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Can good microscale pedestrian streetscapes enhance the benefits of macroscale accessible urban form? An automated audit approach using Google street view images

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HIGHLIGHTS

- Microscale streetscape factors related to safety from traffic and crime and pleasurability are measured using street view images.
- Many microscale factors have moderate to strong correlations with a pedestrian accessibility measure.
- Safety from crime, pleasurability, and composite microscale index are positively associated with higher odds of walking.
- Traffic safety, safety from crime, and composite microscale index positively moderate the effects of a pedestrian accessibility measure.

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ABSTRACT

While pedestrian accessibility measures have been widely used interchangeably with walkability, walkability is not just about accessibility. Microscale streetscape factors can provide qualities that pedestrians seek, including safety from crime, traffic safety, and pleasurability. These qualities can encourage walking through direct contributions or by enhancing the benefits of macroscale accessibility measures, or both. This study examines the main and interaction effects of microscale streetscape factors measured from street view images using computer vision in Atlanta, Georgia, USA. The correlation analysis showed that many microscale factors have moderate to strong correlations with the pedestrian accessibility measure. Binary logistic regressions demonstrated that safety from crime, pleasurability, and composite microscale index have direct contributions to walking mode choice. Regarding moderating effects, traffic safety, safety from crime, and composite microscale index enhanced the benefits of pedestrian accessibility measure. Policies designed to encourage walking can focus on streetscape features for short term efforts. Important caveats for policymakers in using machine-driven data collection are discussed.

1. Background

Walkable built environment has been associated with increased walking and physical activity in numerous active living research. Most studies on the association between walkable built environment and walking used macroscale factors that measure pedestrian accessibility (i.e., the ease of reaching a variety of daily destinations via walking), such as residential density, land use mix, and street connectivity (Adkins, Makarewicz, Scanze, Ingram, & Luhr, 2017; De Vos, Lättman, van der Vlugt, Welsch, & Otsuka, 2022; Frank, Schmid, Sallis, Chapman, & Saelens, 2005; Owen et al., 2007). However, walkability is not just about pedestrian accessibility. A growing number of studies show that microscale features of streetscapes can also play a critical role in improving perceived safety (Harvey, Aultman-Hall, Hurley, & Troy, 2015), attractiveness of walking environments (Adkins, Dill, Luhr, & Neal, 2012), and encouraging walking behavior (Sallis et al., 2015).

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Microscale streetscapes provide various benefits for walking and physical activity. Sidewalks and sidewalk buffers can provide protection from traffic and promote walking (McCormack et al., 2012). In contrast, physical disorder (e.g., graffiti and abandoned houses) can suggest an unsafe social environment and may hinder walking and physical activity (M. Alfonzo, Boarnet, Day, Mcmillan, & Anderson, 2008; Bracy et al., 2014; Cunningham & Michael, 2004; Koo, 2021). Perceived aesthetics of the neighborhood walking environment is another correlate of walking (Ball, Bauman, Leslie, & Owen, 2001). Some studies focused on the overall scale and proportions of the streetscapes and called it the streetscape skeleton (Harvey & Aultman-Hall, 2016, p. 149). The streetscape skeleton can shape the enclosure and human scale of streetscapes, the urban design qualities favorable for walkability (Ewing, 2013; Ewing & Handy, 2009). Enclosed and human scale streetscapes are associated with perceived safety (Harvey et al., 2015; Harvey & Aultman-Hall, 2015), more active use of streets (Ewing, 2013; Zhang, Xie, & Long, 2022), better mental health (Wang et al., 2019), and make transit more accessible (Park, Choi, & Lee, 2015).

Microscale streetscape features can be particularly important because they may moderate the effects of macroscale accessibility factors. Ecological models suggest that safety from crime and protection from traffic can moderate the relationship between macroscale walkability and walking (Bracy et al., 2014). Furthermore, microscale streetscape features (e.g., presence and quality of sidewalks) can be more easily modifiable in the short term than macroscale accessibility factors (e.g., intersection density). Streetscape features therefore can be the target of actionable interventions that may bring both direct and indirect benefits to pedestrians.

Despite the importance of microscale streetscapes, only a limited number of studies examined both macroscale and microscale factors simultaneously (De Vos et al., 2022; Molina-García et al., 2020; Rebecchi et al., 2019; Sallis et al., 2015), partly due to the cost of measuring microscale features (Rundle, Bader, Richards, Neckerman, & Teitler, 2011). As noted in Cerin et al. (2018), only a very few studies examined how and whether pedestrian infrastructure and safety aspects of the environment can moderate the effects of macroscale accessibility measures on walking and physical activity (Bracy et al., 2014; Cerin et al., 2018; Cerin et al., 2013; Cerin et al., 2013). Therefore, our understanding of which microscale streetscape features are important, how strong their moderation effects are, and how generalizable the existing findings are in different settings (e.g., different cities and population subgroups) is limited.

