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How are Neighborhood and Street-Level Walkability Factors Associated with Walking Behaviors? A Big Data Approach Using Street View Images

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Abstract

The built environment characteristics associated with walkability range from neighborhood-level urban form factors to street-level urban design factors. However, many existing walkability indices are based on neighborhood-level factors and lack consideration for street-level factors. Arguably, this omission is due to the lack of a scalable way to measure them. This paper uses computer vision to quantify street-level factors from street view images in Atlanta, Georgia, USA. Correlation analysis shows that some streetscape factors are highly correlated with neighborhood-level factors. Binary logistic regressions indicate that the streetscape factors can significantly contribute to explaining walking mode choice and that streetscape factors can have a greater association with walking mode choice than neighborhood-level factors. A potential explanation for the result is that the image-based streetscape factors may perform as proxies for some macroscale factors while representing the pedestrian experience as seen from eye-level.

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It is widely accepted that urban residents' travel behavior is influenced by the built environment. With growing concerns about the lack of physical activity and the excessive use of automobiles, the characteristics of the built environment that encourage walking and other active modes of transportation have gained prominence. Various walkability indices have been developed to objectively measure the characteristics of the built environment that are conducive to walking behaviors, ranging from indices that focus on neighborhood-level urban form factors (e.g., population density, land use diversity, and street connectivity) to those focusing on street-level urban design factors (e.g., the scale and proportion of streets, the design and condition of buildings, and street furniture). To date, the majority of such indices, particularly ones that have a broad geographic coverage such as Walk Score® (Walk Score, n.d.) and the National Walkability Index (U.S. Environmental Protection Agency, 2015), are constructed with mostly neighborhood-level factors. Street-level factors are included to a limited extent due to the constraints in data availability (Harvey & Aultman-Hall, 2016).

Although walkability indices that are based on neighborhood-level factors have been generally proven to be effective (Chiu et al., 2015; Duncan et al., 2011; Manaugh & El-Geneidy, 2011), the hierarchy of walking needs hypothesis by Alfonzo (2005) suggests that neighborhood- and street-level factors can contribute differently to different levels of walking needs. For example, neighborhood-level factors can be more closely associated with the accessibility need in Alfonzo's hierarchy, which is a basic level of walking need (e.g., having places to go to and being functionally-connected to those places). Street-level factors often are more closely linked with higher-level needs, such as the need for safety, comfort, and pleasurability (e.g., the quality of the experience going to places) (Adkins et al., 2012; Alfonzo, 2005). Street-level factors can be particularly important as a place can have walking-conducive neighborhood-level factors but have poor street-level factors (Bereitschaft, 2017; Zhu & Lee, 2008), and recent studies report the importance of street-level factors in walking behavior (Adkins et al., 2012; Ewing & Clemente, 2013; Foltête & Piombini, 2007; Gallimore et al., 2011).

One of the reasons for failing to incorporate the street-level factors in walkability indices is the difficulty in obtaining objective measurements for large geographic areas (Harvey et al., 2015). Traditionally, street-level factors have often been measured using methods such as audit tools, expert evaluations, or surveys of participants' perceptions. Although these methods have provided invaluable ways to operationalize walkable streetscapes, audit tools and expert evaluations in particular are usually resource-intensive and time-consuming, making it difficult to be scaled up to large areas such as a city or a region.

Recent advances in computer vision techniques and increasingly available street view image datasets offer a unique opportunity to address this limitation by allowing researchers to automatically quantify street-level factors in more scalable ways than the traditional methods. Although a few pioneering studies have tested these techniques along similar lines of research (Dubey et al., 2016; Glaeser et al., 2018; Li et al., 2018; Seiferling et al., 2017; Tang & Long, 2018; Wang, Helbich, et al., 2019; Yin & Wang, 2016; Zhang et al., 2019), only a few focused explicitly on measuring walkability and how the measurements using these techniques relate to walking behavior. Also, few such studies have accounted for factors such as neighborhood-level factors and sociodemographic, behavioral, and trip-related variables, which are important in pedestrians' decision to walk (Alfonzo, 2005).

This study addresses the data limitation for street-level factors by using Google Street View (GSV) images and a semantic segmentation technique. This technique involves a computer vision task that labels each pixel in an image with what the pixel is likely representing. Also importantly, this study incorporates various neighborhood-level factors and other person- and trip-related control variables in the analysis. In particular, it focuses on walkability factors in *mesoscale*, a spatial scale in street-level that is smaller than macro- (neighborhood-level) but larger than micro-scale (detailed design features) that represents the scale and proportion of the major objects of streetscapes. This study aims to answer the following questions: Is there a relationship between neighborhood- and street-level factors when evaluating the walkability of a place? To what extent does the inclusion of street-level or mesoscale factors improve our ability to explain people's walking mode choice? The following section provides a brief overview of past findings, highlights important gaps in the research, proposes a theoretical framework, and introduces the formal hypotheses. Section Three describes the data and analytical methods of this study. Section Four presents the results using correlation analysis and tests the hypotheses using binary logistic regression models explaining the choice of walking compared to the non-walking modes. The last two sections discuss potential explanations for the results, clarify limitations, and highlight the implications of this study.

Literature Review

Built Environment Factors Influencing Walkability

The three "D" variables (3D)—density, diversity, and design, or the five "D" variables (5D), which add destination accessibility and distance to transit to the 3Ds, have been the foundational framework of numerous studies on travel behavior and walkability (Ewing & Cervero, 2010; Smith et al., 2008). Similarly, Handy et al. (2002) list density and intensity of development, land use mix, street connectivity, the scale of streets, and esthetic qualities of a place as the dimensions of the built environment influencing physical activity. The dimensions in these frameworks encompass various spatial scales, and some studies have grouped these dimensions into two broad categories; neighborhood- and street-level factors (Cain et al., 2014; Harvey & Aultman-Hall, 2016; Mertens et al., 2015).

Neighborhood-level factors consist of macro-scale characteristics such as residential density, land use diversity, distance to destinations, and street connectivity (Ewing & Clemente, 2013; Sallis et al., 2011). Density and diversity are aggregate characteristics of the built environment that are often defined and measured at some aerial units (e.g., Census Tracts)—hence the name "neighborhood-level." Density and diversity of different types of land uses contribute to walkability by placing more activities in a given land area and by mixing different types of origins and destinations in proximity (Saelens et al., 2003). Street connectivity relates to the directness of travel on the street network (Saelens et al., 2003). For example, even when the straight-line distance is the same, actual travel distance may be shorter when the street network follows a grid-pattern than when streets are sparsely connected like the ones commonly found in low-density suburbs (Saelens et al., 2003).

