that bicycling risk and the "real experience" is observable; however, minimal work has applied this to understanding the physiological responses (i.e., comfort level) of bicyclists while traveling.

Given that urban bicycling is generally perceived as an unsafe mode, investigating the objective physiological condition of bicyclists is an important research trajectory. Christiaans et al., (1998) and Too (1990) have stated that bicycling comfort is influenced by: environmental, mechanical, biomechanical, and physiological factors. Changes in physiology – most often caused by stressful events – is evidenced by variations in heart rate, blood pressure, breathing rate, and galvanic skin response (GSR) (Selye, 1956; Sharma & Gedeon, 2012). Changes in heart rates have proven to be one of the most effective markers of stress (Palanisamy, Murugappan, & Yaacob, 2013) as it's been associated with: fear (Levenson, 1992), anger (Kahneman, 1973), anxiety (Mesken, Hagenzieker, Rothengatter, & de Waard, 2007), and comfortability (Pecchinenda, 1996). When bicyclists traverse a mixed-mode urban environment they experience a range of these physiological responses which invariably influence heart rates (Doorley et al., 2015). Other past research supports this claim. Doorley et al., (2015) investigated heart rate levels of thirteen bicyclists in three scenarios and found that in the controlled experiment, increased heart rates were associated with elevated traffic levels which was verified by way of their subjective risk perceptions assessed separately. Additionally, a recent study from Kyriakou et al., (2019) utilized wearable biosensors to investigated bicycling and walking stress via heart rate variations. For bicycling, they found that widened multi-purpose bike lanes decreased stress, while conditions related to traffic congestion had the converse effect. These observations were verified from bicyclist eDiaries, video tracks, and interviews.

2. Research Objectives

The purpose of this research is to provide a greater understanding of how the syntactical properties of the environment (aka, urban design related to the configurational properties of the street network design, e.g. connectivity[2], integration[3]) affect the physiological responses – in this case heart rates - of bicyclists while in transition. In this research, we assume that heart rates are related to comfortability (i.e., bicyclist physiological response) while traveling (figure 2). Given this, and in respect to the literature above, the current research had two main goals: a) explore the relationship between bicyclist physiology and urban form using descriptive statistics and geovisualizations, and b) analyze the importance of urban design exposures on bicyclist comfort levels using a global and local model, while controlling for known bicycle mode-share covariates. The overall framework for this research is displayed in Figure 1.

[2] Connectivity measures the number of other segments that each segment intersects within the street network
[3] Integration measures how easy it is to reach all segments within the system from each segment.

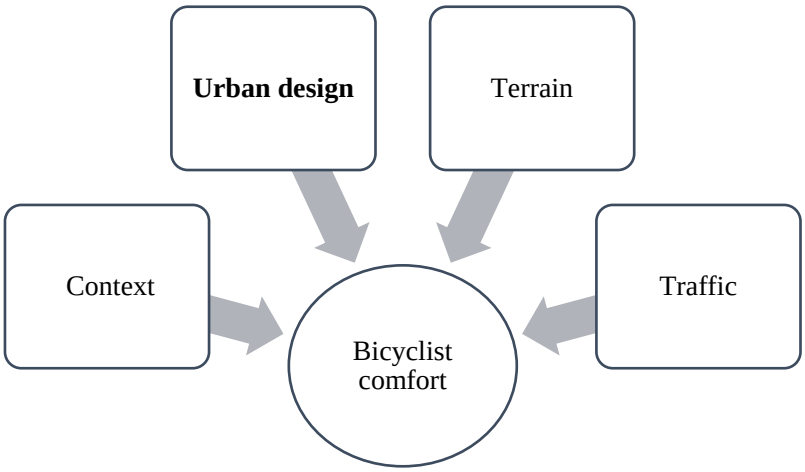

Figure 1. Grounding framework

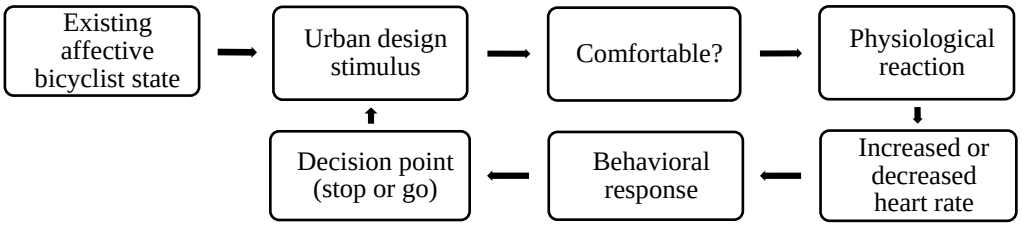

Figure 2. Theoretical flow-chart of bicyclist physiological response to urban design while bicycling

The paper is organized as follows. The next section (3) presents the methods and analysis; focusing on the study area, data collection and processing, and ending with detailing the empirical and geovisualization strategies. In section 4 we detail the empirical and visual findings, and we discuss these results in section 5. Finally, the article concludes and provides recommendations for future work in section 6.

3. Methods and Analysis

3.1. Study area

Our study area was the hilly city of Wuppertal, Germany. Formally an industrial center of the region, the city is now touted as one of the greenest cities in Germany (NRW, 2019) (Figure 3). Wuppertal is colloquially known as the "San Francisco of Germany" due to its hilly terrain and having more steps than any other city in Germany (Rudolph, 2014). As of 2017, the city has an area of 168 km^2 and a population density of 2,100 people/km^2 (Brinkhoff, 2019). The hilly terrain is undoubtedly a barrier for utilitarian bicycling; this is in contrast to its reputation as a prime recreational cycling

area. The city boosts one of the longest (23 km) off-street trails in Germany, the Nordbahntrasse. This former rail-to-trail, is used by bicyclists, pedestrians, commuters, and skaters alike (Reidel, 2017). The trail has helped transform the city, connecting several otherwise disconnected neighborhoods – due to its hilly terrain - and ushering in new commercial development along its path. Despite the popularity of this bicycle facility, overall bicycling mode share remains 2.0% (@urban_future, 2014)

To potentially complement the ongoing recreational bicycling mode share in Wuppertal, we chose an urban neighborhood to examine how bicyclists respond to varying urban designs while traveling. The study area is in close proximity to Bergische University Wuppertal, a major commercial business district (CBD), and the River Wupper (Figure 2). The area encompasses an area of 1.1 km^2 (Figure 2) and contains a variety of land uses, gradients, roadway surface types, corridor contexts, bicycle facilities, and urban design typologies.

