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Streetscapes as part of servicescapes: Can walkable streetscapes make local businesses more attractive?

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ABSTRACT

Attractive local businesses can make cities more walkable by providing desirable destinations to walk to. 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 and examines whether features that make streets more walkable also make local businesses on those streets more attractive. This study measures walkable streetscape features using street view images and computer vision, which are associated with customer satisfaction values derived from Yelp review scores of restaurants in Atlanta, GA, USA. After controlling for various covariates including pedestrian accessibility, restaurant type, and neighborhood-specific characteristics, this study found sidewalk buffers, greenness at eye level, and building-to-street ratio as streetscape features positively associated with customer satisfaction. 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 used measures of pedestrian accessibility (e.g., land use mix, residential density, and distance to destinations) interchangeably with walkability (De Vos et al., 2022), walkability is not just about accessibility (Koo et al., 2021; Sallis et al., 2015). Another important, but less examined, aspect is the safety (i.e., crime or traffic related), aesthetic quality, and pleasurability of the environment that affect the walking experience (Alfonzo, 2005; Shields et al., 2023). 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 (Alexander et al., 1977; Ewing & Handy, 2009; Hayward & Franklin, 1974). 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 (Alfonzo, 2005). Eventually, these characteristics collectively contribute to placemaking, a function that makes the street itself an attractive destination.

The connection between the quality of streetscapes and the appeal of local businesses is evident in Marketing literature through the concept of "servicescape" (Bitner, 1992). This concept encompasses all physical settings and environments that shape the behaviors and perceptions of both customers and employees (Bitner, 1992; Baker et al., 2002; Ryu &

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Han, 2010). It includes aspects such as the facility's interior, exterior, and ambient conditions. For customers who have not yet experienced the service, servicescapes offer cues regarding service quality and the value of merchandise (Turley & Milliman, 2000; Baker et al., 2002). Well-designed servicescapes enhance customer satisfaction (Bitner 1992; Brady & Cronin, Jr., 2001; Ryu & Han, 2010) and can influence subsequent customer behaviors (Cronin, Brady, & Hult, 2000). As a result, business owners strategically design their servicescapes to foster a positive atmosphere.

A wealth of literature has addressed the cognitive and behavioral impacts of indoor servicescapes which can be controlled by the service organizations. The quality of the surrounding outdoor environment such as safety, comfort, and aesthetics of the nearby streets, 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 make streets more walkable and the customer satisfaction of local businesses along the street. Specifically, this study measures streetscape features using Computer Vision and Google Street View images (Google Maps, 2022). The customer satisfaction is extracted from user review scores from Yelp, a crowd-sourced review portal about local businesses (Yelp Inc, 2022). A fractional response (FR) logistic 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 logistic 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

Walkability received significant attention from scholars, practitioners, and the public, generating a wealth of interdisciplinary literature that views walkability from various perspectives (Shields et al., 2023; Wang & Yang, 2019). Some viewed walkability as the characteristics that makes a space traversable, while others considered walkability as a proxy for generally good places to be (Forsyth, 2015; Shields et al., 2023). Many authors, particularly in the field of public health and urban planning, identified factors that induce walking (Alfonzo, 2005; Day et al., 2006; Millstein et al., 2013; Owen et al., 2004; Sallis & Owen, 2015; Shields et al., 2023; Wang & Yang, 2019, 2019). For example, ecological models of health behaviors considers 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. Alfonzo (2005) further developed the framework by arguing that pedestrians have needs (which they seek to fulfill from their environments) for accessibility, safety (from crime), comfort (of being separated from traffic), and pleasurability. 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). Despite the variations, one commonality found in many studies is the idea that factors fostering walkable environment can be grouped into two broadly defined categories: Neighborhood-level urban form and street-level urban design factors (or simply streetscapes) (Sallis et al., 2015; Shields et al., 2023; Tobin et al., 2022; Toker, 2015). Studies have reported that favorable neighborhood-level and street-level factors do not necessarily co-exist (Bereitschaft, 2017) and may contribute to walkability in different ways, as described in the following sections.