Most of the existing walkability indices are constructed based on neighborhood-level factors. Neighborhood-level factors are commonly measured using population, housing or employment data, street network, land or building use, and business location data, which are usually more widely available than data for street-level factors. Walk Score®, one of the most widely used walkability indices, is one such example. Walk Score® (n.d.) calculates its score based on the walking route distance from a given address to potential walking destinations. The calculation also includes pedestrian friendliness metrics such as population density, intersection density, and the average block length.

Street-level factors, in general, are the streetscapes and design details that are smaller in scale than neighborhood-level factors, such as the configuration of street width and building height, the style and material of buildings, street trees and other planters, pedestrian-friendly facades, and street furniture and other fixtures. The street-level factors are commonly defined at eye level and are more visually perceivable than neighborhood-level factors. Street-level factors are closely linked with the scale and esthetic qualities of streets (Handy et al., 2002). These factors shape urban design qualities (e.g., imageability, enclosure, human scale, and transparency) that influence walkability through eliciting individuals' reactions such as a sense of safety, sense of comfort, and level of interest (Ewing & Handy, 2009). These reactions "contribute to an overall perception of walkability and, ultimately, walking behavior" (Adkins et al., 2012, p. 500).

Some studies suggest that street-level factors can further be divided into two subgroups: (1) the structural form of streets and (2) finer design details attached to the structural form (Handy et al., 2002; Harvey & Aultman-Hall, 2016). The structural form determines "three-dimensional space along a street as bounded by buildings or other features (e.g., trees or walls)" (Handy et al., 2002, p. 66). Similarly, Harvey and Aultman-Hall (2016) define streetscapes as "the size and arrangement of large objects such as buildings and trees" (p. 149) and proposes to call it *mesoscale*, a midlevel spatial scale between macro- and micro-scale. The most fine-grained design details, such as memorable details on buildings and pedestrian-friendly façade, are considered microscale. This layer functions like a skin covering the structural form determined by the mesoscale streetscapes (Harvey & Aultman-Hall, 2016). Because microscale design details often involve highly granular features, automatically measuring them can be challenging (Harvey et al. 2017).

Considering both neighborhood- and street-level factors in measuring walkability can be important because neighborhood-level factors alone can be limited in representing various stages of individuals' decision-making process for walking. Alfonzo's hypothesis about the hierarchy of walking needs suggests that the most fundamental walking need is *feasibility*, which is the condition of individuals that makes a walking trip feasible, such as age, physical condition, or available time (Alfonzo, 2005). The next fundamental level of the hierarchy is *accessibility* (e.g., having places to go to and being functionally connected to those places). It is followed by other higher-order needs such as *safety, comfort*, and *pleasurability* (e.g., the quality of the experience going to places). Note that *safety* here pertains closely to safety from crime and incivility while *comfort* is linked with safety from traffic. Pedestrians seek to fulfill the need for accessibility, safety, comfort, and pleasurability when they make the decision to walk (Alfonzo, 2005). These needs would be fulfilled if the characteristics of the built environment offer desirable accessibility, safety, comfort, and pleasurability to pedestrians who are considering walking in it. Therefore, the accessibility, safety, comfort, and pleasurability can be considered both as the needs of pedestrians or the quality of the built environment.

Although there is not a clear distinction in terms of which scales of walkability factors are associated with which level of walking needs, past studies seem to suggest that the accessibility needs can be captured by macroscale (i.e., neighborhood-level) factors while higher-order needs can be more closely proxied by meso- or microscale factors (Adkins et al., 2012; Alfonzo, 2005; Harvey et al., 2015). For example, the accessibility needs of Alfonzo's hypothesis can be operationalized as the distance, the number, and the mix of destinations, and the completeness of walking infrastructure (Alfonzo, 2005). The three higher-order needs, on the other hand, may be operationalized using measures such as the presence of varied streetscapes and public spaces, the width of streets and sidewalks, the existence of sidewalk buffers, street trees, and medians, and street furniture and water fountains (Alfonzo, 2005). Similarly, comfort and safety are associated with the cross-sectional proportion of mesoscale streetscape, the number of buildings per 100 m, and tree coverage (Harvey & Aultman-Hall, 2015; Harvey et al., 2015).

Alfonzo's hypothesis poses that "an individual would not typically consider a higher-order need in his or her decision to walk if a more basic need was not already satisfied" (Alfonzo, 2005, p. 818). From this hierarchical order, it can be conjectured that macroscale factors may have a more fundamental relationship with walking behavior than meso- or microscale factors. Some of the past findings seem to support Alfonzo's hypothesis by showing that microscale factors (e.g., benches at bus stops) tend to have weaker impacts on travel behavior than macroscale factors such as land use mix (Cervero & Kockelman, 1997). However, recent studies report significant effects of some street-level factors (i.e., meso- or microscale factors) even after controlling for neighborhood-level factors (Adkins et al., 2012; Cain et al., 2014; Ewing & Clemente, 2013). Importantly, Alfonzo et al. (2008) empirically examine their hypothesis by sequentially adding the measures of accessibility, safety, comfort, and pleasurability into regression models. They found that the measures of accessibility and safety were significantly associated with the number of walking trips for all purposes as well as for the number of destination walking trips (e.g., going to park, store, work, or school). For recreation trips, only the safety measure was significantly associated with the trip frequency. These studies indicate that both neighborhood- and street-level factors may be contributing to walking behavior, with some studies reporting a higher significance of the street-level factors.

Measuring Mesoscale Streetscapes in the Literature

Because of the high cost of measuring street-level factors through the conventional methods, some studies focused on *mesoscale* factors as they are relatively small in scale and likely to be closely linked with higher-order walking needs (e.g., safety and comfort). Yet, they can be more amenable to objective and automated measurements than even smaller microscale factors (Harvey et al., 2017). Mesoscale streetscapes can be measured with metrics that define the boundary of the void between buildings and trees (Harvey & Aultman-Hall, 2015; Harvey et al., 2015, 2017). Harvey et al. (2015) used GIS and six mesoscale streetscape measurements to explain perceived safety in New York City, New York, USA. They found that street tree canopy, the number of buildings along a block, the cross-sectional proportion, and the length of a street segment have significant positive effects on perceived safety. They also found that the effects of mesoscale streetscape variables on perceived safety are greater than a neighborhood-scale urban form measure (in this study, Walk Score®). Using the same set of mesoscale streetscape measurements, Harvey and Aultman-Hall (2015) investigated the relationship between the mesoscale streetscape and safety from traffic. After controlling for being on arterial roads, they found crashes that occurred on smaller, more enclosed streetscapes are less likely to be severe.