Figure 3. Study area within the context of Wuppertal, Germany.

3.2. Participants

The participants in this research were recruited for this one-day event via advertising throughout the university and city. A total of 28 people (18 males and 10 females) volunteered to be part of this study. The gender of the participants skewed towards males, but matches bicyclist related research in Germany (Ritter & Vance, 2011). Their ages ranged from 20 to 70, and the largest proportion was between 26-30 years old. Each participant gave their informed consent for inclusion before they participated in the study. Prior to the bicycling event, each participant was asked to fill out a short survey prior to the exercise, which entailed collecting basic demographic information, neighborhood experience, and with bicycling confidence. A member of the research team reviewed the consent form and study area map with each participant prior to the bicycling event. The map showed the origin and two destinations, but was void of roadways, scale, or directionality so as to not bias the bicyclist experience. A research team member shadowed each participant during the excursion to ensure their safety and so they remained within the study area. Figure 4 depicts the study area, including the origin and destinations, and bicyclist traces.

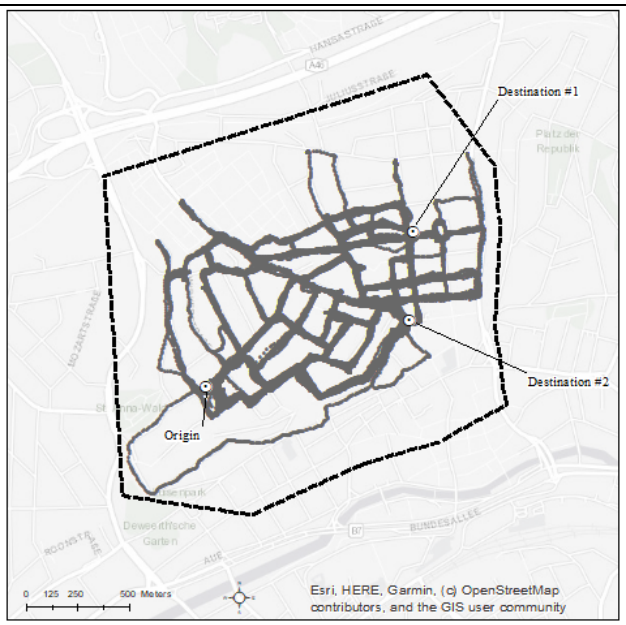

Figure 4. Study area boundary, origin, destinations, and bicyclist traces.

3.3. Naturalistic data collection and processing the outcome variable

The current research utilized a naturalistic data collection strategy (see figure 5) in an uncontrolled setting to assess physiological responses of bicyclists and is in accordance with past works (Marilyn Johnson et al., 2010; Lin, Kourtellis, Katkoori, Chen, & Cruse, 2017). In this study, physiological changes (i.e., heart rate fluctuations) relates to bicyclist comfort levels during riding and in response to urban design metrics. The day-long experiment was conducted on a weekend day and the weather was partly sunny and approximately 60 F°. The research team provided each participant with a similar bicycle with equally inflated tires. The bicycles were rotated among all participants. Each participant was harnessed with a wrist mounted sensor (Garmin VívoSmart®) which recorded heart rate, altimeter, accelerometer, time, and global positioning information, and was recorded at one-second intervals. We chose this duration rate to ensure that a complete dataset was captured in our chosen urban environment. In line with previous naturalistic bicycling studies (M. Johnson, J. Charlton, J. Oxley, & S. Newstead, 2010), participants were required to wear helmets equipped with video cameras (GoPro® Hero 3 and 4) to record head behavior in response to the roadway environment, as well as objective roadway conditions. The color video data also contained a date/time stamp, and unique id number. This aided with joining the data to the road segments for each participant. Each participant was asked to verbally signal any situations that made them uncomfortable. The bicycles themselves were mounted with a tablet encased by a custom-made plastic case. Each tablet contained an application entitled “Sense-it” developed by researchers at Bergische University Wuppertal. The application recorded GPS (latitude and longitude), angularity, acceleration, and gyrometer readings every second.

We utilized a reverse geocoding procedure to plot each of the participant traces (i.e., points) using the GPS coordinates. Each heart rate point layer from the participants were then merged into one contiguous layer using Esri’s ArcGIS software, version 10.6. The result was a GIS layer containing bicyclist heart rate per second, participant ID, coordinates, angularity, acceleration, and gyrometer readings. To increase the integrity of the database, we removed any extraneous records due to GPS locational errors and missing data, resulting in 41,000 records. Due to other unknown sensor data recording errors (i.e., missing heart rates) and redundant records, we instituted a final quality

assurance step which consisted of removing redundant records based on visual analysis and using the "remove duplicate" records tool in ArcGIS. The criteria for deletion was: latitude, longitude, angle, accelerometer, gyrometer, which resulted in a final sample of 3,869 records (i.e., points). Past research has indicated that normalizing physiological data is needed prior to subsequent analysis (Caviedes & Figliozzi, 2018). As a result, we implemented a common spatial averaging technique known as inverse distance weighting (IDW) using ArcMap software. This method has an advantage over previous works in that it uses the actual point values and their proximity to nearby values to create a smoothed raster surface. The equation takes the form:

$$z_j = \left(\sum_{i=1}^{s} z_i \frac{1}{d_{ij}^k} \right) \Big/ \sum_{i=1}^{s} \frac{1}{d_{ij}^k}$$

where:
z_j = is the estimated value at point j
z_i = is the known value at point i
s = is the number of points with known values
d_{ij} = is the distance between point j and point i
k = user defined power (weighting) exponent