2.1.1. Walkable built environment pertaining to accessibility to destinations

Neighborhood-level urban form factors pertain to the accessibility aspect of the built environment (i.e., the distance and ease of travel between two locations). The determinants of accessibility include 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). They are commonly operationalized using such metrics as residential density, land use mix, intersection density, and retail floor area ratio (Frank et al., 2006). Numerous studies found significant positive association between measures of accessibility and walking behavior and physical activity (Bracy et al., 2014; Cole et al., 2015; Dalmat et al., 2021; Frank et al., 2007; Kerr et al., 2007). These metrics are measured at some aerial units of walkable size, for example, Census Tracts or quarter-mile buffers from places of interest. Extending the benefits of accessible built environment beyond walking and physical activity, other advantages are also investigated, including economic benefits. For example, Pivo and Fisher (2011) hypothesized that accessible environments can reduce transportation costs to daily destinations. They used Walk Score to demonstrate that the benefits of accessibility are capitalized into the property values of offices, retail businesses, and apartments.

As neighborhood-level urban form factors 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 (Harvey & Aultman-Hall, 2016; Tobin et al., 2022). Following these studies, in this paper we use the terms 'macro-scale measures', 'urban form', and 'accessibility' synonymously.

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 can be further divided into meso- and micro-scale factors (Harvey & Aultman-Hall, 2016). Meso-scale streetscapes refer to the "size and arrangement of large objects such as buildings and trees" (Harvey & Aultman-Hall, 2016, p. 150). Micro-scale streetscapes pertain to the most fine-grained details that add texture to the 3D space defined by the meso-scale streetscapes, such as the presence and design of sidewalks, signaled crosswalks, the building-to-street ratio, landscape design, and streetlights.

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 (Ewing & Handy, 2009). Enclosed streetscapes create the feeling of being inside an outdoor room, making the streets more comfortable and inviting, thereby inviting more people and activities (Ewing & Handy, 2009; Harvey et al., 2015). More people on streets can mean more 'eyes on the street,' which can lead to an increased sense of safety (J. Jacobs, 1961). As one of the ways to increase enclosure, New Urbanism thinkers and urban designers argue for putting buildings closer to the streets through minimizing setback requirements (Alexander et al., 1977; Jacobs, 1993; Porta & Renne, 2005). For example, Alexander et al. (1977) wrote that the width of the street should not be greater than the height of the buildings to make pedestrian streets comfortable (p. 490). 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 (Harvey et al., 2015). Street trees can also give streetscapes 'human scale' by subdividing the space between buildings, which can sometimes be vast, into more human-sized spaces (Arnold, 1980).

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 are put close to streets were associated with fewer crashes. Harvey and 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 can 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).

2.2. Measuring built environment using street view images

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 in various fields of study including public health, urban planning, and geographic information science (See Biljecki and Ito (2021) for a comprehensive review and Kang et al. (2020) for a review focused on public health studies). One of the most widely used computer vision models in the literature include Fully Convolutional Networks (FCN), Pyramid Scene Parsing Network (PSPNet), and SegNet (e.g., Koo et al., 2021; Tang & Long, 2018; Wang, Liu, et al., 2019), 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. Various indicators of the streetscapes have been reported, including sky view factor (Li et al., 2018), green view index (Ki & Lee, 2021; Long & Liu, 2017), and street canyon (Middel et al., 2019). Streetscape measurements based on the proportion-based approach have demonstrated effectiveness as predictors of various outcomes, such as walking, physical activity, and mental health (Helbich et al., 2019; Koo et al., 2021; R. Wang, Lu, et al., 2019; Yin & Wang, 2016). For example, Koo et al. (2021) used PSPNet and Google Street View images (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. Wang, Lu, et al. (2019) used the proportion of visible sky in street view images to demonstrate that it is significantly associated with reduced depression and anxiety of older adults.

Another approach for utilizing computer vision focuses on detecting the presence (or absence) of streetscape features or objects of interest (Kang et al., 2021; Weld et al., 2019). This detection could be made for one or more individual objects within each image or for entire images (e.g., generating a perceived safety score for a given image as shown in Yao et al. (2019) or creating a label that describes an entire given image as demonstrated in Nguyen et al. (2019); see Kang et al. (2020) for further discussions about this distinction). 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, sidewalk obstructions and surface issues (Weld et al., 2019).