With the introduction of GSV, an increasing number of studies started measuring streetscape characteristics using street view images. Some studies used street view images to virtually audit (i.e., manually auditing streetscapes using street view images as opposed to physically being on the site) the streetscape characteristics (Bader et al., 2017; Clarke et al., 2010; Griew et al., 2013; Rundle et al., 2011). For example, Clarke et al. (2010) compared on-site audit and virtual audit and reported high reliability between the two audit methods. Bader et al. (2017) further demonstrated the effectiveness of virtual audits by illustrating how different sociodemographic groups are associated with the unequal exposure to disorderly neighborhoods. Other studies incorporated computer vision techniques to measure the built environment from street view images automatically and have linked the measurements to various behavioral and health-related outcomes. Focusing on streetscapes and walkability or walking behavior, Yin and Wang (2016) used GSV images collected from 311 street blocks in Buffalo, New York, USA and found a significant relationship between the proportion of sky (i.e., visual enclosure) and pedestrian count and Walk Score®. Wang, Lu, et al. (2019) examined the relationship between neighborhood street walkability and the mental health of older residents in 45 residential neighborhoods in Haidian District in Beijing, China. Using the average of the proportion of sky from street view images taken from road segments within a 1000 m-buffer around each study neighborhood as a proxy for neighborhood walkability (i.e., the lower the proportion of sky, the higher the walkability), they found a positive relationship between walkability and mental health. Similarly using sky visibility to represent enclosure and the visibility of street greenery as streetscape measurements, Li et al. (2018) studied the relationships among enclosure, street greenery and walking trip count in Boston, Massachusetts, USA in various land use types. Wang, Liu, et al. (2019) used street view images to predict perceptions of neighborhood appearance (wealthy, safe, lively, beautiful, boring, and depressing), which were then regressed against the total time and intensity of physical activity. They found positive associations between physical activity with safe, lively, and beautiful appearances and negative associations with depressing and boring appearances of neighborhood environments. Nguyen et al. (2019) used GSV images to characterize the national built environment with the presence of highways, rural, and grassland and examined their association with various health outcomes at county and Census tract levels. They found associations between greater presence of highways and lower chronic diseases and premature mortality as well as between characteristics of rural areas and multiple adverse health outcomes including obesity, physical inactivity, premature mortality. Hankey et al. (2021) used street environment characteristics derived from GSV images as well as other public data sources (e.g., Census, Google Point of Interest) to predict pedestrian and bicycle counts. They found that the inclusion of street-level data improved prediction accuracy and that street-level data can be a useful alternative to Census data. Some studies focused on greenery at eye level and computed green view index (GVI) by calculating the proportion of green shown in street view images. It was found that GVI provide unique information that other conventional data sources do not capture (Larkin & Hystad, 2019; Li et al., 2015) and that street view-derived GVI is more closely associated with walking time than traditional greenery variables (Ki & Lee, 2021).

Although street view image-based measurements have opened a new possibility for measuring meso- and microscale built environmental factors, there remain important research gaps. First, because there are a limited number of studies in the walkability literature that have used street view images and automatic measurement techniques such as computer vision, the effectiveness of this measurement technique is less understood. Second, because the studies often incorporated a limited set of neighborhood-level factors, or entirely excluded them in some cases, the empirical understanding of the relationship between neighborhood- and street-level factors and their relative contribution to walking behavior is limited. Third, the existing walkability studies that incorporated meso- or microscale walkability factors using street view images and computer vision techniques often failed to control for individual travelers' characteristics (Li et al., 2018; Yin & Wang, 2016). Given that the individual travelers' characteristics can be closely associated with the most fundamental layer in the hierarchy of walking needs, that is, the feasibility for walking, it is critical that they are included in the walkability models as controls.

This study attempts to address these limitations in the following ways: First, it uses a more ubiquitously available measure of city-wide mesoscale streetscape factors derived from GSV images with the help of semantic segmentation together with neighborhood-level factors. Second, this study incorporates multiple neighborhood-level and street-level factors to examine how they are related to each other as well as to determine their contribution to walking behavior. Third, it controls for personal- and trip-level variables derived from a travel survey. This study advances the literature on walkable environments by empirically exploring the relationship between neighborhood- and street-level factors and examining how they contribute to walking behavior.

Hypotheses and Theoretical Framework

To translate the preliminary research questions posed in the Introduction into a set of formal hypotheses, we propose here a theoretical framework that synthesizes the empirical findings and discussions in the relevant literature. As shown in Figure 1, the neighborhood- and street-level walkability factors together determine overall walkability. The overall walkability is then combined with travelers' individual-level factors to influence the decision to walk. For consistency, this study heretofore refers to the three scales of walkability measurements as macro-, meso-, and microscale factors. It is important to clarify that this study does not directly measure the walking needs. The concept of "walking needs" is introduced in this study as a theoretical link to illustrate why considering various scales of measurements can be important in explaining walking mode choice. Also, we use street view images and semantic segmentation to extract *mesoscale factors*, and we do not consider microscale factors. The mesoscale factors we measure in this study is limited to some of the operationalizable proxies of the walking needs that are readily measurable using the capabilities of the current state of computer vision models.

With this theoretical framework, the research questions posed in the Introduction can be formally refined into hypotheses. The first hypothesis is that both macroscale and mesoscale factors will have statistically significant

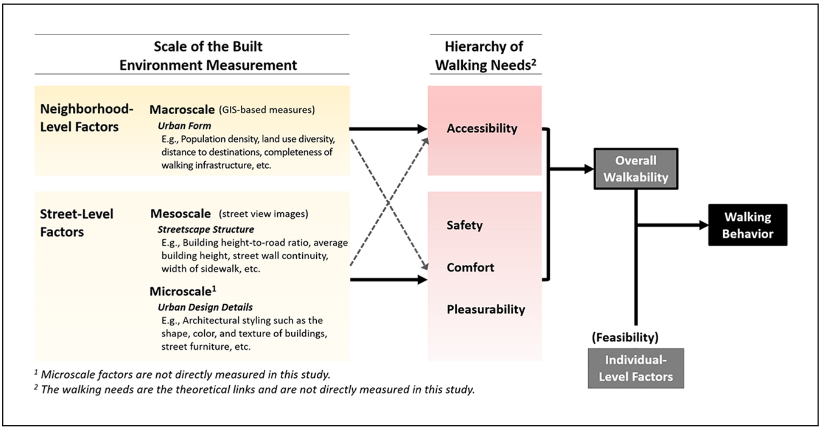

Figure 1. The overall theoretical framework of the analysis.

contributions to walking mode choice models when they are used separately. This hypothesis reflects the recent findings in the literature that challenge the past studies showing weak to insignificant associations of street-level factors on walking behavior. Second, we hypothesize that macroscale and mesoscale factors will together explain the variation in walking behavior better than when they are used separately, given their unique and independent contributions. Note that the second hypothesis is, in essence, testing whether mesoscale factors, as measured using a computer vision technique, will incorporate particular information about the built environment that macroscale factors cannot. If, for example, mesoscale factors turn out to be highly correlated with macroscale factors, we can conclude that mesoscale factors do not have additional useful information about the walkability of the built environment compared to the macroscale factors.