We spatially joined the interpolated values to the bicyclist track point layer thereby producing a completed and normalized database representing heart rates. Next we reviewed each bicyclist video and recorded the quantity of passing autos, approaching autos, parked autos, pavement quality, and type. Using the participant id# and visual analysis, we spatially joined this information to the road polyline layer, obtained from the open source GIS: OpenStreetMap (www.openstreetmap.org). We verified this by comparing the original database to the GIS layer in ArcMap. The new roadway layer was then joined to the point layer – the final unit of analysis- using a polyline to point spatial join. A final quality assurance step was done by manually inspecting the road segment layers' attributes against the point attributes and editing any errors in ArcGIS.

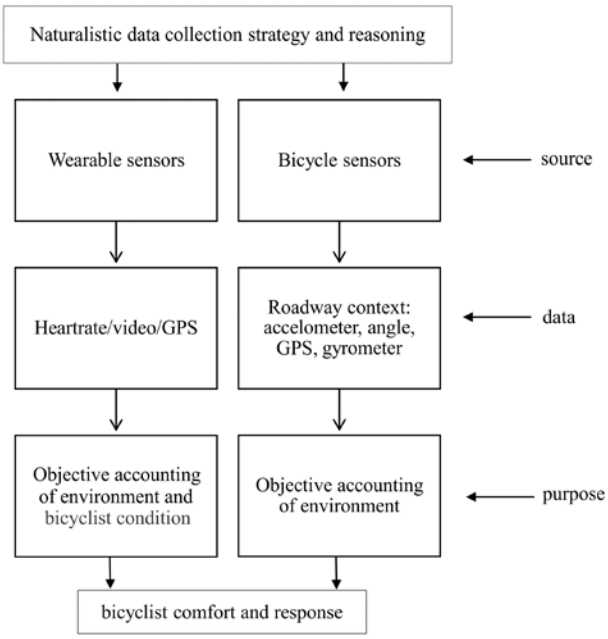

Figure 5. Data collection approach.

3.4. Exposure variables

The main exposure variables in this study were urban design metrics obtained from space syntax. We used the freeware, DepthMap version X software (http://varoudis.github.io/depthmapX/) developed at University College London. The software essentially does what Hillier et.al., (1984) set out to do over three decades ago: describe and analyze the spatial configuration of the environment. This work was largely based on Gibson's (1979) notion that optic flows prompt movement. We implemented a visibility graph analysis (VGA) because it has shown to influence movement (Desyllas & Duxbury, 2001; Turner & Penn, 1999) and is a robust means to quantify how space is experienced (Davies, Mora, & Peebles, 2006). The technique is based on the visibility graph, which mathematically assesses all visible locations in a space and then describes how the spatial structure affects social function (Turner, Doxa, O Sullivan, & Penn, 2001). Stated differently, VGA is well-suited for assessing how visibility changes as one moves through the environment(Michael Batty & Rana, 2004). For additional technical background, the reader is directed to Turner (2004) and Al Sayed (2018). We implemented both global and local analysis; the former uses information from all of the study area's spaces (i.e., vertices) and the latter from an area adjacent to each space in the system (Turner, 2004). The first step in our process was to import the right-of-way polygon (i.e., system drawing) into the software. Each polygon space represented viable traversable areas for bicycling. In addition to the standard VGA outputs: mean depth, point depth entropy, clustering coefficient, and control (Turner, 2004), our analysis included: angular mean depth, connectivity, isovist area, through vision, controllability, entropy, (local and global) integration, and relativized entropy. The overall output was a database which we imported into ArcMap software. The resulting records were reverse-geocoded and the dual set of points were aggregated using the mean; and then assigned to the outcome variable point layer.

3.5. Covariates

It is well known by now that a multitude of environmental conditions influence bicycle use. The reader is encouraged to review Heinen (2010) and Hunt (2007) for a comprehensive survey of indicators. To remain in-line with this body of work, we adjusted our analysis for roadway contextual variables that have a high probability of affecting bicyclist physiological responses. Many of the factors used in this research were obtained from local government sources and OpenStreetMap. These factors included: the most recent land-use types (categorized as: residential, mixed-use, park, commercial, and church), road type (categorized as: oneway, bicycling, pedestrian, residential, secondary, service, tertiary, and unclassified), road speed limit (categorized as: 7 km/h, 10 km/h, 20 km/h, 30 km/h, and 50 km/h), and roadway width (categorized as: 3m, 4m, 5m, 12m, and 16m). We manually measured and digitized the remaining contextual factors using the most recent high resolution color imagery in a GIS; these were: tree density (quantity of visible trees along the roadway normalized by road segment length) and bicycle facility type (categorized as: bicycle rack, signage, separated cycle-track, and bicycle lane). The roadway surface material and condition was in part gathered from the participant bicyclist video data and from high resolution color imagery in a GIS (categorized as: cobblestone, good asphalt, and poor asphalt). This data was assigned to each roadway segment

Since automobiles have entered cities, traffic has deteriorated the space for safe bicycling (Gehl, 2013). Hence, we included several traffic covariates in this research. The data was derived from the participant bicyclist video data. For each road segment, we quantified the number of passing, approaching, and stationary automobiles. We then normalized this using the road segment length to achieve a density value. This information was spatially joined to the outcome variable point layer in a GIS.

