Streetscapes as Part of Servicescapes: Can walkable streetscapes make local businesses more attractive?

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Abstract

The term servicescape has been used to describe the physical settings and environments that affect customers' inference of the service quality of businesses at that location. This study extends the concept of servicescapes to include walkable streetscapes since a pleasant walking experience contributes to the perceived safety and superior aesthetic values of the place. The empirical analysis for the study is based on measures of walkable streetscapes using street view images and computer vision, which are associated with customer satisfaction values derived from Yelp review scores of restaurants in Atlanta, GA. After controlling for accessibility, restaurant type, and neighborhood-specific characteristics, the study found sidewalk buffers, greenness at eye level, and building-to-street ratio are positively associated with customer satisfaction. If a restaurant with review score of 3.7 in unfavorable streetscapes (i.e., streetscape characteristics below 25th percentile) is moved to a highly favorable streetscapes (90th percentile and above), the review score is predicted to increase to 4.1. Planning tools for promoting walkable streetscapes are discussed to improve the street vibrancy and the economic opportunities of local businesses.

1. Introduction

Walkability and attractive local businesses have a reciprocal relationship. Attractive local businesses can make cities more walkable by providing desirable destinations to walk to (Walk Score, n.d.), and walkable urban forms – well-connected street networks, high density development, and mixed land uses – can support local businesses by providing better accessibility that attract more customers (Pivo & Fisher, 2011). The mutually reinforcing relationship between walkable built environments and local businesses has the potential to boost not only economic but also social, environmental, and health benefits.

While past studies often measured walkability in terms of destinations accessed by walking (e.g., Walk Score), walkability is not just about accessibility. Another important, but less examined, aspect is the aesthetic quality and pleasurability of the environment that affect the walking experience. The literature on walkability and urban design argue that various street-level urban design details can enhance the quality of the streetscapes and make streets more enjoyable to pedestrians (Alfonzo, 2005; Ewing & Handy, 2009; Handy et al., 2002). Tall buildings and other vertical elements can create a sense of 'enclosure', an urban design quality that makes streets feel like an outdoor room (Ewing & Handy, 2009). Enclosed streets can attract more pedestrians and commercial activities, which provides natural surveillance and enhanced safety from crime. Enclosure can also elevate traffic safety by reducing risky driving behavior and decreasing the severity of crashes (Harvey & Aultman-Hall, 2015). Similarly, street trees can provide visual complexity, human scale, and additional sense of enclosure to the streetscapes. More fine-grained streetscape details in micro-scale, such as the presence and quality of sidewalks, buffers, well-maintained houses, streetlights, and absence of graffiti, can add texture to the streetscapes, further promoting safety, comfort, and pleasurability. Eventually, these characteristics collectively contribute to placemaking, a function that makes the street itself an attractive destination.

The link between the quality of streetscapes and the attractiveness of local businesses can be found in the Marketing literature, which has introduced the concept of “servicescape”. Coined by Bitner (1992), servicescapes refer to all physical settings and environments that affect behaviors and perceptions of both customers and employees. It includes the facility's interior, exterior, and ambient conditions. Servicescapes influence customers’ inferences of the service quality and the overall satisfaction with the experience of being served. Business owners thereby design their servicescapes to add an atmosphere that enhances those aspects. There is a plethora of research on the cognitive and behavioral impacts of indoor servicescapes which can be controlled by the service organizations. The quality of the surrounding outdoor environment, on the other hand, has been far less discussed as part of the servicescape. Yet, the place-identity within a well-designed streetscape can be conceived to be a part of the retail habitat, which can influence the consumers’ experience (Wolf, 2003; Yüksel, 2013). Although the concept of servicescape offers potential linkages between walkable environments and visitors’ satisfaction, there is a lack of empirical studies that have examined this relationship.

The objective of this study is to fill this gap by examining the relationship between the street-level urban design details that shape the walking experience and customer satisfaction in local businesses along the street. Specifically, this study measures the quality of walkable built environment using Google Street View images and Computer Vision. It examines how the streetscapes are associated with customer satisfaction using user review scores from Yelp, a crowd-sourced review portal about local businesses. A fractional response (FR) regression model was fitted to examine the predicted change in the review scores with respect to the streetscape measures. The rest of the paper describes the underlying theoretical premises, the methodological approach, and reviews the results of the FR regression model. The paper then concludes with some implications of these results for planning and urban design.

2. Literature Review

2.1. Walkable built environment

Many authors in the field of public health and urban planning proposed theoretical models of walkability by examining factors that induce walking. The ecological models from the public health literature identified accessibility, safety, comfort, attractiveness, and convenience as factors impacting walking and other health behaviors (Sallis & Owen, 2015). Specifically focusing on walking, Owen et al. (2004) identified that destination accessibility, walking infrastructure (sidewalks and trails), level of traffic on roads, and aesthetic attributes of the outdoor environment were associated with walking. Similarly, the hierarchy of walking needs hypothesis by Alfonzo (2005) argues that pedestrians seek to fulfill their needs for accessibility, safety from crime, protection from traffic, and pleasurability in that order. Various ways for quantifying these characteristics have been developed in different fields (e.g., urban design, transportation, and public health) as well as for different purposes of walking (e.g., utilitarian versus recreational walking), each of which puts emphasis on different aspects of the built environmental characteristics.

Note that pedestrians have various needs that they seek to fulfill as they walk. For example, Alfonzo (2005) posed that pedestrians have needs for accessibility, safety, comfort, and pleasurability. If the environment in which they consider walking possesses these characteristics, the needs would be fulfilled. Therefore, this paper views accessibility, safety, comfort, and pleasurability as both the needs of pedestrians and the characteristics of the built environment (Koo et al., 2021).

2.1.1. Walkable built environment pertaining to accessibility to destinations

The characteristics of the walkable built environment can be grouped into two broadly defined categories. The first category is about accessibility of the built environment, which relates to the distance and ease of travel between two locations. Accessibility is shaped by proximity (i.e., Euclidean distance between different land uses) and connectivity (i.e., directness of travel between origin and destination determined by the design of street networks) (Saelens et al., 2003, p. 81). Because proximity and connectivity are determined by ways in which land is used and the street network is designed (Saelens et al., 2003, p. 81), they are commonly operationalized using such metrics as residential density, land use mix, intersection density, and retail floor area ratio (Frank et al., 2006). These metrics are measured at some aerial units of walkable size, for example, Census Tracts or quarter-mile buffers from places of interest. The accessibility measures have been used in studies that examined economic benefits of walkable environment. Pivo & Fisher (2011) hypothesized that accessible environments can reduce transportation costs to daily destinations, which can be desirable for those who live or work close by. They used Walk Score to demonstrate that the benefits of accessibility are capitalized into the property values of offices, retail businesses, and apartments.

As the accessibility metrics summarize characteristics of an area, some studies have termed these characteristics ‘macro-scale’ in a relative sense compared to the meso- and micro-scale characteristics of each street pertaining to the quality of the walking experience. Following these studies, in this paper we use the terms ‘macro-scale measures’, ‘urban form’, and 'accessibility' synonymously. The meso- and micro- scale measures comprise the second category of walkability characteristics in this study.

2.1.2. Walkable built environment pertaining to the quality of streetscapes

The second category of walkability characteristics is about the quality of the walkable built environment that relates to the sense of safety from crime, protection from traffic, and pleasurability (Alfonzo, 2005). The sense of safety, comfort, and pleasurability are shaped by various street-level built environmental factors. Street-level built environmental factors are further divided into meso- and micro-scale factors in which meso-scale streetscapes refer to the "size and arrangement of large objects such as buildings and trees" (Harvey & Aultman-Hall, 2016, p. 150), and micro-scale streetscapes pertains to fine-grained details that add texture to the 3D space defined by the meso-scale streetscapes.

Meso-scale features, such as tall buildings on narrow streets and street trees, give streets 'enclosure' – an urban design quality formed by buildings and other large objects blocking the lines of sight. Enclosed streetscapes create the feeling of being inside an outdoor room, making the streets more comfortable and inviting, thereby encouraging more social and economic activities (Ewing & Handy, 2009; Harvey et al., 2015). More activities on streets can mean more 'eyes on the street,' leading to an increased sense of safety (Jacobs, 1961). As one of the ways to increase enclosure, New Urbanism thinkers argue for putting buildings closer to the streets through minimizing setback requirements. Street trees can also provide similar benefits: they can provide additional 'enclosure' through their overhead canopies even in places where buildings are sparsely distributed or low in height. Street trees can also give streetscapes 'human scale' by subdividing the space between buildings, which can sometimes be vast, into more human-sized spaces. Trees can make streetscapes more enticing by providing visual complexity to the streetscapes through the movement, color, and shape of their branches and leaves (Harvey et al., 2015).