Data and Methods

National Household Travel Survey Data

All data used in this study were collected for the City of Atlanta, Georgia, USA. We extracted travel data from the 2017 National Household Survey (NHTS). The NHTS Georgia add-on data was provided by the Georgia Department of Transportation, from which we acquired information about the location of the trip origin, the mode, purpose, and the travel distance of the trips, basic socioeconomic and demographic information, and other behavioral characteristics for each trip, which served as the unit of analysis. To retain a sufficient sample size while reducing the computation resources required to process GSV images, we limited our analysis to trips that have origins within the city boundary and did not consider the built environment of destinations. Following Cervero and Duncan (2003), we limited the analysis to trips "that were unlikely to involve carrying significant amounts of items or goods" (9) and included trips that traveled for family/personal business, school or religious activities, socializing/recreational purposes, for eating out, or for grocery or other types of shopping. We also narrowed the analysis to trips that traveled less than or equal to 1 mile, which is roughly the 90th percentile of the travel distance of walking trips in the data, as distances greater than that can quickly become challenging for walking. We removed people who are less than 10-years of age and those who are using supportive devices such as wheelchair from analysis as their choice to walk can be affected by factors outside the scope of this study (e.g., the availability of caregivers). We also excluded item-nonresponses, missing values, and unrealistic data entries as determined by the data provider, the Federal Highway Administration. Finally, we coded the travel mode into a binary variable with labels walking and non-walking and used it as the dependent variable.

The sociodemographic and other behavioral variables derived from NHTS include age, gender, race, educational attainment, number of vehicles owned by the household, household income, driver status, number of walking activities in the past 7 days, and the travel distance of each trip. These variables were included as control variables.

Google Street View Data

The image sampling method used in similar past studies can be categorized into two large groups: one group that focuses on capturing the built environment of intersection locations (e.g., Nguyen et al., 2019) and the other group that uses multiple images along the entire span of street segments with some fixed distance intervals such as 20, 50, or 100 m (e.g., Ki & Lee, 2021). It is common for both methods to use 360° panoramic images for each image location, with some exceptions that relied on particular portions of images or directions (e.g., Yin et al., 2015). While focusing on intersections allows the measurement of streetscapes at important nodes of street networks with fewer images for a given areal unit, it is limited in capturing the streetscape characteristics that pedestrians experience as they move from one intersection to another. In contrast, while collecting images for the entire span of segments can provide a comprehensive view of the streetscapes, it requires a much greater number of images and computational resources for processing the images.

The GSV images used in this study were identified and downloaded using the following method, which combines the two approaches in the literature. First, four points were plotted for each street segment; two points at the middle of a street segment (heretofore, midpoints) and two points at either end of the street segments (heretofore, endpoints) using ArcGIS 10.5.1 and the road shapefile from Topologically Integrated Geographic Encoding and Referencing (TIGER) database. All points that are within 20-m from expressway centerlines were deleted. Second, the heading of the camera was calculated differently for midpoints and endpoints. For midpoints, heading directions were calculated such that the sightline of the street view images is parallel to the street segment and that one image would be facing the opposite direction of the other image (i.e., looking back and forth toward the directions of walking; see Figure 2B and C). For endpoints, heading directions were calculated such that the sightline is parallel to the segment and that the image is looking into the street that is being measured. All other parameters were set to the default values. This procedure is applied to all street segments in the city to calculate parameters needed to download street view images through the GSV application programming interface (API). We downloaded a total of 70,676 images that were 640 by 640 pixels each to cover the entire city area (see Figure 2A).

The NHTS was conducted between April 2016 and April 2017, and the metadata of GSV images showed that 92.1% of the images were taken between 2016 and 2018, indicating that nearly all of the street view images used in this study are temporally well-aligned with the NHTS data.

The collected images were processed through a semantic segmentation model called the Pyramid Scene Parsing Network (PSPNet) developed by Zhao et al. (2017). Built based on the fully convolutional network architecture (Long et al., 2015), a pre-trained PSPNet takes a raw image as an input, processes the image using pre-trained weights, and outputs a category with the highest probability as a prediction for each pixel. These weights are trained on ADE20K, a database that provides annotated images with 150 categories (Zhou et al., 2017). After the scene parsing through PSPNet was completed, we counted the number of pixels per category in each image. As shown in Figure 3, the seasonality did not appear to be a significant consideration as trees without leaves were correctly labeled.

The output from PSPNet was examined to filter out any locations of anomalous images, such as pictures of indoor spaces. This excluded 571 image locations from our dataset, leaving 70,105 image locations. Next, the number of pixels of each category shown in images taken at the same location

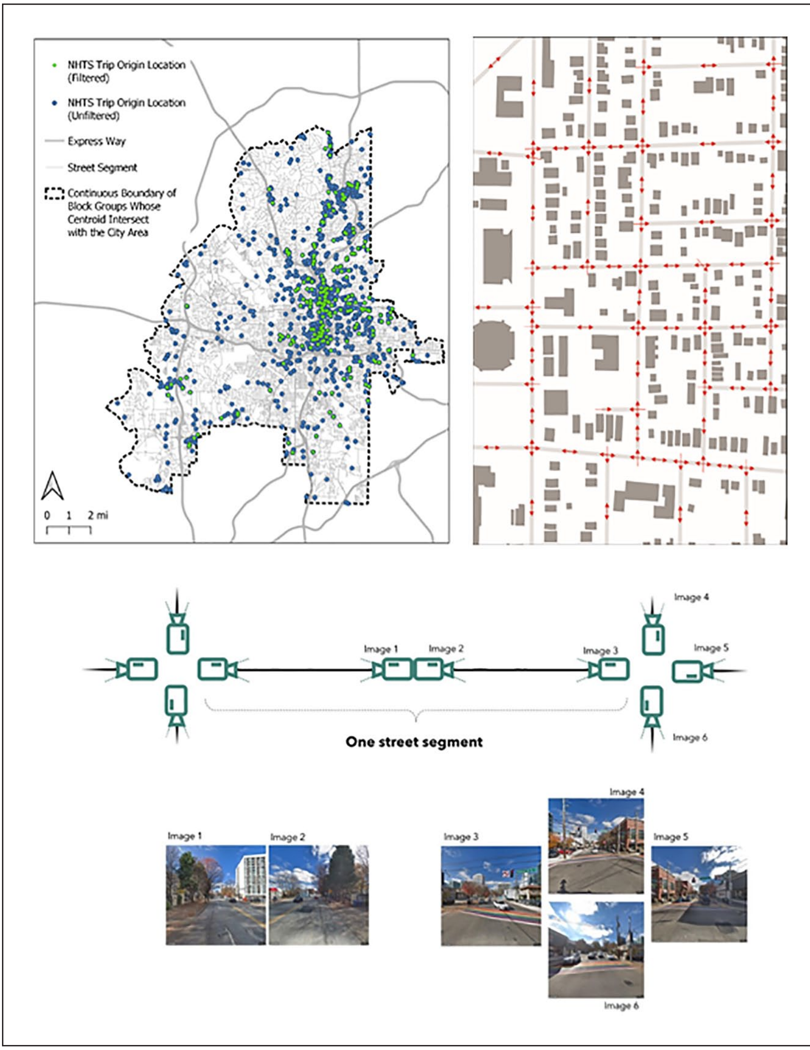

Figure 2. (A) The location of points where Google Street View images were downloaded, (B) the headings of the downloaded images, and (C) examples of downloaded Google Street View images.