We considered two terrain variables in this study due to their past associations with bicycling and comfort levels: slope (Providelo & da Penha Sanches, 2011) and roadway vibration (Mason et al., 2016). Using the roadway length and elevation data, we calculated the minimum, maximum, and mean slope for each road segment. This data was spatially joined to the participant GPS traces. To objectively quantify the degree of vibration the bicyclist participant experienced, we implemented the dynamic comfort index (DCI), as described by Bil et al., (2015), using the accelerometer data obtained from the Garmin VívoSmart®. The index relies on the acceleration per second from each bicyclist and ranges between 0-1, where elevated values pertain to more comfortable roads.

3.6. Exploratory Data Analysis

Two descriptive analyses were implemented in this study to reach objective “a.” First, we first charted the relationships among our outcome and main exposure variables using Microsoft Excel. The main purpose was to determine if there were apparent relationships between bicyclist physiology and urban design, focusing on logical trends between the datasets. Next, a series of univariate analyses were implemented to descriptively highlight statistical and spatial associations among the outcome and exposure variables. The approach is coined “geovisualization” and has become a common means for understanding complex socio-ecological processes and is part of a suite of EDA tools (Mennis & Guo, 2009; Shaker, 2016). In detail, two spatial univariate geospatial maps were created to explore the spatial patterning of bicyclist physiological responses using GIS. A univariate map was first produced to reveal the spatial distribution of bicyclist heart rates within the study area. Specifically, we implemented an inverse distance weighting (IDW) method to interpolate this factor throughout the study area, and visualize the manifestation of bicyclist heart rates throughout space. The method is a means to assess point data (via GPS coordinates) and is grounded in the notion that the value at each point has an influence on neighboring value and diminishes with distance (O Sullivan, 2010). To obtain optimal results, we used a Manhattan weighting distance, a power function of 1, and 12 maximum neighbors. To determine the presence of statistically significant clusters (i.e., spatial

autocorrelation) of heart rates, a common local "hot-spot" analysis, the Getis Ord G_i index was implemented (Getis & Ord, 1992). The advantage of this local technique is that clusters of high or low values are observable (A. S. Fotheringham, C. Brunsdon, M. Charlton, 2000) and thus provides insight into underlying specific geographic processes. Using ArcMap's spatial analysis toolbox, we implemented the G_i index on the heart rate outcome variable. The output was a vector point layer with G_i values, *p*-values, and *z*-scores: a high *z*-score indicates clusters of high values and low *z*-scores indicate clusters of low values (Getis & Ord, 1992). We then queried statistically significant ($p < 0.05$) *z*-scores and exported the results as a new layer. Next, we interpolated these values throughout the traversable space to create a continuous raster surface layer of these scores. This univariate map provided observable significant "hot-spots" and "cold-spots" to compare against the heart rate visualizations.

3.7. Explanatory modeling

Two inferential models, a linear regression model (i.e., ordinary least squares, OLS) and spatial autoregression (SAR) model to estimate the relationship between bicyclist physiological responses and space syntax metrics using SPSS (IBM Inc.) version 22 software (see objective "b"). These models assess relationships globally and locally, respectively. Prior to model development, we investigated the potential of all independent variables covariates using four-pronged approach was enacted. We first tested each of the potential independent variables (i.e., urban design, terrain, traffic, and context) for normality, and applied the square root to remove any skewed factors. Then, we implemented a Pearson product-moment correlation analysis between the outcome and exposure variables (i.e., space syntax factors). Those which were statistically significant ($p < 0.05$) were retained for further analysis. We then carried out the same procedure for the remaining covariates (i.e., context, terrain, and traffic factors). The correlation analysis was conducted using SPSS (IBM Inc., version 22) statistical software. Third, we examined multicollinearity among all of the IV's by using the variance inflation factor (VIF) index: values less than 5 indicate non-collinearity (Song, Kwan, & Zhu, 2017). Lastly, we included variables based on priori grounds. The final independent variables, with definitions and descriptive statistics, are shown in table 1.

Table 1. Descriptive statistics and definitions for all selected model variables (n = 3,869).

Variable	Description	Mean	Std. Dev.
Dependent variable			
Heart rate	Heartbeats per second representing physiological responses during bicycling	128.17	10.39
Independent variables			
Urban Design			
Controllability	Mean semi-global measure representing how controllable a space is relative to the viewing area of its neighbors	.20	.08
Clustering Coefficient	Mean local measure of intervisibility within current neighborhood; normalized by the square root	.93	.04
Through vision	Mean local measure of the longest length of vision through any one visible location. Normalized by the square root	45.91	19.24
Integration	Average global depth of a space (r = *n*) to all spaces in the system (ranges from most to least integrated)	2.22	0.32
Context			
Church	Dummy variable: yes = 1, no = 0, (reference)		
Residential	Dummy: yes = 1, no = 0	0.68	0.47
Mixed-land use	Dummy: yes = 1, no = 0	0.15	0.35

Park	Dummy: yes = 1, no = 0	0.08	0.27
Commercial	Dummy: yes = 1, no = 0	0.00	0.07
Tree density	Quantity of trees (# trees per road segment): normalized by the square root	9.87	2.78
One-way roads	Dummy variable, 1=yes, 0=no. Roads classified as one-way per video analysis and street centerline data	0.55	0.50
Spd10orLess	Dummy variable, 1=yes, 0=no. Posted speed limits 10 km/h or less for each road	0.05	0.22
WidthGrtr12m	Dummy variable, 1=yes, 0=no. All roads greater than 12 meters wide	0.03	0.16
Road-asphalt	Dummy variable, 1=yes, 0=no. Asphalt roads good	0.28	0.45
Bicycle signage	Dummy variable, 1=yes, 0=no. Presence of a bicycle sign	0.01	0.08
Terrain			
Max slope	Maximum unit rate of altitude increase per road segment, normalized by square root	23.60	14.61
Traffic			
Stationary autos	Density of parked automobiles along road corridor, normalized by road length	14.40	13.55

The OLS model was then implemented for predicting bicyclist physiology (i.e., heart rates) based on our selected independent variables. The Akaike Information Criterion (AIC) and coefficient of determination, R^2, was used to fit the model and allow for comparisons. The latter is the preferred measure as it is an indicator of model fit and complexity. The exposure variables and covariates (i.e., adjustment factors) were simultaneously added to the model using SPSS (IBM Inc., version 22) statistical software. To test for model violations, we enacted an *ex post facto* analysis that consisted of analyzing the standardized residuals for autocorrelation using Global Moran's *I*. This is a common procedure to determine if the independence of observations assumption is violated (Wagner & Fortin, 2005). The method produces an index ranging from -1 to +1. Statistically significant positive values indicate clustering and negative values indicate dispersion (Burt, 2009).