GSV offers unparalleled spatial coverage and allows for the detailed and comprehensive assessment of urban morphologies and streetscapes, particularly when it is combined with emerging computer vision technology (Ewing & Clemente, 2013; Naik et al., 2014; Rundle et al., 2011). As elucidated by various studies (Badland et al., 2010; Clarke et al., 2010; Hara et al., 2013), the fusion of GSV with advanced computational tools not only paves the way for a deeper understanding of urban structures but also fosters a more holistic approach to studying human-environment interactions. In essence, the synergy between GSV and computer vision technologies is bridging the gap between the physicality of urban spaces and the data-driven analyses that guide our understanding of human-environment interactions.

2.3. 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, Parasuraman, Grewal, & Voss, 2002; Ryu & Han, 2010). While services are intangible and can be experienced only after the customer goes through the process of being served, the

Table 1
Variables and data source.

Category		Variable	Data Source
Dependent variable		Average review scores	Yelp
Local business characteristics		Number of reviews	Yelp
		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 m; 2009–2019)	Atlanta Police Department
Walkable built environment	Macro-scale (urban form)	Distance from the city center (unit: km)	–
		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 (unit: count/m)	

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 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, Miles, & Cannon, 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, Gan, Dubelaar, & Oppewal, 2011; Lin & Worthley, 2012), smell and scent (Chebat & Michon, 2003; Han & Ryu, 2009;), temperature (Pinto & Leonidas, 1995; 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, Purani, & Sahadev, 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. Hahm, Yoon, & Choi (2019) showed that better streetscapes not only affect 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, Willems, & Joye, 2012; Purani & Kumar, 2018; Hamed, El-Bassiouny, & Ternès, 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.

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 and Fisher, 2011). 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

As a proxy for customer satisfaction, we use data from Yelp, a crowd-sourced online platform that provides customer reviews and ratings about various types of businesses. Using Yelp's Application Programming Interface (API) called Yelp Fusion, we collected information about individual businesses, such as location, average review score, number of reviews, type of business, and price level. The information on 1415 restaurants in the City of Atlanta was initially retrieved. For the validity of the average review score, we filtered out observations with <10 reviews, which resulted in a sample size of 1198 (see Appendix for the discussion on choosing the optimal cutoff value).

Among many types of local businesses, this study focuses on

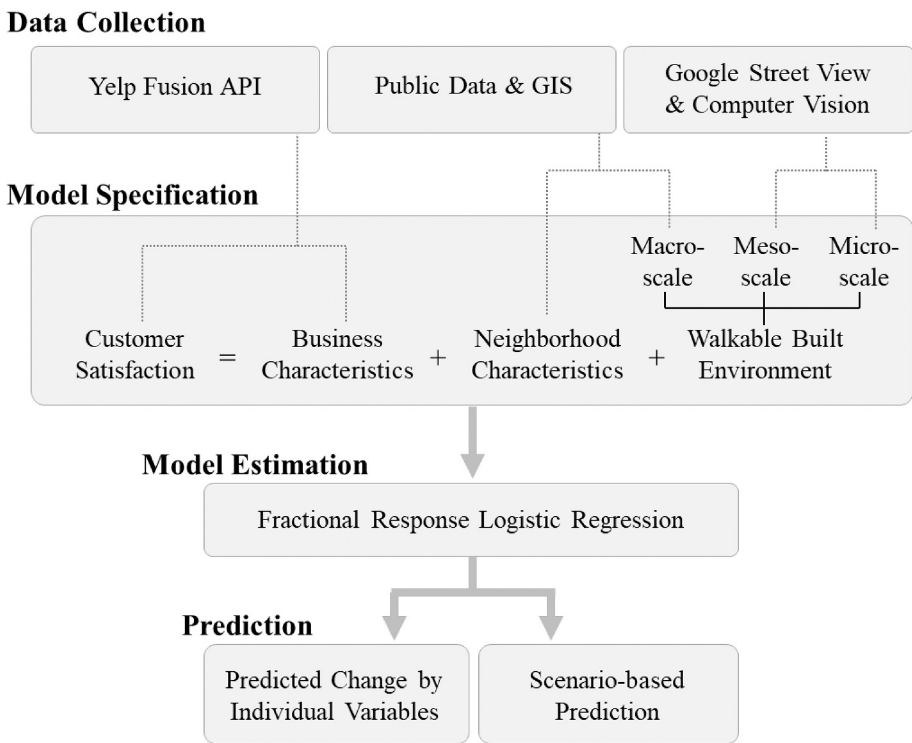

Fig. 1. Research Flowchart.