but with different headings (directional) were averaged to represent the overall streetscapes of each location, reducing the number of image locations down to 31,351. These measures were then joined to the NHTS trip origins

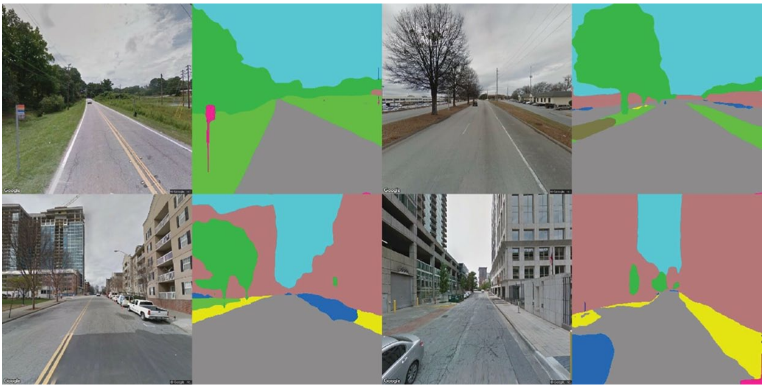

Figure 3. Examples of Google Street View images and their output from the computer vision processing by PSPNet.

by drawing a buffer centered at each trip origin location and averaging the number of pixels of each category shown in images that fall in the buffer. The average length of street segments in the city of Atlanta is 148.8 m, and we used 150-m as the buffer distance. Operationally, the GSV images that are within about a block from the origin location were used to represent the streetscape of that specific origin location.

The final step was to select objects relevant to mesoscale streetscapes from the 150 categories and convert the average number of pixels of the selected categories into mesoscale measures of walkable streetscapes. In selecting relevant object categories, we selected objects that are (1) consistent with the definition of mesoscale factors (e.g., bench, streetlight, and signboard are examples of excluded items for this reason), (2) usually found in outdoor spaces (e.g., wall, desk, and sofa were among those that were excluded for this reason), and (3) a part of the human-controlled environment (e.g., mountain and river, for example, are excluded for this reason; but landscape features such as trees and grass are included). The initial screening of potential mesoscale factor objects included building, tree, road, grass, sidewalk, plant, house, path, and skyscraper. Note that path and skyscraper were excluded as they were rarely detected. For example, over 75% of the NHTS trip origin points had nearly zero occurrences of path and skyscraper. Finally, vehicle categories are included in the consideration as they can block the view of the road on which they operate. We included only car category as other vehicle categories such as bus and truck are rarely detected. A total of eight categories was selected to represent mesoscale streetscapes, including building, house, sidewalk, tree, road, grass, car, and plant. Detailed examples of each category are provided on the ADE20K website.[1] Based on the literature on urban design, built environment and active transport, and past studies on using street view images for measuring the built environment, we formulated the following three indices (Chen, 2017; Li et al., 2018; Tang & Long, 2018; Wang, Lu, et al., 2019; Yin & Wang, 2016; Zhang et al., 2019). The 'building-to street-ratio' was calculated as the ratio of the proportion of buildings and houses to the sum of the proportion of sidewalk, road, and car. The "greenness" was computed as the sum of the proportion of tree, grass, and plant. The "sidewalk-to-street proportion" was measured as the proportion of the share of sidewalk to the sum of the share of sidewalk, road, and car. Heretofore, these three variables are called streetscape factors (see below for equations).

$$\begin{array}{r} building-to \\ -street\ ratio \end{array} = \frac{\%\,building\ pixels + \%\,house\ pixels}{\%\,sidewalk\ pixels + \%\,road\ pixels + \%\,car\ pixels}$$

$$greenness = \%\,tree\ pixels + \%\,grass\ pixels + \%\,plant\ pixels$$

$$\begin{array}{r} sidewalk-to \\ -street\ proportion \end{array} = \frac{\%\,sidewalk\ pixels}{\%\,sidewalk\ pixels + \%\,road\ pixels + \%\,car\ pixels}$$

Macroscale Factors

Macroscale factors were selected and measured based on the 5D framework (Ewing & Cervero, 2010), which includes density, diversity, design, destination accessibility, and distance to transit. To represent the intensity of land uses, this study used employment density computed for a quarter-mile buffer around each NHTS trip origin instead of the commonly used residential density. One of the reasons the residential density was popularly used in the past studies examining the association between walkability and walking or physical activity is that the studies often focused on home-based trips (Cervero & Duncan, 2003; Frank et al., 2005; Manaugh & El-Geneidy, 2011; Park et al., 2015). Employment density was chosen for this study over residential density because only about 50% of the trips in the data after filtering are home-based trips, and residential density may misrepresent the compactness of land uses in some cases. For example, the residential density of central business districts may not correctly reflect the intensity of daily pedestrian flow caused by the concentration of economic activities in the area. The 2015 employment data was downloaded from the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) at the Census Block scale. The employment density was computed as the number of jobs of all Census Blocks whose centroid intersects with the buffer divided by the area of the buffer. Diversity represents the degree to which different land uses are mixed in a given area, commonly measured using entropy indices. This study computed diversity using parcel-level land use data and the following formula:

$$diversity = 1 - \left(\frac{\sum_{i=1} n_i \left(n_i - 1 \right)}{N \left(N - 1 \right)} \right)$$

where n is the area of each land use category i in a quarter-mile buffer around each NHTS trip origin (i = residential, commercial, institutional, and office uses); and N is the area of residential, commercial, institutional, and office uses combined.

The design in the 5D framework involves not only urban design details but also the design of street networks (Ewing & Cervero, 2010). We used intersection density computed as the number of all intersections falling into the quarter-mile buffer of NHTS trip origins divided by the area of the buffer. Destination accessibility was measured using Walk Score® collected through the API for each location of NHTS trip origins. We did not implement any buffers for Walk Score® because the construction of Walk Score® already contains a similar mechanism in which the distance to nearby destinations is considered with a distance decay function (Walk Score, n.d.). Distance to transit was computed as the network distance from each NHTS origin to the nearest rail transit station in miles.