The OLS model has the following general form:

$$Y_a = \alpha + \beta_1 X_{1a} + \beta_2 X_{2a} + \cdots + \beta_m X_{ma} + \varepsilon_i$$

where:

Y_a = bicyclist physiological response

α = intercept

X_{ma} = explanatory variable m at position xy

β_m = model coefficient for variable m

Most modeling approaches assume spatial stationarity; however, this a rare occurrence, especially with geographic data (Dormann, 2007). Thus, we implemented a spatial autoregressive model (SAR) to account for possible spatial autocorrelation of outcome and independent variables. SAR approaches accomplish this task by including a spatial autoregressive term that incorporates spatial locations directly into the equation via a neighborhood proximity matrix (Teklenburg,

Timmermans, & Van Wagenberg, 1993). Using the freeware Geoda software, version 1.12, we developed a spatial error (SAR_{error}) and spatial lag regression (SAR_{lag}) model, using the aforementioned variables (table 1). We reviewed both model diagnostics and tests of significance (i.e., Lagrange-test), and selected the SAR_{lag} model as the final model in this study. The model is based on three parameters: latent Gaussian specification, a weights matrix, and a correlation parameter (Ver Hoef, Peterson, Hooten, Hanks, & Fortin, 2018). The model accounts for spatial dependency through a linear relation between the response variable and a spatially lagged variable using a maximum likelihood estimator and a neighborhood weighting matrix (A. S. Fotheringham & Rogerson, 1994). We tested the standardized residuals for autocorrelation using Global Moran's *I*.

The SAR_{lag} model takes the form:

$$y = pWy + X\beta + \varepsilon$$

where:

Wy = is the spatially lagged variable for weights matrix W

y = is an N by 1 vector of observations on the dependent variable

X = is an N by K matrix of observations on the explanatory variables

ρ = is the spatial autoregressive parameter

β = is a K by 1 vector of regression coefficients

ε = is an N by 1 vector of error terms

4. Results

The results are presented in two subsections: 4.1, exploratory associations, and 4.2, global and local modeling results. The first section highlights the statistical and geovisualizations concerning bicyclist heart rates and urban design. The global and local modeling results are the product of numerous regression models. We discuss their coefficients and diagnostics, with a focus on our main exposure variables in the last subsection.

4.1. Exploratory associations

Our first objective in this study ("a") was to examine the relationships between bicyclist physiology (measured by heart rates) and urban design factors from space syntax descriptively and visually. Figure 6 shows a series of scatterplots with trend lines, that specifically displays the associations between heart rate and our chosen exposure variables. It is clearly evidenced that all three urban design metrics have a negative effect on heart rates (Figures 6a, 6b, and 6d). Stated differently, as the clustering coefficient, through vision, and integration increase, bicyclist physiology decreases. The last urban design metric, controllability, had an inverse effect (Figure 6c). This figure indicates that controllability had the most pronounced effect on bicyclist physiology. The descriptive association basically tells us that as the visual field of each space equals that of its neighbors, bicyclist heart rate increases.

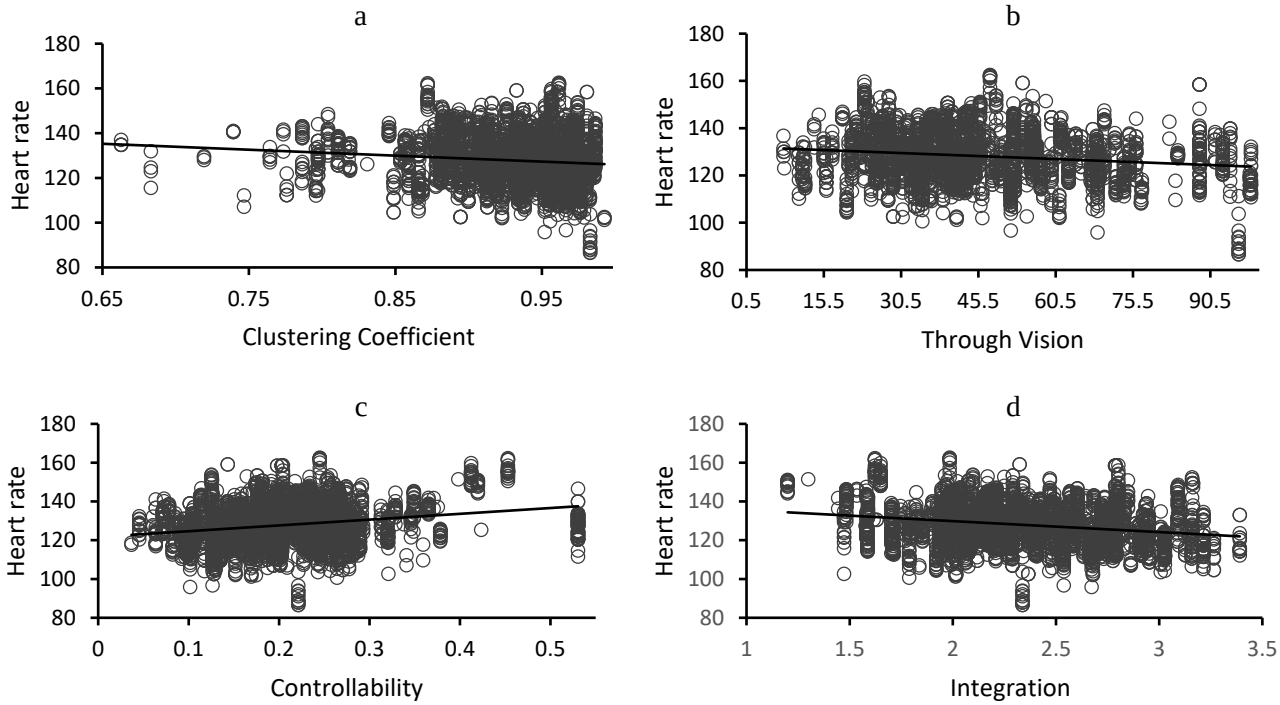

Figure 6. Scatterplots of urban design metrics and heart rates.