restaurants, cafes, and bars (which are collectively referred to as 'restaurants' in this study) for the following reasons: First, Yelp has a particularly extensive amount of review data on restaurants (Asghar, 2016). Second, because factors affecting customer satisfaction are likely to vary by business type, focusing on restaurants would make modeling of the relationship between the streetscapes and customer satisfaction more parsimonious (Asghar, 2016). This study focuses on restaurants in the City of Atlanta, Georgia, USA. The unit of analysis is individual restaurant Point-of-Interest (POI). The review score is measured on a scale of one to five, with increments of 0.5, where one represents the most dissatisfying experience and five represents the most satisfying customer experience. One limitation of Yelp is that it provides review scores for each business in the form of an average score calculated over an unspecified timeframe, which may differ for each business and is outside the control of API users.

Independent variables are grouped 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).

Two measures of neighborhood characteristics are considered, including the number of crimes within 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-m 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 an unspecified time window. See Fig. 1 for the overall research flowchart.

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 (U.S. Census Bureau, 2022b). 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 (U.S. Census Bureau, 2022a). One job reported in LODES is one person whose origin and destination for commuting is known. Population and employment density were then summed to represent the combined density of people who live or work in a neighborhood. 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 m in length or had <10 GSV images, we considered other street segments within a 150-m buffer and assigned the maximum among these other street segments to the restaurant. This study used a total of 51,317 GSV images.

For each street segment, seven factors pertaining 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 street 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 related to streetscape enclosure and urban greenery using the equations shown below and averaged across all images of each street segment.

$$\text{Building} - \text{to} - \text{street ratio at eye level} = (\%\text{building} + \%\text{house})/(\%\text{sidewalk} + \%\text{road} + \%\text{car})$$

$$\text{Greenness at eye level} = \%\text{tree} + \%\text{grass} + \%\text{plant}$$

Five micro-scale features[1]—crosswalks, walk signals, sidewalks, buffers, and streetlights—were measured using a custom-trained computer vision model named Mask R-CNN developed in Koo et al. (2022). To increase the likelihood of capturing objects of interest in GSV images, the collection of images needs to be more comprehensive for detecting micro-scale features compared to meso-scale measures (Koo et al., 2022). For a given street segment, two images are downloaded at each intersection so that the combination of the two images can cover the entire road width and the sidewalk curves on both sides of the road. In addition to the images at intersections, GSV images along the main stretch of the street segment are downloaded at 5-m intervals. At each interval location, three images were downloaded such that the images are looking left and right sides of the road, as well as upward. Duplicate images were deleted to prevent potential double counting issues.

The detection results for micro-scale features were used to calculate the proportion of images containing sidewalks, proportion of images containing buffered sidewalks, the presence of crosswalk and walk signal, and the density of streetlights for each street segment. The proportion of images containing sidewalks represents the proportion of images of each street segment in which sidewalks are detected. Similarly, the proportion of images containing buffered sidewalks is the proportion of images of each street segment in which buffered sidewalks are detected. 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. When calculating these proportions, the total number of images of each street segment was used as the denominator instead of the length of the segment because GSV images are captured at relatively fixed distance and the total number of images along a given street segment is often proportional to the length of street segment. We chose to use continuous measurements for the sidewalks and buffered sidewalks over a binary measure (i.e., present or absent) because 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 a binary classification arbitrary. Regarding the traffic safety related to street crossing, this study used the detection results of crosswalks and walk signals to construct 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 custom-trained Mask R-CNN, with the intersection over union threshold of 0.3, are shown in Table 2. Note that this study uses images that are looking both horizontally (i.e., left and right sides of the road) and upward to include streetlights above the 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 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. Fractional response logistic regression model

The dependent variable is Yelp review scores, which range between 1 and 5 at 0.5 increments. This study initially considered linear regression, ordinal regression, or multinomial logistic regression for statistical modeling, these models were found to be unsuitable due to the following reasons: (1) conventional linear regression model was not chosen because it can generate predicted values that lie outside the lower and upper bounds of the dependent variable, (2) ordinal logistic regression model was not chosen because the proportional odds assumption was not met for our data, and (3) multinomial logistic regression model was not selected because treating the dependent variable as an unordered categorical data would lose the information about the ordered nature of the variable and also fail to meet the assumption of the Independence of Irrelevant Alternatives (IIA). As an alternative, In this study, a FR logistic regression model was utilized. This model operates similarly to binary response logistic regression models, but the difference is that the dependent variable can be a fraction or proportion. The advantage of this model is that it provides upper and lower bounds (i.e., 0 and 1) and is not restrained by the proportional odds assumption, which is seen in 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.