Analytical Methods

This study first used Pearson's correlation test to examine the relationship between macroscale and streetscape factors to answer the first research question posed in the Introduction—is there a relationship between neighborhood- and street-level factors? Next, this study tested the two hypotheses posed in the second section by developing a series of logistic regression models. The decision to make a trip by walking is modeled using binary logistic regression models. These models use trip mode (i.e., walking or non-walking) as the dependent variable. The Base Model includes only the control variables. Model 1 adds macroscale factors to the Base Model to examine how the macroscale factors are associated with the walking mode choice. Model 2 includes streetscape factors instead of macroscale factors. Model 3 includes all variables considered in this study. The macroscale factors include Walk Score®, employment density, land use diversity, intersection density, and distance to transit. The streetscape factors include building-to-street ratio, greenness, and sidewalk-to-street proportion. Because the number of variables varies in different models, we selected Adjusted McFadden's R^2 (adjusted R^2) and Bayesian Information Criteria (BIC) to evaluate the model fit as these measures adjust for the number of variables included in the model.

Results

Descriptive Statistics

The NHTS data before the data filtration contained 2,189 trip records that have origin locations inside the study area. After applying the filtration explained in the previous section, the data contained 329 trip records. Note that 11 NHTS origin locations did not have GSV images within 150-m and were excluded from the analysis. The application of the 150-m buffer reduced not only the NHTS origin locations but also the total number of GSV images used in the analysis down from 70,676 images to 8,149 images (roughly 11.5%) because there are many city areas where NHTS trip origin locations are too sparsely distributed and therefore many GSV images falling outside the 150-m buffer.

The final data used for the analysis included a total of 318 trips, of which 204 trips (64.2%) were walking trips, and 114 trips (35.8%) were non-walking trips. Because this filtering process removed trips that originated from outside the city area and those that traveled too far a distance, the final data captured trips that were generally feasible for walking. Table 1 shows descriptive statistics of the variables used in the analysis.

Correlation between Macro and Streetscape Factors

The correlation analysis showed strong correlations between the streetscape factors and macroscale factors in general, as shown in Table 2. An exception was the correlation coefficients among land use diversity and the streetscape factors, which recorded lower values that ranged between 0.068 and 0.437 in magnitude. Three macroscale factors—intersection density, distance to transit, and WalkScore—showed relatively consistent correlation coefficients with the three streetscape factors. In contrast, employment density and land

Table 1. Descriptive Statistics of the Variables.

Variable	Min	Median	Mean	Max	Std. dev.
Dependent variable					
Trip mode	Walking: 204 (64.2%)				
	Non-walking: 114 (35.8%)				
Independent variable					
Age	11.0	40.0	42.7	85.0	17.0
Gender	Female: 134 (42.1%)				
	Male: 184 (57.9%)				
Race	White: 209 (65.7%)				
	African American: 88 (27.7%)				
	Others: 21 (6.6%)				
Education	Less than high school: 11 (3.5%)				
	High school or higher: 307 (96.5%)				
Count of household vehicles	0.0	2.0	1.6	6.0	1.0
Household income	5,000.0	87,499.5	96,603.1	249,998.0	71,583.1
Driver status	Driver: 278 (87.4%)				
	Non-driver: 40 (12.6%)				
Number walking trips in past 7 days	0.0	7.0	9.8	40.0	9.2
Travel distance (miles)	0.009	0.389	0.440	0.995	0.275
Distance from rail transit station	0.0	0.8	1.2	4.5	1.0
Employment density (count of jobs/km^2)	0.0	2822.0	11647.0	68623.6	17105.9
Intersection density (count of intersections/km^2)	10.0	53.7	60.1	159.2	29.2
Land use diversity	0.000	0.259	0.308	0.731	0.230
Destination accessibility (Walk Score®)	7.0	81.5	76.1	98.0	18.4
Building-to-street ratio	0.0	0.2	0.3	1.1	0.3
Greenness	0.031	0.185	0.205	0.563	0.116
Sidewalk-to-street proportion	0.000	0.105	0.109	0.580	0.062

Table 2. Correlation between Streetscape Factors and Macroscale Factors.

	Employment density	Land use diversity	Intersection density	Distance to transit	Walk Score®
Building-to-street ratio	0.785***	0.266***	0.681***	−0.611***	0.652***
Greenness	−0.512***	−0.437***	−0.474***	0.412***	−0.564***
Sidewalk-to-street proportion	0.242***	0.068	0.406***	−0.457***	0.433***

***Significant at <1% level.

use diversity showed varying levels of correlations with different streetscape factors. Employment density, for example, showed the strongest correlation across the board with building-to-street ratio with $r=0.785$, while it was weakly correlated with sidewalk-to-street proportion with $r=0.242$.

Additionally, the streetscape factors are correlated with each other. Building-to-street ratio is positively correlated with sidewalk-to-street proportion (r=0.439, p < 0.001) but negatively associated with greenness (r=−0.651, p < .001). Greenness and sidewalk-to-street proportion have negative correlation (r=−0.212, p < .001). These negative correlations are not surprising as most of tree canopy is located in low-density, single-family residential lots (Giarrusso & Smith, 2014) where sidewalks are often scarce. We checked the variance inflation factor (VIF) for all models in the subsequent analyses to ensure that multicollinearity does not severely bias the model results.

The Relative Significance of the Macroscale and Streetscape Factors

The results from the binary logistic regressions are presented in Table 3. We generated standardized coefficients for ease of comparison. Note that Table 3 presents the standardized coefficients in odds ratio form, reporting the odds of walking. No serious multicollinearity issue was found as the highest VIF across all models was 4.94. The control variables in the Base Model were generally significant at α = .05 except for gender, race, and education. Among the person-level control variables, age, the count of household vehicles, household income, driver status, and the number of walking activities in the past 7 days were statistically significant, suggesting the importance of controlling for individual factors.

After accounting for the covariates, Model 1 showed that higher employment density and intersection density are positively and significantly associated with a greater odds of walking at α = .05 and α = .1, respectively, offering a substantial improvement in model fit over a model with only control variables (the likelihood ratio test between Base Model and Model 1: $\chi^2(5)$ = 33.057, p < .001).

Model 2, which included the streetscape factors instead of the macroscale factors, provided a better model fit than Model 1 both in terms of adjusted R^2 and BIC. It showed that building-to-street ratio had the largest odds ratio and z-value among all built environment variables, making it one of the most significant predictors of a greater odds of walking. Similarly, greenness had a sizable odds ratio and was statistically significant, suggesting a positive association with a greater odds of walking. Sidewalk-to-street proportion was not significant.