These meso-scale characteristics can also contribute to traffic calming. In more enclosed and complex streetscapes (e.g., streetscapes with buildings close to each other as well as to the streets (i.e., reduced building setbacks) and ample street trees), drivers can be more alert to the unexpected hazards and engage in less risky driving behaviors (Harvey & Aultman-Hall, 2015). Dumbaugh and Rae (2009) found that high-density developments in which buildings front on the street were associated with fewer crashes. Harvey & Aultman-Hall (2015) similarly reported that crashes are less likely to result in injury or death on smaller, more enclosed, tree-lined streetscapes.

Micro-scale streetscape factors have direct influences on the sense of safety, comfort, and pleasurability. Pedestrian infrastructure, such as sidewalks and buffers between the road and sidewalks, can separate the pedestrians from vehicular traffic, contributing directly to comfort and a sense of road safety. Walk signals and marked crosswalks can be particularly important for traffic safety: a study in six states found that pedestrian crashes were most common at or near intersections (Stutts et al., 1996). As perceptions of risk for injury by motorized traffic deter decisions to walk (Jacobsen et al., 2009; Noland, 1995), increased traffic safety can facilitate walking and invite more pedestrians. As more pedestrians make streets safer by providing increased surveillance, providing better pedestrian infrastructure designed for traffic safety also contributes to safety from crime. Streetlights are another infrastructure important for the perceived safety from crime. While darkness increases the incidences of criminal activity and heightens the fear of being victimized, streetlights have the opposite effect. A well-lit area can reduce crime, as well as the fear of crime, and increase pedestrian activity after dark (Painter, 1996). The perception of safety can also be influenced by various indicators of incivilities in micro-scale. Such indicators include rundown houses, boarded or broken windows, litters and overgrown landscapes, and excessive graffiti (Alfonzo, 2005).

Although the term walkability has often been used to refer to more attractive, well-designed places (Forsyth, 2015), having high accessibility does not necessarily translate to high quality streetscapes. While walk Score describes places with high scores as 'walker's paradise,' Bereitschaft (2017) found that neighborhoods with approximately equal Walk Score can have differences in the quality of streetscapes. Neckerman et al. (2009) also reported that street trees, landmark buildings, cleanliness, crime rate, and vehicular crashes were significantly different across neighborhoods after controlling for macro-scale urban form. (Leslie et al., 2005) found two neighborhoods that differ in walkability (i.e., walkability as measured by intersection density, dwelling density, and land use mix) have similar levels of perceived traffic and crime safety. It is easily conceivable that neighborhoods with the same residential density (e.g., 75 dwelling units per hectare) can be realized either as low-density row houses, as a single high-rise apartment tower, or something in between, each with significantly different building geometries, setbacks, street trees, and other urban design details (Lehmann, 2016).

2.1.3. Measuring meso- and micro-scale features

One major challenge in incorporating meso- and micro-scale features in empirical studies has been the high cost of measurement when scaled up to neighborhood or higher geographic levels. To overcome this challenge, computer vision technology and street view image services are increasingly being used to measure meso and micro-scale features. One of the most widely used computer vision models in the literature include Pyramid Scene Parsing Network (PSPNet) and SegNet (e.g., Koo et al., 2021; Tang & Long, 2018), which assign each pixel in a given image a class label (e.g., building, tree, road, sidewalk, sky) – a task commonly referred to as semantic segmentation. With a semantically segmented image, it is possible to quantify how visually dominant each class is by examining their relative proportions. For example, if an image contains a high proportion of buildings and cars and a low proportion of sky, it suggests highly enclosed streetscapes possibly in densely developed urban areas. Images with dominant proportions of sky and road along with few buildings and trees are likely representing main streets in auto-oriented suburbs. Streetscape measurements based on the proportion-based approach have demonstrated effectiveness as predictors of various outcomes, such as walking, physical activity, and mental health. Koo et al. (2021) used PSPNet and GSV to measure building-to-street ratio, greenness, and sidewalk-to-street proportion. Two of these measures showed significant association with walking mode choice. Ki and Lee (2021) used Fully Convolutional Network and GSV to extract Green View Index and demonstrated its effectiveness in explaining walking time.

Another approach for utilizing computer vision focuses on detecting the presence (or absence) of streetscape features or objects of interest (Hosseini et al., 2022; Kang et al., 2021; Weld et al., 2019). Although the presence-based approach seemed to be less widely used for streetscape measurements, studies have reported its effectiveness for the planning and public health literature. Nguyen et al. (2019) created a series of computer vision models, each of which detects the presence of one of the following objects or characteristics: street greenness, crosswalk, single lane road, building type, and utility wires. Similarly, Zhang et al. (2021) trained several models to detect traffic lights, stop signs, walk signals, streetlights, crosswalks, and curb cuts in

Atlanta and transformed them to parameters at the street level for a navigation app called ALIGN. Recent efforts have shown significant advances in detecting more intractable walking-related issues on sidewalks such as the presence and absence of curb ramps (and their absence), sidewalk obstructions and surface issues (Weld et al., 2019),

2.2. Servicescapes and Streetscapes

In retail and food service settings, physical surroundings are important factors, along with the quality of their services and products, in creating their brand image and enhancing customer satisfaction (Bitner, 1992; Turley & Milliman, 2000; Baker et al., 2002; Ryu & Han, 2010). While services are intangible and can be experienced only after the customer goes through the process of being served, the physical environment constantly provides atmospheric cues from which customers can infer the quality of service and the value of the merchandise (Turley & Milliman, 2000; Baker et al., 2002). Pleasant physical surroundings also affect overall satisfaction (Bitner 1992; Brady & Cronin, Jr., 2001; Ryu & Han, 2010). Customers' satisfaction associated with the perceived quality and value ultimately influences their behavioral intentions (e.g., avoidance or patronage) (Cronin, Jr. et al, 2000).

In the service marketing literature, those elements that act as stimuli of creating a place identity and incurring a behavioral response are collectively referred to as servicescapes. The "scape" can be conceived as narrowly as the internal environment, and as broadly as a city or town (Hall, 2008). Traditionally, however, a vast majority of the literature (Ryu & Han, 2010; Lin & Worthley, 2012; Miles et al., 2012) has focused on the interior characteristics that can be easily controlled by the business owner. For example, Miles et al (2012) explored how the facility aesthetics (e.g., color, décor, and architectural style), cleanliness, and interior layout affect customer satisfaction based on a survey and found that all three factors are associated with increases in the satisfaction level.

In addition, numerous studies have been carried out to examine how the customers' behavior is influenced by ambient conditions such as music and sound (Morrison et al., 2011; Lin & Worthley, 2012), smell and scent (Chebat & Michon, 2003; Han & Ryu, 2009;), temperature (Pinto & Leonidas, 1994; Heung & Gu, 2012), and lighting (Areni & Kim, 1994; Summers & Hebert, 2001). For example, Lin and Worthley (2012) analyzed how customer satisfaction and behavior are influenced by music and color which they claim are the two most salient atmospheric elements in servicescapes; they found a significant association. Both tangible and intangible elements all together contribute to our perception of the place holistically (Bitner, 1992; Namasivayam & Mattila, 2007).

Many studies describe the link between servicescapes and satisfaction response based on environmental psychology (Babin & Attaway, 2000; Tombs & McColl-Kennedy, 2003; Kumar et al., 2013). Simply put, the studies explain that our affect—emotion or desire that influences behavior or action—is the mediator between the two: in other words, servicescape elements are holistically linked to positive/negative mood which then dictates our cognitive processes such as quality inference, satisfaction/dissatisfaction, and post-purchase responses.