$$y_i^{'} = (y_i - min(Y)/(max(Y) - min(Y))$$

This transformation changes the original range of 1–5 to 0–1, where 0 being the most unsatisfactory restaurant and 1 being the most satisfactory restaurant. With the transformed dependent variable, the FR logistic regression model is fitted. The statistical analysis was conducted in R 4.0.2 using *glm* function with quasibinomial distribution.

Note that in the FR logistic regression model, it is not appropriate to assume that the upper bound of ρ^2 (i.e., a measure of goodness of fit) is 1, which in theory is attainable only when the dependent variable is binary (Hauser, 1978, as cited in Mokhtarian & Bagley, 2000). When the dependent variable continuously ranges between 0 and 1, we can manually calculate the theoretical maximum log-likelihood by

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

where f_{in} is a fraction of choosing alternative i for individual n. The manually calculated theoretical maximum log-likelihood is used to determine the fit of the regression models in this study.

A few adjustments were made to the independent variables as well. First, we log-transformed highly right-skewed variables if the

[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.

[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.

transformation contributed to better model fits. Second, 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.

Because the dependent variable is transformed from 1-to-5 scale to 0-to-1 scale and then fitted the FR regression, the coefficient estimates from the FR logistic regression does not reflect the original 1-to-5 scale, making the interpretation of the coefficients less intuitive. To help with interpretation, we first focus on only the direction and the statistical significance of coefficient estimates. Next, this study presents two types of predictions using the estimated coefficients to convey the effects of coefficients in more intuitive ways. First, we present the predicted changes in the review score in 1-to-5 scale when each independent variable is increased by one standard deviation (1-SD) from its mean, while holding other variables constant at their mean (for continuous variables) or mode (for categorical variables). Next, this study presents a scenario-based prediction to illustrate how the review scores are predicted to change if a restaurant currently in an unfavorable streetscape is moved to locations that have better streetscapes while holding other variables constant.

4. Result

4.1. Descriptive statistics

We present descriptive statistics before discussing the regression models and their diagnostics to provide an overview of the data used in the analysis (see Table 3). The mean review score was 3.6, and the average number of reviews was 253. The average number of crimes may appear high, but it is the cumulated count over a decade. The average Walk Score was 77.9, suggesting that restaurants are generally in areas with high accessibility, although the range was wide. For greenness, roughly 13% of the pixels in an image were green on average. The average building-to-street ratio suggested more open meso-scale streetscapes in general, with a few highly enclosed streetscapes. Sidewalks and buffered sidewalks suggest that, on average, about 65% and 20% of a given street segment was lined with sidewalks and buffered sidewalks, respectively. The density of streetlight suggests that there was one streetlight roughly every 8 m on each side of a street. 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. We did not find any visual sign of spatial autocorrelation (see Fig. A1 in Appendix).

4.2. Regression

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. Being fast-food, the number of crimes, population and employment density were negatively associated with review scores. Among the streetscape characteristics, the proportion of buffered sidewalks, greenness, and building-to-street ratio were positively and significantly related with review scores, indicating that more enclosed streetscapes with greenery and physical separation from traffic can contribute to customer satisfaction. The proportion of sidewalks was not significantly associated with review scores. Among all polynomial terms we tested, only Walk Score showed a statistically significant polynomial term, suggesting a convex (i.e., U-shaped) relationship. When Walk Score is low, it had negative relationship with review scores, which flips to a positive relationship at 66 or higher. At its mean (i.e., 78), Walk Score had a positive impact on review score.

Note that the variance inflation factors (VIF) showed that the variables do not have severe multicollinearity. The ρ^2, the model fit measure, is 0.098 and the adjusted ρ^2 is 0.074. The theoretical maximum log-likelihood value of this study is −672.0, which leads to the theoretical maximum ρ^2 value of 0.19. This maximum value suggests that the

Table 3
Descriptive statistics of continuous variables.