Model 3 showed that when all available variables enter the model, the model fit was worse compared to Model 2 as measured by adjusted R^2 and BIC. Land use diversity was the only significant variable among the macroscale factors, while building-to-street ratio and greenness remained significant. This result suggests that streetscape factors make a unique and

Table 3. Results of the Logistic Regression Models (Dep.Var = Walking/Non-Walking in Binary).

		Base model	Model 1	Model 2	Model 3
Constant		0.598 (−0.566)	1.625 (0.524)	0.832 (−0.193)	0.724 (−0.316)
Personal-, trip-level covariates	Age	0.602** (−2.973)	0.688* (−1.993)	0.645* (−2.293)	0.640* (−2.216)
	Gender—male (base: female)	1.229 (0.648)	1.013 (0.037)	1.183 (0.474)	1.168 (0.424)
	Race – African American (base: white)	0.781 (−0.622)	0.400 (−1.855)	0.682 (−0.855)	0.499 (−1.361)
	Race – all other races (base: white)	3.225† (1.779)	1.042 (0.058)	1.870 (0.896)	1.020 (0.027)
	Education – high school or higher (base: less than high school)	3.260 (1.345)	2.043 (0.816)	3.355 (1.361)	4.401 (1.559)
	Count of household vehicles	0.642* (−2.231)	0.618* (−2.134)	0.624* (−2.133)	0.603* (−2.240)
	Household income	1.714** (2.886)	1.386 (1.524)	1.237 (1.008)	1.295 (1.160)
	Driver status—non-driver (base: driver)	3.151† (1.683)	5.204* (2.193)	5.852* (2.371)	7.521* (2.427)
	Number walking activities in the past 7 days	2.438*** (4.666)	2.540*** (4.565)	2.356*** (4.512)	2.542*** (4.629)
	Trip distance	0.246*** (−7.670)	0.286*** (−6.401)	0.268*** (−6.423)	0.251*** (−6.387)
Macroscale factors	Employment density		2.645** (2.616)		1.079 (0.161)
	Land use diversity		1.292 (1.313)		1.758* (2.422)
	Intersection density		1.516† (1.784)		1.150 (0.521)
	Distance to transit		0.786 (−0.907)		0.800 (−0.815)
	Walk Score®		0.769 (−1.043)		0.878 (−0.488)
Streetscape factors	Building-to-street ratio			5.533*** (4.954)	4.945** (3.058)
	Greenness			1.608* (2.119)	2.070** (2.655)
	Sidewalk-to-street proportion			0.867 (−0.743)	0.791 (−1.181)
No. of observation		318	318	318	318
LL		−134.074	−117.545	−115.253	−111.080
Adj. McFadden's R^2		0.301	0.356	0.377	0.373
Bayesian info. criteria		331.530	327.283	311.176	331.640

The regression results are in $\frac{OddsRatio^{***}}{(z-statistic)}$ format, where the Odds Ratio is the exponent of the standardized coefficient from the logistic regression.

*Significant at the 5% level. **Significant at the 1% level. ***Significant at <1% level. †Significant at the 10% level.

independent contribution to explaining walking mode choice even after controlling for other macroscale factors. The significance of this contribution is also shown in a likelihood test result comparing Model 1 and Model 3 ($\chi^2(3)=12.93$, $p=.005$). Furthermore, the comparison between Model 2 and Model 3 revealed that once the streetscape factors are included, macroscale factors do not seem to provide substantive improvements in model fit. This finding is corroborated by a likelihood ratio test result comparing Model 2 and Model 3 ($\chi^2(5)=8.346$, $p=.138$). Note that although the VIF values were not alarmingly high, the high correlations between some macroscale and streetscape factors could inflate the variance of the coefficient estimates in Model 3. To confirm that multicollinearity has not polluted the results, we further investigated how the results change when different variable selection methods are used (e.g., various stepwise regression methods or excluding insignificant variables). We observed that the exclusion of variables reduced the VIF down to 2.087, but the relative importance of macroscale and streetscape factors in model fit did not change regardless of the method of variable selection. The relative size of the coefficient estimates and the statistical significance of macroscale and streetscape factors were also identical to Model 3 (these model results are available upon request).

Discussions

Reflecting on the two hypotheses, the results offer many notable findings. The first hypothesis—that both macroscale and mesoscale factors will have statistically significant contributions to walking mode choice models when they are used separately—is supported by our data. Model 1 showed that macroscale walkability factors can add statistically significant improvements to the model fit compared to the model with only the control variables. Similarly, the streetscape factors contributed significantly to the model fit, providing a statistically significant improvement. One notable finding is that streetscape factors (i.e., mesoscale factors) provided noticeably better model fits than that provided by macroscale factors. This result lends further support to the previous research that reported the importance of street-level walkability factors (e.g., Alfonzo et al., 2008). The second hypothesis—that the macroscale and streetscape factors will have their unique contributions to the models when they are used together, improving the fit of the walking mode choice models more than when they are used separately—is not supported. The best model fit overall was observed not in a model that used both macro and streetscape factors but in Model 2, which only contained the streetscape factors.

These findings warrant an important question: Why did the streetscape factors derived from street view images and a computer vision technique perform better than macroscale factors in explaining walking behavior? Although future research is needed to better answer this question, some possible explanations can be drawn from past studies and our correlation analysis. First, street view images may provide a more accurate representation of the actual built environment that pedestrians experience. Street view images taken at the pedestrians' perspective can correctly represent the complex interactions of large street objects that jointly create the visual stimuli of pedestrians, which 2-dimensional GIS-based methods are limited in representing. Taking street trees as an example, even when the street tree coverage measured from overhead-view is similar, its visual dominance at pedestrian perspective can vary depending on various conditions, such as the height of trees and buildings that are lined with the trees, the vertical shape of its crown, other large objects blocking the view, and the curve and slope of the street segment. Jiang et al. (2017) found that remotely sensed tree cover density does not match well with eye-level measures of tree cover density except when tree cover is very sparse. Using overhead-view and eye-level view measures in Hong Kong, Lu et al. (2019) found that cycling behavior is positively associated with eye-level street greenness but not with overhead-view greenness. Similarly, a study conducted in Seoul, Korea found that green view index derived from street view images at eye-level is more closely associated with walking time than the traditional greenery variables (Ki & Lee, 2021).