Following the same line of thought, external spaces, which include the street environment have also been shown to provide a variety of environmental stimuli that affect customers' emotions at the beginning and finale of the service experience. Though less explored, there are existing studies exploring the link between streetscapes and customer satisfaction. Yüksel (2013) surveyed 280 shoppers and asked about their thoughts on the street environment (e.g., bad/good, attractive/unattractive, or boring/stimulating), their expected quality of service and merchandise, and their behavioral intentions. The study found that those factors are all correlated. Based on a GPS-based analysis, Hahm et al. (2019) showed that better streetscapes not only affect the behavioral intentions but also lead to more consumption by offering a high permeability to the frontages (i.e., stores and restaurants). In addition, greenery is gaining attention as an important factor in contributing to the quality of servicescapes because of its restorative effects (Brengman et al., 2012; Purani & Kumar, 2018; Hamed et al., 2019). Studies found that indoor plants and greenery can influence customers' psychological states (e.g., reducing stress and eliciting a pleasant mood), which ultimately have an impact on customers' satisfaction and behavior. Based on these findings, we speculate that streets with a sufficient amount of tree canopy would have an equally important impact on customers' affect and cognitive processes.

In a nutshell, a well-designed, walkable street can reinforce the place-identity (Hall, 2008), provide positive stimuli to improve consumers' moods, and make their overall service experience more pleasing and satisfactory.

The objective of this study is to examine the hypothesis that *meso- and micro-scales of built environmental measures will contribute positively to customer satisfaction*. Note that the literature does not provide sufficient empirical basis on which to hypothesize the relationship between walkable urban form (i.e., macro-scale measures) and customer satisfaction. However, the term walkability has conventionally been used by many to represent a better overall design or just a better place to be (Forsyth, 2015). For example, one of the most widely used macro-scale measures, Walk Score, was shown to be associated with more desirable housing properties and more expensive commercial real estate (Pivo & Fisher, 2003). Although macro-scale measures are not technically a part of streetscapes, this paper hypothesizes based on the association between accessibility and property values that macro-scale measures would also positively contribute to customer satisfaction. The following sections discuss the methods, results, and implications of the empirical testing of the hypothesis.

3. Method and Data

3.1. Local business characteristics and customer satisfaction

The objective of this study is to examine the relationship between customer satisfaction and walkable streetscapes. As a proxy for customer satisfaction, we use data from Yelp, which publishes crowd-sourced reviews about service businesses. Using Yelp's Application Programming Interface (API) called Yelp Fusion, we collected information on individual businesses, such as location, average review score, number of reviews, type of business, and price level. One caveat of the data is that the review score is averaged over an unspecified period, which varies by individual business and cannot be controlled by API users.

Among many types of local businesses, this study focuses on restaurants, cafes, and bars (which are collectively referred to as 'restaurants' in this study) because Yelp has a particularly extensive amount of review data on restaurants. In addition, since factors that affect customer satisfaction are presumed to vary depending on the type of business, focusing on restaurants would make modeling the relationship between the streetscapes and customer satisfaction more parsimonious. For this study, we will use the restaurants in the City of Atlanta (appearing in Yelp Fusion API) as the sample and the restaurant Point-of-Interest (POI) as the unit of analysis. The review score ranges from one to five at 0.5 intervals, which represents how satisfied/dissatisfied the reviewer was with the experience.

Independent variables are classified into three categories: 1) local business characteristics, 2) neighborhood characteristics, and 3) walkable built environment (see Table 1). The local business characteristics include the number of reviews, type of business (i.e., whether it is a restaurant, café, or bar), whether the business is a fast-food outlet or not, and the price level. The price level ranges from one (i.e., cheapest) to four (i.e., most expensive).

Neighborhood characteristics include the number of crimes in the walking distance and the distance from the city center. The number of crimes was calculated as the sum of all crimes occurred between 2009 and 2019 within 400-meter radius from each local business. We did not filter down to specific years for the crime data because the Yelp review score was collected over unspecified time window.

3.2. Measuring walkable built environment

3.2.1. Macro-scale measures for accessibility

The commonly used measures for accessibility were selected from the literature, including population and employment density, distance from the city center, and Walk Score. Population density was calculated by (1) identifying the Census Block Group in which business establishments were located and (2) dividing the total population of the Census Block Group by its area. The population information was derived from the 2019 American Community Survey (ACS) 5-Year Estimate. Similarly, employment density was calculated by dividing the total number of jobs by the area of the Census Block Group of business location. The number of jobs was extracted from the 2019 Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) data. Population and employment density were then summed. The distances from the city center were calculated by measuring the Euclidean distance between each business location and the Atlanta City Hall in kilometers.

3.2.2. Meso- and Micro-scale features for quality of streetscapes

Meso- and Micro-scale streetscape characteristics were quantified for the street segment closest to the coordinate of the business location. If the closest street segment to the restaurant was shorter than 50 meters in length or had less than 10 GSV images, we considered other street segments within a 150-meter buffer and assigned the maximum among these other street segments to the restaurant. This study used the total of 51,317 street view images.

For each street segment, seven factors related to the quality of streetscapes were measured through computer vision-based measurement methods developed by Koo et al. (2021) and Koo et al. (2022). Two meso-scale measures – building-to-street ratio and greenness – were measured through the proportion-based approach in Koo et al. (2021). Four GSV images were downloaded for each street segment, two at each intersection that are looking towards the streets being considered and two at the middle of the segment that are looking back-to-back. These images were then processed through a pre-trained PSPNet to extract the proportions of building, house, sidewalk, road, car, tree, plant, and grass in each image. The performance metrics for PSPNet can be found in Zhao et al. (2017). These proportions were transformed into two indices using the equations shown below.

Building-to-street ratio at eye level = (% building + % house) / (% sidewalk + % road + % car)

Greenness at eye level = % tree + % grass + % plant

Five micro-scale features[1]—crosswalks, walk signals, sidewalks, buffers, and streetlights—were measured using an automated method developed in Koo et al. (2022). This method applies

[1] Some features in Koo et al. (2022) are ephemeral in nature. For example, the presence of trip hazards, building maintenance quality, and graffiti can change quickly, particularly in neighborhoods with gentrification or degradation. Because the review score data from Yelp is an average over unspecified time periods, these ephemeral measures are excluded in this study.

custom trained computer vision models called Mask R-CNN. For any given street segment, two images are downloaded for each intersection, and three images (looking left, right, and upward) are downloaded at distance intervals of 5 meters. After applying the computer vision model to the GSV images, the detection results were aggregated by each segment.

There are two variables about traffic safety on sidewalks: the proportion of images in which sidewalks are detected for each street segment and the proportion of images in which buffered sidewalks are detected for each street segment. For example, a street segment that has a complete sidewalk on one side of the street but no sidewalk on the other side would get 0.5 for the proportion of sidewalk. If half of the sidewalk on this street was buffered, the proportion of buffered sidewalk would be 0.25. These proportions are calculated using the number of images as the denominator because GSV images are captured at relatively fixed distance and are proportional to the length of street segment. We chose to use continuous measurements because the presence of sidewalks and buffers are difficult to be classified into binary variables; it is common that sidewalks and buffers can be found only in a portion of the stretch of a street segment or be severed by driveways, making the decision on what it means for a street segment to have sidewalks or buffers arbitrary. Crossing infrastructure is a categorical variable with three levels: (1) no crossing infrastructures, (2) either one of crosswalk or walk signal, and (3) both crosswalks and walk signals. The density of streetlight is measured by dividing the number of streetlights detected on a street segment by the length of the street segment[2]. The model performance metrics of the computer vision models used to detect the micro-scale features, with the intersection over union threshold of 0.3, are shown in Table 2. Note that this study uses

[2] Note the density of the streetlights can be overestimated even when computer vision was perfect if (1) a sequence of Google Street View images captures the same streetlights more than once due to them being too close to each other (Koo, 2021) and/or (2) the street view image near intersections can contain streetlights on other street segments.

images that are looking both horizontally and upward to include streetlights above eye line. When streetlights are located close to the camera, the GSV image can only capture the bottom of streetlights (i.e., only the pole) but not the light fixture, in which case streetlights are indistinguishable to utility poles. When the entire shape of streetlights is visible, it is often found far from the camera, and the low image resolution often blurs the details of streetlights. This blur may have contributed to the low recall value of streetlight detection from eye level in Table 2.