The two univariate geovisualizations are depicted in Figure 7. The interpolated heart rate values are displayed in Figure 7a. The higher values are represented in areas with steep gradients (i.e., west and northwest areas). This pattern was also generally found near the southeastern areas of the study area where traffic and commercial land-uses dominate. To help illustrate the significance of the spatial patterning of heart rates, Figure 7b depicts the hot-spots (i.e., *z*-scores) of heart rate values in the study area at the $p < 0.05$ significance level. In general, the map reflects the spatial patterning found in Figure 6a, but with key differences. Figure 7b shows a preponderance of clustered elevated values (i.e., high-high autocorrelation) in areas with steeper gradients (i.e., north and western areas) and in close proximity to intersections: which are typically areas of greatest conflict for bicyclists. We found that most low-low values clustered along narrow residential roads in the northern section of the study area. The result seems logical, as risk exposure on these road types is typically low (Aldred, Goodman, Gulliver, & Woodcock, 2018). Overall, the geovisualizations point to the nuanced and spatially variant relationships among bicyclist, urban form, and physiology (i.e., comfortability).

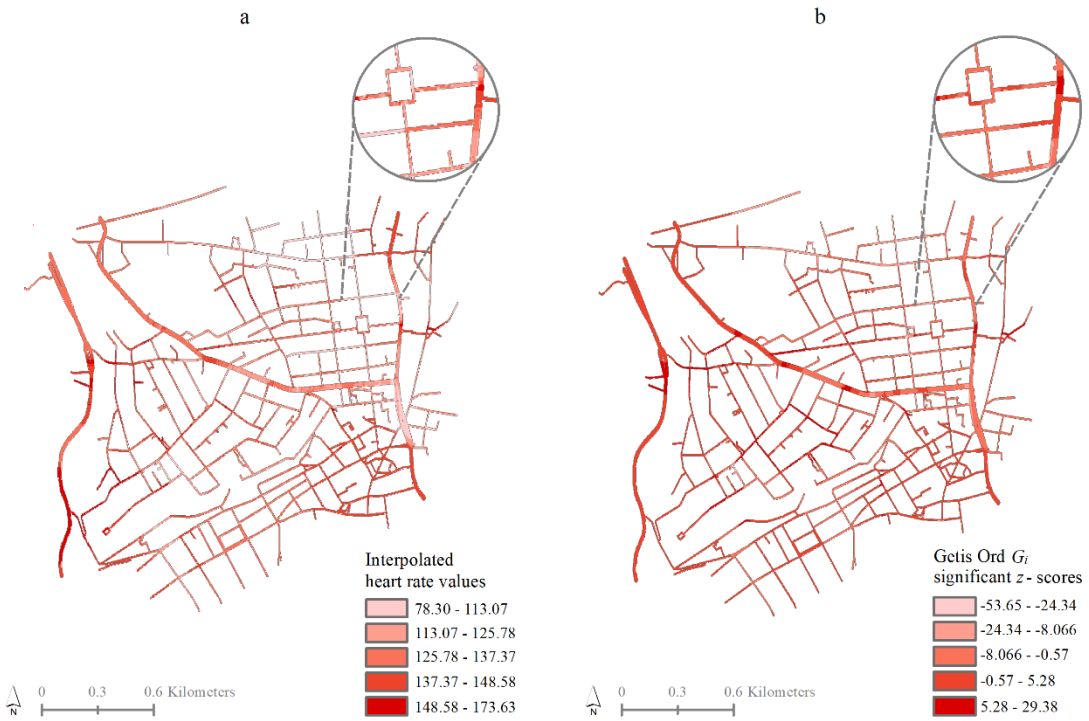

Figure 7. Geovisualizations of interpolated bicyclist heart rates and localized hot-spot clustering (*z*-scores) ($p < 0.05$).

4.2. Global and local model results

In reaching objective "b" in this study, we implemented two regression models: OLS and SAR_{lag}. The model diagnostics from each model are depicted in Table 2. The OLS diagnostics show that the models' strength was marginal; explaining 22% of the variation when each of the selected independent variables were considered. The model was significant (p-value < 0.001) and the residual test of non-stationarity using Moran's I indicated strong positive spatial autocorrelation (0.557, p-value < 0.05). The SAR_{lag} model diagnostics were more encouraging. The outputs showed a significant increase in R^2 (.687) and AIC (25126.5), representing an improvement of 32% and 11%, respectively, over the OLS model. Even though the Moran's I test of SAR_{lag} residuals showed slight autocorrelation (0.052, p-value < 0.05), the index was markedly less than the OLS output, suggesting a better fit.