Second, the moderate to high correlations between streetscape factors and some of the macroscale factors indicate that the image-based measurement may be good proxies for these factors. The correlation analysis showed that employment density and intersection density, the two macroscale factors that had significant associations with the odds of walking in Model 1 (i.e., the model that contained all macroscale factor and no streetscape factors), are significantly correlated with streetscape factors, particularly building-to-street ratio and greenness. These correlations make sense because high employment density translates to large and tall buildings to accommodate jobs, resulting in high building-to-street ratios. The high demand for development, particularly in the city center, can lead to a lack of potential spaces for trees and urban vegetation (Koo et al., 2019), supporting the observed negative correlation between employment density and greenness. Also, such locations in Atlanta often have grid-like street patterns with ample intersections. In contrast, low-density locations that are highly dependent on automobiles often have low buildings with wide roads for vehicular traffic, resulting in low building-to-street ratios. The ability for streetscape factors to capture some important macroscale factors related to walkability is attractive because it allows us to rely on fewer variables that can be derived from street view images only.

The five walking needs and urban design qualities are discussed in this study as theoretical links between the built environment measurements and walking behaviors. While the exact mechanism through which the streetscape factors are linked with walking mode choice has several aspects that are outside the scope of this study, the coefficient estimates and the statistical significance of streetscape factors appear to be in alignment with the literature. A large building-to-street ratio and more greenness may provide a greater sense of enclosure, a sensation that makes street spaces seem like an outdoor room (Ewing & Handy, 2009; Harvey et al., 2017), which is formed chiefly due to sightlines being blocked by buildings and trees. Enclosure is discussed frequently in the literature to link the built environment, particularly mesoscale factors, with a greater perceived safety (Harvey et al., 2015) and comfort (Harvey & Aultman-Hall, 2015), more pedestrians on the streets (Yin & Wang, 2016), and better mental health of elderly (Wang, Lu, et al., 2019).

It is important to note that the statistical insignificance of many macroscale factors does not mean they are not important. The inclusion of macroscale factors in Model 1 provided a significantly better model fit compared to Base Model. As mentioned in Cervero et al. (2009), the 5Ds are "overlapping Venn diagrams" (209), and we suspect the insignificance of individual macroscale factors is due these overlaps. In fact, when we tested using one macroscale factor at a time instead of using all five of them simultaneously in Model 1, all five macroscale factors had statistical significance at $\alpha = .01$ (these results are omitted for brevity).

This study has several limitations that could be the basis for future research. First, this study only considered trip origins due to limitations in data availability and computational resources. Second, because we do not know the spatial resolution of Walk Score®, we cannot be certain that the Walk Score® we queried through the API returned scores for the exact *X* and *Y*-coordinates of the trip origin. If the Walk Score® database is calculated with some distance intervals and returns a score of the nearest data point, it is possible that the geographical mismatch between trip origins and the nearest Walk Score® point may have biased the performance of Walk Score®. Third, this study was limited by the design of the survey data which provided personal and trip-level variables. The limited sample size did not allow us to parse out our dataset based on more detailed trip purposes and types. Some of the variables that are insignificant in the regression results may also be due to the limited sample size. The categorization in the survey dataset that merged similar trip purposes made it difficult for us to extract the exact trip purposes that Cervero and Duncan (2003) used. As theoretically suggested by the hierarchy hypothesis and empirically presented by Manaugh and El-Geneidy (2011), different walkability indices that are built on different walkability factors can have varying effectiveness depending on trip purposes or types. These limitations can be addressed in future studies by using primary data collection methods, as opposed to analyzing secondary data such as NHTS, as self-collected data can be designed for specific research purposes and designs. For example, some studies using self-collected data measured streetscape characteristics of the actual trip routes (e.g., Park et al., 2015). Considering that the streetscapes can have a larger variation even within a relatively small area, measuring streetscape factors at route-level may better capture the experience of travelers than measuring them using buffers and may result in even more substantial improvements to walking mode choice models. As the NHTS does not provide the exact route of travel, we were not able to measure the streetscapes at the route-level. Fourth, because we were limited by the capabilities of the computer vision technologies at the time of this study, the measures of mesoscale factors incorporated in this study have room for improvement. Future studies may build on these findings for more refined measures as more advanced technologies become available. Similarly, the availability, image age, and the variance of image age of street view images tend to be associated with socioeconomic status (Fry et al., 2020). Although we demonstrated image ages generally overlap with 2017 NHTS, the degree to which these issues may have introduced biases to the result of this study is unknown. Fifth, this study was conducted in a single city of Atlanta, which is known for its low-density development pattern. This unique development pattern may have influenced the results, and the generalizability of the finding is unknown. Future studies will benefit from incorporating a more diverse urban environment across multiple cities and regions. Importantly, this study has potential sources of biases such as selective mobility (i.e., the tendency of people to sort themselves into different neighborhoods to live or places to visits throughout a day based on their socioeconomic or other relevant status) and uncertain geographic context problem (i.e., a bias coming from using some arbitrary areal units for analyses due to the lack of knowledge about the precise ways in which the environment influences people's behavior) (Kwan, 2018, p. 1486). The degree to which the results of this study may be biased due to these issues is unknown. The potential biases call for future research with a more robust study design.

Conclusion

Due to its pedestrian perspective, wide coverages, and fine-grained spatial resolution, street view images provide a unique opportunity to refine the ways in which walkable environments are measured and advance our understanding of how the streetscape is linked with walking. In this study, we used GSV images to quantify the mesoscale attributes of streetscapes. We examined the relationship between mesoscale and macroscale walkability factors and whether a computer vision-based measure of the streetscapes would contribute to explaining walking mode choice in addition to macroscale factors. The streetscape factors showed better model fits than macroscale factors, suggesting that the streetscape factors appear to be substitutes of macroscale factors rather than work synergistically with them. We provided potential explanations for this result: the image-based streetscape factors as presented in this study may perform as proxies of some macroscale factors to some degree while providing the benefit of better representing pedestrian experience from eye-level view.

The methods and results of this study can be extended in various ways. Practitioners can benefit from future research on how policies governing the built environment translate into streetscapes. It can provide practical guidelines on, for example, how zoning and building codes, tree ordinances, and transportation plans can be leveraged to provide more walkable streetscapes. This translation is needed because such policies are often more relevant to the overhead-view measures, but the streetscape factors as presented in this study represent the streetscapes that arise as a result of the interplay of building height, the width of sidewalks and streets, and greenery in perspective view at eye level. Future research can also add microscale factors into the discussion to form a comprehensive framework for walkability measures that span macro-, meso-, and microscale factors. Provided that there exists a causal linkage between the built environment and walking behavior, this framework may provide practitioners a basis on which to articulate the expected outcome of their plans and designs.

The results of this study suggest a promising outlook for using big data such as GSV images and computer vision models in urban planning, public health, geography, and other related research. Considering the global coverage of GSV images, the fact that measurements from street view images can perform as a proxy of some macroscale factors and can offer an even greater model fit than macroscale factors can open new possibilities for research not only in data-rich regions such as the U.S. but also in regions where data constraints are a major barrier.

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Note

1. https://groups.csail.mit.edu/vision/datasets/ADE20K/

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