Table 1.Variables and data source

Category		Variable	Data Source
Dependent variable		Average review scores	Yelp
Local business characteristics		Number of reviews	
		Type of business (restaurant / café / bar)	
		Fast food (yes / no)	
		Price level (1 - 4)	
Neighborhood characteristics		The number of crimes in the walking distance (400 meters; 2009-2019)	Atlanta Police Department
		Distance from the city center (unit: km)	-
Walkable built environment	Macro-scale (urban form)	Population and employment density (unit: person/km^2)	2019 LEHD LODES
		Walk Score	Walk Score
	Meso-scale (streetscape)	Building-to-street ratio at eye level	Google Street View
		Greenness at eye level	
	Micro-scale (sctreetscape)	Proportion of sidewalk	
		Proportion of buffered sidewalk	
		Crosswalk & walk signal (None present / One of the two objects present / Both objects present)	
		Density of streetlights	

Table 2. Micro-scale feature detection results

	Precision	Recall	F1 Score	Number of ground truth instance
Walk signal	0.929	0.637	0.756	102
Crosswalk	0.860	0.804	0.831	168
Sidewalk	0.765	0.543	0.635	433
Buffer	0.850	0.528	0.651	161
Streetlights (from eye level)	0.917	0.458	0.611	144
Streetlights (looking up)	0.879	0.903	0.891	113
Lightpole (from eye level)	0.831	0.954	0.888	108

3.3. Analysis

The dependent variable is the average Yelp review scores, which range between 1 and 5 at 0.5 increments. In terms of model selection, we considered various models including linear regression, ordinal regression, or multinomial logistic regression. However, they were found to be unsuitable in our study for the following reasons: (1) conventional linear regression models can generate predicted values that lie outside the lower and upper bounds of the variable (i.e., one and five, respectively, in our data), (2) the proportional odds assumption required for ordinal logistic regression was not met for our data, and (3) when the variable is treated as unordered categorical data, it loses the information about the ordered nature of the variable as well as fails to meet the assumption of the Independence of Irrelevant Alternatives (IIA). As an alternative, this study employed a FR regression model which works in the same way as the binary response models, but the dependent variable is a fraction/proportion. This model has advantages in that it provides upper and lower bounds (i.e., 0 and 1) and is not restrained by the proportional odds assumption as in the ordinal logistic regression.

To transform our score values into proportion-like values, we first scaled the variable to range between zero and one using the equation below.

$$y_i` = (y_i - \min(Y)/(\max(Y) - \min(Y)$$

In this case, the range is from 0 (i.e., unsatisfactory restaurant) to 1 (i.e., satisfactory restaurant). With the transformed dependent variable, we fitted the FR regression model. The statistical analysis was conducted in R 4.0.2 using *glm* function with quasibinomial distribution. To make the interpretation of the magnitude of the coefficient estimates, we first focus on interpreting the direction of associations (i.e., positive or negative) and the statistical significance from the regression result table. Next, we report the predicted changes in the dependent variables with respect to increase in each of the statistically significant independent variables. In the prediction phase, we re-transform the dependent variable back to the original scale between one and five for interpretability.

We tested polynomial terms for all continuous built environment variables and retained only the statistically significant ones. While it was hypothesized that high-quality restaurants will be commonly found in areas with high accessibility, the preliminary analysis of our data suggested that there exist some restaurants in secluded areas that received high review scores. Such a pattern can arise if the relationship between the built environment measurements and review scores is non-linear.

4. Result

4.1. Descriptive statistics

The descriptive statistics and the spatial distribution of the review score of each restaurant are presented in the Appendix (Table A1, Table A2, and Figure A1). From the mean and median values, we noted that the variables – the number of reviews, the number of crimes in the walking distance, the distance from the city center, the population and employment density, the building-to-street ratio at eye level, and the density of streetlight – are considerably right-skewed. Among the six skewed variables, we took log on all of them except the distance from the city center, which contributed to improving the model fit (i.e., log-likelihood). We also noted that some variables have a category that has a small number of samples (e.g., there are only 20 restaurants with price level 4), but it did not cause a complete (or quasi-complete) separation issue in the model (as shown in Table 3). We did not find any visual sign of spatial autocorrelation.

4.2. Regression

The regression results are shown in Table 3. The variance inflation factors (VIF) were examined, from which we confirmed that the variables do not have severe multicollinearity. The ρ^2, the model fit measure, of the model is 0.098 and the adjusted ρ^2 is 0.074. Note that, in the fractional response regression model, it is not appropriate to assume that the upper bound of ρ^2 is 1, which is theoretically attainable only in the binary case (Hauser, 1978, as cited in Mokhtarian and Bagley, 2000). In the case of our model where the dependent variable continuously ranges between 0 and 1, we can manually calculate the theoretical maximum log-likelihood by

$$\sum_n \sum_i f_{in} * \ln(f_{in}))$$

where f_{in} is a fraction of choosing alternative *i* for individual *n*. The theoretical maximum log-likelihood value, -672.0, leads to the theoretical maximum ρ^2 value, 0.19, which suggests that the ρ^2 of 0.098 in this model is a modest result.

Most of the business-specific characteristics were significantly associated with the review scores. The number of reviews, being cafes, and of higher price levels were positively associated with the review scores. If the business is in the fast-food category, it is strongly and negatively associated with review scores. The number of crimes in the walking distance (400 meters) was negatively associated with review scores. The population and employment density was significantly but negatively associated with the review scores. The proportion of buffered sidewalks, greenness, and building-to-street ratio were positively and significantly related with review scores. However, the proportion of sidewalks was not significantly associated with review scores. Two meso-scale variables – greenness and building-to-street ratio – were both significantly and positively associated with review scores. Among all polynomial terms tested, only Walk Score showed a statistically significant polynomial term. The significant and positive coefficient indicated by the quadratic term for Walk Score suggests a convex (i.e., U-shaped) relationship. The negative relationship flips to positive when Walk Score is 66, which is lower than its mean, 78.

Table 3. Result of the fractional response logistic regression model

Category		Variable		coefficient	t-statistic
-		Constant		2.561^{***}	4.94
Local business characteristics		Number of reviews (ln)		0.094^{***}	5.09
		Type of business (base: restaurant)	Cafe	0.158^{*}	2.07
			Bar	-0.006	-0.12
		Fast food		-0.917^{***}	-11.8
		Price level (base: 1)	2	0.520^{***}	7.03
			3	0.601^{***}	6.10
			4	0.664^{***}	3.53
Neighborhood characteristics		The number of crimes in the walking distance (ln)		-0.114^{***}	-3.72
		Distance from the city center		-0.023^{*}	-2.53
Walkable built environment	Macro-scale (urban form)	Population and employment density (ln)		-0.081^{*}	-2.13
		Walk Score		-0.032^{**}	-3.22
		Walk Score^2		0.0002^{**}	3.28
	Meso-scale (streetscape)	Greenness at eye level		0.580^{*}	2.06
		Building-to-street ratio at eye level (ln)		0.119^{**}	2.85

	Micro-scale (streetscape)	Crosswalk & walk signal (base: None)	Either	-0.117	-1.08
			Both	-0.135	-1.24
		Proportion of sidewalk		-0.289	-1.74
		Proportion of buffered sidewalk		0.427 *	2.41
		Density of streetlights (ln)		-0.105	-1.79
Number of observations				1,198	
Log-likelihood of equally-likely model				-830.4	
Log-likelihood of this model				-748.7	
Theoretical maximum log-likelihood				-672.0	
ρ^2				0.098	
Adjusted ρ^2				0.074	
Theoretical maximum ρ^2				0.191	

*** significant at p < 0.001; ** significant at p < 0.01; * significant at p < 0.05

Table 4 provides the predicted changes in the dependent variable (i.e., review scores) in the original scale (i.e., between one and five) with respect to the changes in each of the statistically significant independent variables while holding other variables constant at their mean or mode. Note that the values of the two log-transformed variables in the model, population and employment density and building-to-street ratio, were displayed in the delogged, original scale in Table 4 for interpretability while the predicted changes were calculated using their logged values. Due to the non-linear nature of the logistic regression model, the amount of predicted changes can be larger if the increase in the independent variable occurred in the middle of the range than in other parts of the range.

The business-specific variables generally show sizable effects on review scores. One standard deviation (SD) increase in the number of reviews (which is equivalent to 399 more reviews than the mean) is associated with an increase in review scores by 0.10. Being a cafe was associated with an increase in review scores by 0.13, but being fast food was associated with a decrease in review scores by 0.88. This was the largest change across all independent variables this study considered. While changing the price level from the second cheapest to the cheapest was associated with a 0.48 decrease in review scores, raising the price level to higher and the highest levels was linked with 0.07 and 0.12 increases in review scores, respectively. One standard deviation increase in the number of crimes in the walking distance (which is equivalent to 1,591 increase from the mean) is associated with 0.1 decrease in review scores. Review scores were negatively associated with the distance from the city center. Being 1 SD further from the city center than the mean (i.e., additional 3.4 km away from the city center than the mean) was associated with a 0.07 lower review scores.