The coefficients displayed in table 2 provide insight into how urban design factors – while accounting for adjusting covariates - influenced bicyclist physiology while riding. Since the SAR_{lag} model was the superior model, and the directionality of the coefficients was consistent with the OLS output, the spatial model findings are elaborated on here. The strongest urban design factor influencing bicyclist heart rates was controllability (coeff. = 4.228, $p < 0.01$) and the second was integration (coeff. = -1.058, $p < 0.05$). For every one unit increase in controllability and integration, heart rates increased 4.228 and decreased 1.058 beats, respectively. In terms of the contextual factors, the density of commercial land-uses had the strongest negative effect on bicyclist heart rates in when compared to church land uses (coeff. = -7.925, $p < 0.0001$). Three remaining covariates exhibited reasonable associations to bicyclist heart rates and were statistically significant (max. $p < 0.05$) in the SAR_{lag} model. The factors included: tree density, one-way roads, and good asphalt roads; of these,

tree density had the least influence on heart rates. Unsurprisingly, the density of parked automobiles, exerted a negative, albeit marginal, influence on bicyclist heart rates (coeff. = 0.020, $p < 0.05$). We can infer from this that for every one unit increase in parked automobiles heart rates increased only 0.020 beats. Despite some marginal coefficients, the results from both models clearly indicate that urban design factors, as well as several covariates, affect bicyclist physiology.

Table 2. Ordinary least squares (OLS) and spatial lag regression (SAR_{lag}) modeling results, standard errors (SE), standardized coefficients, VIF index, and significant *p*-values related to association with bicyclist heart rates. n = 3,869.

	OLS Model[a]			**SAR_{lag} Model[b]**	
Independent variables	Coefficient	SE	VIF	Coefficient	SE
Urban Design					
Controllability	0.132****	2.669	1.775	4.228***	1.547
Clustering coefficient	-0.100****	4.267	1.303	-	-
Through vision	-0.107****	0.011	1.461	-	-
Integration	-0.127****	0.855	2.733	-1.058**	0.466
Context					
Land use					
Residential	-0.377****	0.668	3.455	-1.745****	0.404
Mixed-land use	-0.066**	0.798	2.866	-1.547**	0.478
Park	-0.341****	0.855	1.936	-2.412****	0.525
Commercial	-0.037**	2.642	1.093	-7.925****	1.714
Roadway					
Tree density	-0.135***	0.078	1.710	-0.003*	0.002
One-way roads	0.049**	0.402	1.432	0.741**	0.249
Spd10orLess	-0.047**	0.854	1.312	-	-
WidthGrtr12m	-0.105***	1.274	1.492	-	-
Road-asphalt	-0.191***	0.402	1.163	-0.383*	0.230
Bicycle signage	-0.072***	2.306	1.087	-	-
Terrain					
MaxSlope	-0.082***	0.013	1.383	-	-
Traffic					
Stationary autos	0.143***	0.014	1.358	0.020**	0.008
Fit Statistics					
R^2	0.222			0.687	
Akaike information criterion	28315			25126.5	
log-likelihood	-14140.5			-12545.2	
Schwarz criterion	28421.4			25239.2	
F statistic	57.479			-	-
Model *p*-value	< 0.001			-	-
Standard error of regression	9.392			5.941	
rho	-			0.898	
Residual Moran's *I*	0.557			0.052	

Notes: [a]= The R^2 values represent the full model; all covariates entered simultaneously [b]= maximum likelihood approach and Inverse Distance Weighting (power = 1) scheme implemented. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$, - no relation observed.

5. Discussion

Our naturalistic methodology, coupled with precise geo-locational data obtained from wearable and mobile sensors, allowed for a detailed examination into the interrelationships among human physiology, bicycling, and urban design; while adjusting for common covariates. The geovisual analysis showed that heart rates were spatially variant throughout the study area, pointing to nuanced

associations between bicyclist and environment, and our models confirmed this by highlighting which salient urban designs affected bicyclist comfort levels most. Overall, our findings add to the growing literatures on bicycling-urban design connections obtained from space syntax; and the use of naturalistic investigations using mobile sensors to assess bicycling physiology (i.e., comfortability).

Our first task (see objective "a") was to statistically and visually describe the relationship between heart rates and urban design. The descriptive statistics provided initial insights into non-causal relationships between our four urban design metrics and heart rates. Even though the trends were not strong, they provided clues into the links between our outcome and main exposure variable. To visualize the aggregated bicyclist heart rates and presence of clustering, we twice instituted a common interpolation technique (i.e., IDW) in a GIS. The univariate maps showed where heart rates varied; and more importantly, the locations of clustered elevated and reduced values in the study area. The presence of clustering was an important finding as it shed light on underlying processes with high spatial accuracy, and warranted the implementation of a spatial model. In detail, the maps showed that reduced heart rates were present along narrow residential streets and that the opposite occurred near intersections and steep gradients. Detailed visualizations such as these may be useful for driving focused efforts on determining where stressful bicycling conditions exist.

The results of our modeling approach emphasized the significance of urban design in moderating bicycling physiology (i.e., comfort levels); accomplishing our second research objective ("b") in turn. Urban design was measured using syntactic measures implemented in Depthmap. Controllability and integration emerged in both models as significant factors associated with heart rate fluctuations while bicycling. The SAR_{lag} model indicated that the most significant factor in eliciting a physiological response was controllability. Since increased levels of this factor means that the visual area of each cell equals that of its neighborhood cells combined (Turner, 2001), we can deduce that areas which have equitable visibilities (i.e., large viewsheds among all spaces) negatively affect bicyclist physiology (i.e., decreased comfortability). This is a new finding but supported by similar studies on pedestrian mobility. Knoll et al., (2018) found that open public spaces with high visibility – especially with motorized traffic - increased pedestrian stress. Our result also may also suggest that these spaces may be noisy due to traffic, and hence elicited an increase in discomfort while bicycling. Based on these findings, certain interventions are suggested. Building off the work of Karimi (2012), roadways in the city where controllability is high should be modified to create "channels" to help balance the different modalities and create optic flows, which are essential for guiding people through a landscape (Gibson, 1979). This begs the question then: what does an "optic flow" look like to a bicyclist? One answer might be separated bicycle lanes (i.e., cycle-tracks). These have been forwarded as the most effective means to maximize bicyclist safety and comfort, mostly because they increase automobile passing distances and create sight lines that may encourage this mode share (Beck et al., 2019).