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	1947	1591	0	1527	13,777
Distance from the city center (km)	5.0	3.4	0.17	4.0	15.4
Population and employment density (person/km2)	9335	9042	657	5416	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

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%

Table 4
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
		Business type (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
		Population and employment density (ln)		−0.081	*	−2.13
Walkable built environment	Macro-scale (urban form)	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				1198	
	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 5
Predicted changes in the review score when each of the significant independent variable is increased from the mean by 1-SD.

Significant independent variable	Mean or mode of each variable	Mean + 1 SD	Predicted changes in review Score
Number of reviews	253	652	+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	1947.3	3538.7	−0.10
Distance from the city center	5 km	8.4 km	−0.07
Population and employment density	9335	18,377	−0.07
Walk Score	78	94	+0.12
Greenness at eye level	13%	23%	+0.05
Building-to-street ratio at eye level	33.9%	63.3%	+0.09
Proportion of buffered sidewalk	20%	34%	+0.05

adjusted ρ^2 of 0.074 in this model is a modest result.

Because the coefficient estimates in Table 4 are not in the original scale of review score and are not intuitive, Table 5 provides the predicted changes in the 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. The log-transformed variables are also shown in the de-logged, original scale in Table 5. The business-specific variables generally show sizable effects on review scores. The 1-SD increase in the number of reviews (i.e., +399 from 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, which was the largest change across all independent variables. While raising the price level from the cheapest to the second cheapest was associated with a 0.48 increase in review scores, raising the price level higher was linked with much reduced amount of increases. The 1-SD increase in the number of crimes in the walking distance (i.e., +1591 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., +3.4 km) was associated with a 0.07 lower review scores.

When the population and employment density is 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 again that the U-shaped relationship of Walk Score means that the same 1-SD change can lead to different amounts 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 (i.e., 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 (i.e., 15 percentage points increase), the review score increased by 0.05.

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, Fig. 2a shows the image of the restaurant facing a street for which the three meso- and micro-scale factors shown to be significant in Table 4 – 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, and the observed review score of the restaurant

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

Fig. 2. 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 Fig. 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 Fig. 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**)

Table 7
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)

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 increased by varying amounts. 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 all 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, Fig. 2b 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 Fig. 2a to 2b, the score will increase by 0.24.

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. One possible explanation is rooted in the fact that the widely used conceptualization of walkability, as well as its quantitative measures such as population 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 both good accessibility and good place/urban design (Forsyth, 2015), because highly accessible places are often well-invested and maintained. In fact, our data corroborated these connotations – the two macro-scale measures showed significant and positive correlations with the streetscape features that constitute good urban design (See Table 7 as well as the scatter plots in Fig. A2). The coefficient estimates for Walk Score and the density variable in Table 4 may be different from the expectation because the estimates represent the effect of accessibility on 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.

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 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.

The two meso-scale features—building-to-street ratio and greenness—both 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, Willems, Brengman, & Wolf, 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.

There are important limitations of this study that need to be clarified. First, the computer vision models used in this study may have introduced noises and possibly biases to the streetscape measurements. As illustrated in Table 2, the computer vision models showed lower recalls than precisions, indicating that there can be many objects that existed on streets and the computer vision models failed to detect them. Second, 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 are overlapped and counted more than once. We suspect that the 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. Third, we measured the streetscapes of only the closest street to the restaurant. 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. Fourth, 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. Fifth, 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.

6. Conclusions and implications

This study examined the impact of walkable urban forms and streetscapes on customer satisfaction, positing that streetscapes can function as part of servicescapes. Two key insights emerged from the results. Firstly, while accessibility is often synonymous with positive walkability, it does not necessarily translate to improved customer experiences. Secondly, three streetscape features – the building-to-street ratio, greenness, and the proportion of buffered sidewalks – exhibit strong positive correlations with customer satisfaction. These findings underscore the crucial role of urban design elements, such as a sense of enclosure and green spaces, in determining satisfaction.

Planning and policy tools for modifying the three 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. The road diet is one well-known strategy that can achieve this goal, particularly if it increases sidewalk buffers. 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 heights (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 enhance servicescapes, which would also improve the economic opportunities of the businesses on those streets.

CRediT authorship contribution statement

Bon Woo Koo: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Uijeong Hwang:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Subhrajit Guhathakurta:** Conceptualization, Resources, Supervision, Writing – review & editing.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compenvurbsys.2023.102030.

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