When the population and employment density increased by 1 SD, the review score decreased by 0.07. On the other hand, when Walk Score increased by 1 SD from the mean, the review score increased by 0.12. Note that the U-shaped relationship of Walk Score means that the same 1 SD change can lead to different amount of changes or even decrease in the review score depending on the starting value. Meso- and micro-scale features also showed noticeable effects: when the greenness and building-to-street ratio increased by 1 SD (equivalent to 10 and 29 percentage points increase, respectively), the review scores increased by 0.05 and 0.09, respectively. With 1 SD increase in the proportion of buffered sidewalks (equivalent to about 15 percentage points increase), the review score increased by 0.05.

Table 4. Predicted changes in the review score with respect to each of the significant variables

variable	Base (score: 3.76)	Change to	Score change
Number of reviews	253	652 (+1 S.D.)	+0.10
Cafe	No	Yes	+0.13
Fast food	No	Yes	-0.88
Price level	2	1 (cheapest)	-0.48
		3	+0.07
		4 (most expensive)	+0.12

The number of crimes in the walking distance	1,947.3	3,538.7 (+1 S.D)	-0.10
Distance from the city center	5km	8.4km (+1 S.D.)	-0.07
Population and employment density	9,335	18,377 (+1 S.D.)	-0.07
Walk Score	78	94 (+1 S.D.)	+0.12
Greenness at eye level	13%	23% (+1 S.D.)	+0.05
Building-to-street ratio at eye level	33.9%	63.3% (+1 S.D.)	+0.09
Proportion of buffered sidewalk	20%	34% (+1 S.D.)	+0.05

5. Discussion

This study hypothesized that walkable urban form (i.e., macro-scale built environment) and walkable streetscapes (i.e., meso- and micro-scale built environment) would both be positively associated with customer satisfaction. However, the result suggests that the hypothesis was fully supported only for the meso-scale measures. Only one of the four micro-scale features showed the expected positive contribution to the customer satisfaction. Macro-scale measures – population and employment density and Walk Score – showed a negative and a quadratic relationship with customer satisfaction, respectively.

These unexpected findings about macro-scale measures warrant further examination. The widely used conceptualization of walkability, as well as its quantitative measures such as population and employment density and Walk Score, is largely based on the concept of accessibility which measures proximity and connectivity (Saelens et al., 2003). Accessibility by definition is not about the quality of the walking experience. However, as indicated in the literature, the term walkability has been carrying favorable connotations and often been associated with not only good accessibility but also generally good place/urban design (Forsyth, 2015). This favorable connotation is the basis on which this study hypothesized a positive relationship between macro-scale measures and review scores. It is likely that this connotation has been generated because in high walkability areas, there is a tendency for good urban design elements to coexist. In fact, our data corroborated this narrative – the two macro-scale measures generally showed significant and positive correlations with the micro-scale features (See Table 5 as well as the scatter plots in Figure A2). Note that the regression coefficients for Walk Score and the density variable represent their relationship with review scores *after* controlling for the effect of meso- and micro-scale measures. In other words, the ease of accessing a certain destination does not necessarily have a positive impact on the customer satisfaction, but what matters is the quality of streetscape people experience while accessing the destination.

Table 5. Correlations between two macro-scale measures and five meso & micro-scale measures

	Walk Score	**Population and employment density**
Greenness	-0.31 (p=0.000)	-0.31 (p=0.000)
Building-to-street ratio	0.62 (p=0.000)	0.74 (p=0.000)
Proportion of sidewalk	0.59 (p=0.000)	0.57 (p=0.000)
Proportion of buffered sidewalk	0.23 (p=0.000)	0.18 (p=0.000)
Density of streetlight	0.45 (p=0.000)	0.48 (p=0.000)

Meso-scale features showed the most consistent association with review scores among the variables of interest: both building-to-street ratio and greenness showed positive and statistically significant coefficients. Building-to-street ratio may be contributing to the customer satisfaction by providing a sense of enclosure to the streetscape. The literature also reported that more enclosed streetscapes tend to be linked with less severity of automobile crashes and a higher sense of safety (Harvey et al., 2015; Harvey & Aultman-Hall, 2015). The positive effect of greenness is also aligned with the findings from existing studies on the benefits of urban greening on commercial activities (Wolf, 2004; Joye et al., 2010) and studies on the restorative effect of greenery on the customer's mood and satisfaction (Brengman et al., 2012; Purani & Kumar, 2018; Hamed et al., 2019). Greenness can also add to the sense of enclosure and complexity.

Most micro-scale features relevant to traffic safety were not significantly linked with review scores except the proportion of buffered sidewalks. Buffered sidewalks can contribute to customer satisfaction by providing protection from traffic and adding greenery to the streetscape. The insignificance of the proportion of sidewalks and the presence of walk signals or crosswalks was unexpected. One possible explanation is that both sidewalks and crossing infrastructures are ubiquitous on commercial streets, particularly in urban areas. For example, our data showed that about 95% of the restaurants are located on streets with walk signals and/or crosswalks.

The results indicated that when Walk Score is higher than 66 it starts providing positive influence on the customer satisfaction. Although future studies are needed to clarify this behavior of Walk Score, a potential explanation may be based on the understanding that there can be two opposing characteristics of an environment that can both be considered attractive to different types of customers. On the one hand, quiet and secluded places with ample surrounding space can be attractive to certain customers. On the other hand, vibrant commercial strips bustling with people can also be considered attractive to particular types of customers (Whyte, 1980). This U-curved pattern is also found in Ram & Hall (2017) which examined the relationship between Walk Score and TripAdvisor ranking.

To provide a more concrete illustration of effect sizes of meso- and micro-scale features, we selected one actual restaurant from our data and predicted how the review score would change in response to the changes in meso- and micro-scale features. As the baseline, Figure 1a shows the image of the restaurant facing a street for which the three meso- and micro-scale factors shown to be significant in Table 3 – the proportion of buffered sidewalk, greenness, and building-to-street ratio – are in the bottom quartile (i.e., below 25th percentile). As shown in the first row of Table 6, the predicted review score by our fitted regression model for this restaurant is 3.699 – the observed review score of the restaurant is 3.5. The following rows in Table 6 illustrate the predicted review score when the proportion of buffered sidewalk, greenness, and building-to-street ratio are changed to their 50th, 75th, 90th percentiles. When the three variables are increased to their 50th and 75th percentiles, the predicted review scores are 3.866 (i.e., about 0.17 increase from the baseline) and 3.989 (i.e., about 0.29 increase from the baseline). When the three variables are increased to their 90th percentile, the predicted score is increased by about 0.41 (which is 0.53 SD), making the predicted score 4.112. To provide a visual example, Figure 1b illustrates an example image of streetscapes for which the three variables are between 50th and 75th percentiles. It is predicted that, if streetscapes change from Figure 1a to 1b, the score will increase by 0.24.

(a) Restaurant in an unfavorable streetscape (b) Restaurant in a favorable streetscape

Figure 1. Example Restaurants in different streetscapes

Table 6. Prediction results of the review score in response to the hypothesized changes in meso- and micro-scale features

	Proportion of buffered sidewalk	**Greenness at eye level**	**Building-to-street ratio at eye level**	**Predicted score**
Street in Figure 1a (baseline)	2.6% (6th percentile)	4.5% (17th percentile)	11.0% (24th percentile)	3.699
50th percentile	16.7%	11.8%	24.4%	3.866 (**+0.17**)
Street in Figure 1b	23.5% (68th percentile)	15.3% (65th percentile)	34.7% (64th percentile)	3.938 (**+0.24**)
75th percentile	26.8%	18.3%	46.6%	3.989 (**+0.29**)
90th percentile	41.2%	27.0%	75.9%	4.112 (**+0.41**)

There are important limitations of this study that need to be clarified. With regards to the use of computer vision and street view images, this study is one of the earliest attempts to utilize automated methods for measuring micro-scale features in applied research. Potential sources of bias have not been fully examined in the literature. The most obvious one is the insufficient performance of the computer vision models used. As illustrated in Table 2, the measures of precision tend to be much higher than recall except for crosswalks. Precision values indicate that if the models detected the presence of some objects, it is generally reliable. However, the low recall values indicate that there can be many objects that existed on streets and the computer vision models failed to detect them. Another important potential source of bias is that there can be gaps and overlaps between one GSV image to the next one. Assuming that GSV images are downloaded with 90-degree field of view (i.e., the default setting of GSV API), gaps and overlaps can occur when two consecutive images are located too far, which leads to gaps, or too close, which leads to overlaps. With gaps or overlaps, some variables can be biased if the object of interest was located where gaps existed and be left undetected, or an object of interest was located where two GSV images overlapped and be counted more than once. We suspect that the noticeably high maximum value of the density of streetlight variable (i.e., 2.17 streetlights per meter on one side of the street) in this study may be attributable to this double-counting issue. More sophisticated methods for downloading GSV images will need to be developed to arrive at better representation of the streetscapes.