The second important finding in this study were the interactions between bicyclists and integration. Increased values mean that spaces with higher levels of visual integration are those that are easier to reach from everywhere, hence it has been considered a measure of access and connectivity in the space syntax literature (Haq, 2018). Our observations reflect previous research which found that integration corresponds well to pedestrian movement (M. J. Koohsari et al., 2016), and stress (Knöll, Li, Neuheuser, & Rudolph-Cleff, 2015); as well as bicycle mode choice (Rybarczyk & Wu, 2014). In this research these associations largely hold true. We found that bicycling comfort levels (i.e., reduced heart rates) were elevated along roads that were highly connected and accessible. This outcome lends credence to two important planning and policy initiatives: complete streets, where streets are designed to encourage walking and bicycling (LaPlante & McCann, 2008), and pro-social design, which sets out to facilitate social interactions via efficient urban design (Gruebner, 2019). The results of our study also suggest that integrated roadways may require less mental effort, thereby increasing comfortability, in part because they allow for reduced speeds, stopping opportunities, and places for prospect and refuge-a core landscape feature satisfying basic human psychological needs and an underexplored bicycling facility design consideration (Appleton, 1996; Stephens, 2010). Our

finding also demonstrated that integrated spaces, which were afforded by intricate urban design features, offer bicyclists extended lengths of sight and a minimal amount of turns, which likely furthered comfort levels for bicyclists. From a planning and policy perspective, this is key because bicycle route connectivity is lacking in most major cities, and it behooves planners to focus on interventions which create street-scale urban corridor spaces that promote comfortable bicycling environments and pro-social designs so as to elevate this mode share.

Our findings demonstrated that context, terrain, and traffic conditions also mattered while bicycling. We showed that the density of trees along road segments was statistically significant and decreased heart rates, albeit with minimal influence. Therefore, we cannot be certain that additional tree plantings (or a reduction) will induce a mode shift or increase perceived bicyclist safety in this neighborhood; however, the result lends weight to the need for further research on corridor level tree canopy effects on bicycling (B. E. Saelens, J. F. Sallis, & L. D. Frank, 2003). We found that each of the land-use types, especially commercial activity, reduced heart rates while bicycling. Because this finding seems counterintuitive relative to past works indicating mixed-land uses invariably increase this mode share, we can infer from our finding that bicyclists may have been unaware of the differences between these two land use types or that these corridors offered the right amount of visual stimuli (i.e., bicycle racks, wider roads, shoppers, etc.) to ease stressful situations; a finding in part supported by (Moudon et al., 2005). We also found logical relationships between roadway contextual conditions and bicycling comfort. The strongest covariates from the local model were one-way roads and road surface quality (i.e., good asphalt); the density of parked automobiles possessed the least amount of influence. The negative influence of one-way streets on bicycling comfort may be attributed to the fact that on many of these roads bicyclists could legally travel against traffic flows, evidently decreasing bicycling comfortability (i.e., increased heart rates). Interventions that could reverse this effect include reversing this policy, installing bicycle lanes, or implementing separated cycle tracks. Collectively, our findings suggest that bicyclists felt most comfortable (i.e., reduced heart rates) in roadway environments that had a minimal amount of parked cars, offered smooth roadways for bicycling, and contained bi-directional roads.

6. Conclusions

Increasing objective and perceived bicycling safety (i.e., comfortability) is critical in order to elevate this mode share. While many naturalistic studies have measured risk, the current research investigated bicyclist physiology in an urban environment using mobile sensing technology. In doing so, we made noteworthy contributions to the literature. We demonstrated that salient urban designs affect bicyclist comfort differently while moving. This was first evidenced in our geovisualizations, where it was shown that elevated and reduced heart rates were spatially linked to specific environmental and urban design attributes (aka, slope, intersections, and residential streets), suggesting that bicyclists respond dynamically to local conditions while in transition and this evidence, as well as methodology, should be strongly considered by planners and policy makers. The robustness of the local model substantiated this. We discovered with marked significance that urban designs which offered expansive spaces with no clear pathways (elevated controllability values) increased bicyclist discomfort (i.e., elevated heart rates), while roadways which were connected and very accessible (high integration values), had the converse effect. All our above contributions provide actionable insights and tools for policy makers to enact efficient plans and policies set on increasing active transportation modes like bicycling. However, notable limitations, which inform future research directions, should be outlined.

The analysis included a small sample of bicyclists (n = 28) and a relatively small study area (1.1 km^2). Additionally, the sample mostly comprised people who were generally confident in bicycling and didn't include persons with disabilities. Therefore, to make our results more generalizable to other study areas, personal bicyclist characteristics and consideration of other study areas, is needed for

future work. The study also lacked consideration of weather and so future research should also consider seasonal variation on bicyclist physiology as this is an important predictor of this mode (Ahmed, 2013). Another limitation is that we did not account for trip type or traffic conditions during different times of the day. How bicyclists respond to urban design may depend on if it's a leisurely or utilitarian trip, and when the trip occurs; therefore, future work using this methodology should consider these variables (Willis, Manaugh, & El-Geneidy, 2013). Our hot-spot analysis also proved limiting as it is confirmatory methodology and did not explicitly account for the underlying movement properties (i.e., sequential effect of moving between spaces) of our participants. The "in-between" experience – a finding noted in previous works on pedestrians (Bielik, Schneider, Kuliga, Valášek, & Donath, 2015; Neale et al., 2017) – was not directly highlighted or visualized in this study and therefore future works should incorporate an exploratory visual analytics strategy to more fully explore the sequential effects associated with moving objects (Andrienko & Andrienko, 2012). Lastly, an interesting next step for this research would be to compare and contrast the observations in this study to virtual bicycle agents (i.e., an agent base model) using the same origin and destinations. This would hopefully validate the importance of specific urban design metrics on bicycling physiology, and settle the debate on which interventions would be most effective for increasing comfortability to promote this mode in other cities.

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