The measures of streetscapes and servicescapes are necessarily sensitive to how they are defined and operationalized. In this study we measured the streetscapes of only the closest street to the restaurant, assuming that the customer satisfaction primarily comes from the streetscape of the adjoining street. While it is possible that the scope of servicescapes can be larger than one adjoining street, we took the most conservative approach because we failed to find past studies that provided guidance on how large the scope should be. In addition, the degree to which the street environment was involved in the customer experience can vary by individuals. While some customers may have enjoyed the view of the street or being in the outdoor seating, others may have had little interaction with the streetscapes. Moreover, whether and the extent to which COVID19 pandemic had affected the review scores is unknown. Also, the average review scores of each restaurant on Yelp is based on reviews accumulated over an unspecified period of time, and Yelp API does not provide information on how long the reviews have been collected. Because both Walk Score and GSV API return the most recent information for a given coordinate, there might have been temporal mismatch between review scores and the environmental measurements, and the degree of mismatch may vary by individual reviews. This mismatch may have been another reason for the insignificant results of some streetscape variables, particularly those that can change quickly over time, such as the presence of graffiti, boarded houses, or trip hazards.

6. Planning Implications

The findings provide many implications for urban planners, urban designers, and other related professions. The primary finding of the analyses is that the walkable streetscape is positively associated with customer satisfaction, which should be considered along with many other transportation, environment, and public health benefits when evaluating the urban design and complete street projects.

Planning and policy tools for modifying the three meso- and micro-scale features influencing customer satisfaction include: road diet, setback regulations, urban greening, and providing buffered protection to the pedestrian zone. It is important to point out that the measure of building-to-street ratio can be increased through either increasing building heights or decreasing street width. This indicates that increasing building-to-street ratio may be possible even in areas where increasing the overall density (e.g., constructing more buildings and/or building them taller) is not feasible. Road diet is one well-known strategy that can achieve this goal. Another way to increase building-to-street ratio is by reducing building setbacks, which is the space between the street and the facade of buildings. Many New Urbanism thinkers and Complete Street advocates argued for the importance of setback regulations for increasing permeability to frontages as well as for enhancing the overall enclosure of the streetscapes.

Planting street trees can be another effective strategy for providing the sense of enclosure. It can be accompanied by providing sidewalk buffers since they can share the furniture zone of sidewalks. Both trees and buffers can offer protection from moving vehicles while providing restorative effects. These may be easier to implement than making significant modification to the built environment such as increasing building heights or reducing the distance between the building front and the street.

One important consideration in increasing greenness is that heavily developed areas (e.g., areas with very high building-to-street ratio) tend to have less space available for street trees and landscapes (Giarrusso, 2018), creating an inverse relationship (Koo et al., 2019). For instance, our data showed a negative correlation between building-to-street ratio and greenness with $r = -0.499$ ($p < 0.001$). The negative correlation indicates that while greenness and building-to-street ratio have complementary effects on creating streetscapes for pleasant consumer experience, achieving an adequate level of development density and securing ample greenery can be conflicting goals in some areas, particularly highly built-up areas in which space for vegetation can be scarce. One approach useful in densely built-up areas is to leverage planning tools that relax the regulation on floor area ratio (FAR) to developers who agree to provide publicly accessible spaces within their lot, such as privately owned public spaces (POPS). Such policies can allow planners to not only increase both building height (e.g., higher building-to-street ratio) but also acquire space for greenery that is otherwise expensive to acquire. Planners should take context-sensitive approaches to promote street environments that enhances servicescapes, which would also improve the economic opportunities of the businesses on those streets.

References

Alfonzo, M. A. (2005). To Walk or Not to Walk? The Hierarchy of Walking Needs. Environment and Behavior, 37(6), 808–836. https://doi.org/10.1177/0013916504274016

Areni, C. S., & Kim, D. (1994). The influence of in-store lighting on consumers' examination of merchandise in a wine store. International journal of research in marketing, 11(2), 117-125.

Babin, B. J., & Attaway, J. S. (2000). Atmospheric affect as a tool for creating value and gaining share of customer. Journal of Business research, 49(2), 91-99.

Baker, J., Parasuraman, A., Grewal, D., & Voss, G. B. (2002). The influence of multiple store environment cues on perceived merchandise value and patronage intentions. Journal of marketing, 66(2), 120-141.

Bereitschaft, B. (2017). Equity in microscale urban design and walkability: A photographic survey of six Pittsburgh streetscapes. Sustainability (Switzerland), 9(7), 1233. https://doi.org/10.3390/su9071233

Bitner, M. J. (1992). Servicescapes: The impact of physical surroundings on customers and employees. Journal of marketing, 56(2), 57-71.

Brady, M. K., & Cronin Jr, J. J. (2001). Some new thoughts on conceptualizing perceived service quality: a hierarchical approach. Journal of marketing, 65(3), 34-49.

Brengman, M., Willems, K., & Joye, Y. (2012). The impact of in-store greenery on customers. Psychology & Marketing, 29(11), 807-821.

Chebat, J. C., & Michon, R. (2003). Impact of ambient odors on mall shoppers' emotions, cognition, and spending: A test of competitive causal theories. Journal of business research, 56(7), 529-539.

Cronin Jr, J. J., Brady, M. K., & Hult, G. T. M. (2000). Assessing the effects of quality, value, and customer satisfaction on consumer behavioral intentions in service environments. Journal of retailing, 76(2), 193-218.

Dumbaugh, E., & Rae, R. (2009). Safe Urban Form: Revisiting the Relationship Between Community Design and Traffic Safety. Journal of the American Planning Association, 75(3), 309–329. https://doi.org/10.1080/01944360902950349

Ewing, R., & Handy, S. (2009). Measuring the unmeasurable: Urban design qualities related to walkability. Journal of Urban Design, 14(1), 65–84. https://doi.org/10.1080/13574800802451155

Forsyth, A. (2015). What is a walkable place? The walkability debate in urban design. URBAN DESIGN International, 20(4), 274–292. https://doi.org/10.1057/udi.2015.22

Frank, L. D., Sallis, J. F., Conway, T. L., Chapman, J. E., Saelens, B. E., & Bachman, W. (2006). Many Pathways from Land Use to Health: Associations between Neighborhood Walkability and Active Transportation, Body Mass Index, and Air Quality. Journal of the American Planning Association, 72(1), 75–87. https://doi.org/10.1080/01944360608976725

Giarrusso, T. (2018). Assessing Urban Tree Canopy in the City of Atlanta: Detecting Changes between 2008 and 2014. Atlanta: Georgia Tech Research Corporation.

Hahm, Y., Yoon, H., & Choi, Y. (2019). The effect of built environments on the walking and shopping behaviors of pedestrians; A study with GPS experiment in Sinchon retail district in Seoul, South Korea. Cities, 89, 1-13.

Hall, C. M. (2008). Servicescapes, designscapes, branding, and the creation of place-identity: south of Litchfield, Christchurch. Journal of Travel & Tourism Marketing, 25(3-4), 233-250.

Han, H., & Ryu, K. (2009). The roles of the physical environment, price perception, and customer satisfaction in determining customer loyalty in the restaurant industry. Journal of hospitality & tourism research, 33(4), 487-510.

Hamed, S., El-Bassiouny, N., & Ternès, A. (2019). Hospital servicescape design for inpatient wellbeing. Services Marketing Quarterly, 40(1), 1-32.

Handy, S. L., Boarnet, M. G., Ewing, R., & Killingsworth, R. E. (2002). How the built environment affects physical activity. American Journal of Preventive Medicine, 23(2), 64–73. https://doi.org/10.1016/s0749-3797(02)00475-0

Harvey, C., & Aultman-Hall, L. (2015). Urban Streetscape Design and Crash Severity. Transportation Research Record: Journal of the Transportation Research Board, 2500(1), 1–8. https://doi.org/10.3141/2500-01

Harvey, C., & Aultman-Hall, L. (2016). Measuring Urban Streetscapes for Livability: A Review of Approaches. The Professional Geographer, 68(1), 149–158. https://doi.org/10.1080/00330124.2015.1065546

Harvey, C., Aultman-Hall, L., Hurley, S. E., & Troy, A. (2015). Effects of skeletal streetscape design on perceived safety. Landscape and Urban Planning, 142, 18–28. https://doi.org/10.1016/j.landurbplan.2015.05.007

Hosseini, M., Sevtsuk, A., Miranda, F., Cesar Jr., R., & Silva, C. (2022). Mapping the Walk: A Scalable Computer Vision Approach for Generating Sidewalk Network Datasets from Aerial Imagery (SSRN Scholarly Paper No. 4086624). https://doi.org/10.2139/ssrn.4086624

Heung, V. C., & Gu, T. (2012). Influence of restaurant atmospherics on patron satisfaction and behavioral intentions. International Journal of Hospitality Management, 31(4), 1167-1177.

Jacobs, J. (1961). The death and life of great American cities. Random House.

Jacobsen, P. L., Racioppi, F., & Rutter, H. (2009). Who owns the roads? How motorised traffic discourages walking and bicycling. Injury Prevention, 15(6), 369–373. https://doi.org/10.1136/ip.2009.022566

Kang, B., Lee, S., & Zou, S. (2021). Developing Sidewalk Inventory Data Using Street View Images. Sensors, 21(9), 3300. https://doi.org/10.3390/s21093300

Joye, Y., Willems, K., Brengman, M., & Wolf, K. (2010). The effects of urban retail greenery on consumer experience: Reviewing the evidence from a restorative perspective. Urban Forestry & Urban Greening, 9(1), 57-64.

Ki, D., & Lee, S. (2021). Analyzing the effects of Green View Index of neighborhood streets on walking time using Google Street View and deep learning. Landscape and Urban Planning, 205, 103920. https://doi.org/10.1016/j.landurbplan.2020.103920

Koo, B. W. (2021). Measuring Street-Level Walkability through Big Image Data and Its Associations with Walking Behavior (Doctoral dissertation, Georgia Institute of Technology).

Koo, B. W., Boyd, N., Botchwey, N., & Guhathakurta, S. (2019). Environmental Equity and Spatiotemporal Patterns of Urban Tree Canopy in Atlanta. Journal of Planning Education and Research, 0739456X19864149. https://doi.org/10.1177/0739456X19864149

Koo, B. W., Guhathakurta, S., & Botchwey, N. (2021). How are Neighborhood and Street-Level Walkability Factors Associated with Walking Behaviors? A Big Data Approach Using Street View Images. Environment and Behavior, 00139165211014609. https://doi.org/10.1177/00139165211014609

Koo, B. W., Guhathakurta, S., & Botchwey, N. (2022). Development and validation of automated microscale walkability audit method. Health & Place, 73, 102733. https://doi.org/10.1016/j.healthplace.2021.102733

Kumar, D. S., Purani, K., & Sahadev, S. (2013). Conceptualising visual servicescape aesthetics: An application of environmental psychology. The Marketing Review, 13(4), 347-376.

Lehmann, S. (2016). Sustainable urbanism: Towards a framework for quality and optimal density? Future Cities and Environment, 2(1), 8. https://doi.org/10.1186/s40984-016-0021-3

Leslie, E., Saelens, B., Frank, L., Owen, N., Bauman, A., Coffee, N., & Hugo, G. (2005). Residents' perceptions of walkability attributes in objectively different neighbourhoods: A pilot study. Health & Place, 11(3), 227–236. https://doi.org/10.1016/j.healthplace.2004.05.005

Lin, I. Y., & Worthley, R. (2012). Servicescape moderation on personality traits, emotions, satisfaction, and behaviors. International Journal of Hospitality Management, 31(1), 31-42.

Miles, P., Miles, G., & Cannon, A. (2012). Linking servicescape to customer satisfaction: exploring the role of competitive strategy. International Journal of Operations & Production Management.

Namasivayam, K., & Mattila, A. S. (2007). Accounting for the joint effects of the servicescape and service exchange on consumers' satisfaction evaluations. Journal of Hospitality & Tourism Research, 31(1), 3-18.

Neckerman, K. M., Lovasi, G. S., Davies, S., Purciel, M., Quinn, J., Feder, E., Raghunath, N., Wasserman, B., & Rundle, A. (2009). Disparities in Urban Neighborhood Conditions:

Evidence from GIS Measures and Field Observation in New York City. Journal of Public Health Policy, 30(S1), S264–S285. https://doi.org/10.1057/jphp.2008.47

Nguyen, Q. C., Khanna, S., Dwivedi, P., Huang, D., Huang, Y., Tasdizen, T., Brunisholz, K. D., Li, F., Gorman, W., Nguyen, T. T., & Jiang, C. (2019). Using Google Street View to examine associations between built environment characteristics and U.S. health outcomes. Preventive Medicine Reports, 14, 100859. https://doi.org/10.1016/J.PMEDR.2019.100859

Noland, R. B. (1995). Perceived risk and modal choice: Risk compensation in transportation systems. Accident Analysis & Prevention, 27(4), 503–521. https://doi.org/10.1016/0001-4575(94)00087-3

Owen, N., Humpel, N., Leslie, E., Bauman, A., & Sallis, J. F. (2004). Understanding environmental influences on walking: Review and research agenda. American Journal of Preventive Medicine, 27(1), 67–76. https://doi.org/10.1016/j.amepre.2004.03.006

Painter, K. (1996). The influence of street lighting improvements on crime, fear and pedestrian street use, after dark. Landscape and Urban Planning, 35(2), 193–201. https://doi.org/10.1016/0169-2046(96)00311-8

Pinto, M. B., & Leonidas, L. (1995). The impact of office characteristics on satisfaction with medical care: a" before and after" analysis. Health Marketing Quarterly, 12(2), 43-54.

Pivo, G., & Fisher, J. D. (2011). The Walkability Premium in Commercial Real Estate Investments. Real Estate Economics, 39(2), 185–219. https://doi.org/10.1111/j.1540-6229.2010.00296.x

Purani, K., & Kumar, D. S. (2018). Exploring restorative potential of biophilic servicescapes. Journal of Services Marketing.

Ram, Y., & Hall, C. M. (2017). Walkable places for visitors: Assessing and designing for walkability. In The Routledge international handbook of walking (pp. 311-329). Routledge.

Ryu, K., & Han, H. (2010). Influence of the quality of food, service, and physical environment on customer satisfaction and behavioral intention in quick-casual restaurants: Moderating role of perceived price. Journal of Hospitality & Tourism Research, 34(3), 310-329.

Saelens, B. E., Sallis, J. F., & Frank, L. D. (2003). Environmental correlates of walking and cycling: Findings from the transportation, urban design, and planning literatures. Annals of Behavioral Medicine, 25(2), 80–91. https://doi.org/10.1207/S15324796ABM2502_03

Sallis, J. F., & Owen, N. (2015). Ecological Models of Health Behavior. In K. Glanz, B. K. Rimer, & K. Viswanath (Eds.), Health Behavior: Theory, Research, and Practice (5th Edition, pp. 43–64). Jossey-Bass.

Stutts, J. C., Hunter, W. W., & Pein, W. E. (1996). Pedestrian Crash Types: 1990s Update. Transportation Research Record, 1538(1), 68–74. https://doi.org/10.1177/0361198196153800109

Summers, T. A., & Hebert, P. R. (2001). Shedding some light on store atmospherics: influence of illumination on consumer behavior. Journal of business research, 54(2), 145-150.

Tang, J., & Long, Y. (2018). Measuring visual quality of street space and its temporal variation: Methodology and its application in the Hutong area in Beijing. Landscape and Urban Planning. https://doi.org/10.1016/J.LANDURBPLAN.2018.09.015

Tombs, A., & McColl-Kennedy, J. R. (2003). Social-servicescape conceptual model. Marketing theory, 3(4), 447-475.

Turley, L. W., & Milliman, R. E. (2000). Atmospheric effects on shopping behavior: a review of the experimental evidence. Journal of business research, 49(2), 193-211.

Walk Score. (n.d.). Walk Score Methodology. https://www.walkscore.com/methodologyhtml

Weld, G., Jang, E., Li, A., Zeng, A., Heimerl, K., & Froehlich, J. E. (2019). Deep Learning for Automatically Detecting Sidewalk Accessibility Problems Using Streetscape Imagery. The 21st International ACM SIGACCESS Conference on Computers and Accessibility, 196–209. https://doi.org/10.1145/3308561.3353798

Wolf, K. (2003). Retail and urban nature: Creating a consumer habitat. Population and Environmental Psychology Bulletin, 29(1), 1-6.

Wolf, K. L. (2004). Nature in the retail environment: Comparing consumer and business response to urban forest conditions. Landscape Journal, 23(1), 40-51.

Whyte, W. H. (1980). The social life of small urban spaces. Conservation Foundation.

Yüksel, F. (2013). The streetscape: Effects on shopping tourists' product/service quality inferences and their approach behaviors. Journal of Quality Assurance in Hospitality & Tourism, 14(2), 101-122.

Zhang, G., Guhathakurta, S., Sanford, J., & Woo Koo, B. (2021). Application for Locational Intelligence and Geospatial Navigation (ALIGN): Smart Navigation Tool for Generating Routes That Meet Individual Preferences. In S. C. M. Geertman, C. Pettit, R. Goodspeed, & A. Staffans (Eds.), Urban Informatics and Future Cities (pp. 191–209). Springer International Publishing. https://doi.org/10.1007/978-3-030-76059-5_11

Zhao, H., Shi, J., Qi, X., Wang, X., & Jia, J. (2017). Pyramid scene parsing network. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2881-2890).

824

Appendix

Table A1. Descriptive statistics of continuous variables

Variable	Mean	SD	Min	Median	Max
Review scores	3.58	0.79	1	3.5	5
Number of reviews	253.3	399.3	10	116	4660
The number of crimes in the walking distance	1,947	1,591	0	1,527	13,777
Distance from the city center (km)	5.0	3.4	0.17	4.0	15.4
Population and employment density (person/km2)	9,335	9,042	657	5,416	38,491
Walk Score	77.9	15.7	6	84	97
Greenness at eye level	13.2%	9.6%	0%	11.8%	52.6%
Building-to-street ratio at eye level	33.9%	29.4%	1.4%	24.4%	148%
Proportion of sidewalk	65.5%	21.0%	0%	64.8%	100%
Proportion of buffered sidewalk	19.5%	14.7%	0%	16.7%	100%
Density of streetlight	0.29	0.19	0	0.25	4.34

Table A2. Descriptive statistics of categorical variables

Variable	category	Count	Proportion
Type of business	Restaurant	754	62.9%
	Cafe	80	6.7%
	Bar	294	24.5%
	Cafe & bar	35	2.9%
Fast food	Yes	114	9.5%
Price level	1	132	11%
	2	890	74.3%
	3	156	13%
	4	20	1.7%
Crossing infrastructure (crosswalk & walk signal)	None	59	4.9%
	Either	487	40.7%
	Both	652	54.4%

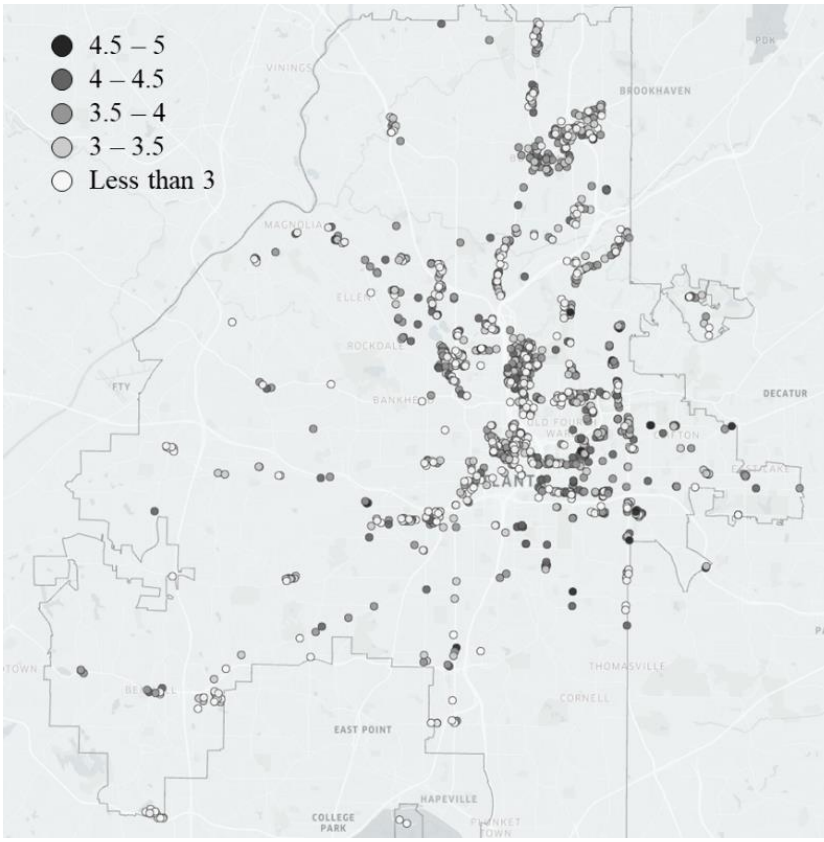

Figure A1. Distribution of review score of restaurants in Atlanta, GA

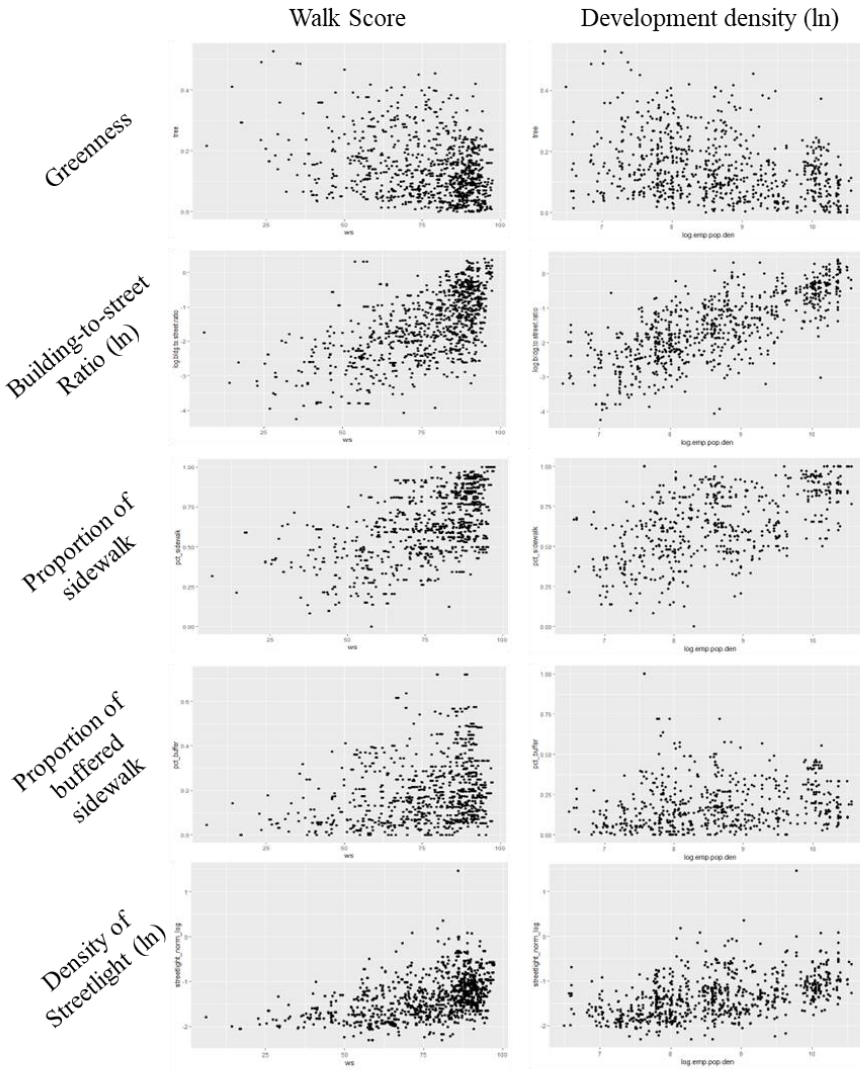

Figure A2. Scatterplot between two macro-scale measures and five meso+micro-scale measures