One major challenge in incorporating streetscape features in research and planning practice is the difficulty in data collection (Adams, Phillips, Patel, & Middel, 2022). Given that streetscape features are often measured through surveys or manual audits, the data collection process can be resource-intensive (Rundle et al., 2011; Wilson et al., 2012). Recent efforts have attempted to overcome this limitation by applying computer vision technology to street view images (Koo, Guhathakurta, & Botchwey, 2021; Nguyen et al., 2019). However, no existing studies examined the moderating effects of streetscape features using computer vision and street view images, limiting our understanding of the feasibility of using such methods.

The purpose of this study is to examine the main effect of microscale streetscape features, as well as their interaction effects on Walk Score, on walking mode choice in Atlanta, Georgia using computer vision and street view images. We hypothesize that the pedestrian accessibility in macroscale as represented in Walk Score and each of microscale streetscape features are positively associated with walking mode choice (i.e., main effects). We also hypothesize that each streetscape feature would function as moderator of the effects of the accessibility measure on walking, offering synergistic effects.

2. Related works

2.1. Walkable built environment and walking needs

Despite its popularity, the term walkability has no agreed-upon definitions (Shashank & Schuurman, 2019; Tobin et al., 2022). Nonetheless, many studies adopted the idea that factors contributing to walkability can be roughly grouped into two broad categories of macroscale and microscale (Adkins et al., 2012; Aghaabbasi, Moeinaddini, Zaly Shah, & Asadi-Shekari, 2017; Annunziata & Garau, 2020; Bereitschaft, 2017; Bivina, Gupta, & Parida, 2019; Cain et al., 2014; Rebecchi et al., 2019; Sallis et al., 2015, 2022; Tobin et al., 2022; Toker, 2015). In general, macroscale factors refer to urban form factors that shape proximity and connectivity. Proximity refers to straight-line distance between origins and destinations, which are commonly measured using, for example, residential density and land use mix (Saelens, Sallis, & Frank, 2003, pp. 81, 82). Connectivity relates to the ease of moving from origins to destinations through existing street networks. The common measures of connectivity include intersection density and average block length. (Saelens et al., 2003, pp. 81, 82). They are used as aerial measures focusing on individuals' neighborhoods or small areas within walkable distances (e.g., 400 m ~ 1 km) from some places of interest (Cerin et al., 2013; Hoehner, Brennan Ramirez, Elliott, Handy, & Brownson, 2005; Zhao, Chow, Li, Ubaka, & Gan, 2003).

Microscale features refer to street-level details of urban design and pedestrian infrastructures (Sallis et al., 2015). The list of individual streetscape features in the literature is extensive. In the field of public health, various audit tools were developed and validated to collect information on diverse aspects of microscale streetscapes, such as the Microscale Audit of Pedestrian Streetscapes (MAPS), Neighborhood Environment Walkability Scale (NEWS), and the Irvine Minnesota Inventory (IMI). For example, Microscale Audit of Pedestrian Streetscapes (MAPS) asks respondents 120 questions about aesthetics and social characteristics, pedestrian safety devices at crossings, sidewalk presence and quality, features along sidewalks (e.g., streetlights, street trees, and seating), steepness, physical disorder, aesthetics and pedestrian-friendly building facades (e.g., building accent colors and windows on the ground floor), building setbacks and heights, the use of buildings along the streets, and the presence of public parks. In the field of urban design, Ewing and Handy (2009) identified 38 physical features of streetscapes that shape favorable urban design qualities for walking, including historic buildings, outdoor dining, proportion of street wall and sky ahead, street furniture, building height, ground floor with windows, and the numbers of people, buildings, accent colors, and public art. Similarly, Alfonzo et al. (2008) audited 22 physical features to construct urban design indices for walkability, including sidewalks, mixed uses, windows facing streets, street lighting, abandoned buildings, graffiti, sidewalk buffers, street width, speed bumps, street trees, and street furniture.

Macro and microscale factors are associated with walking by offering various built environment qualities that pedestrians seek (Alfonzo, 2005; Ewing & Handy, 2009; Owen, Humpel, Leslie, Bauman, & Sallis, 2004). Various qualities have been identified as influencing walking using diverse yet conceptually consistent terms, such as accessibility, traversibility, compactness, safety, comfort, convenience, level of interest, liveliness, attractiveness, physically enticing, and pleasurability (Alfonzo, 2005; Bornioli, Parkhurst, & Morgan, 2019; Ewing & Handy, 2009; Forsyth, 2015; Owen et al., 2004; Sallis & Owen, 2015). These qualities can influence pedestrians' decisions to walk (or not to walk) in certain environments by offering (or failing to offer) qualities that pedestrians seek (Alfonzo, 2005). Alfonzo (2005) and Day, Boarnet, Alfonzo, and Forsyth (2006) offer a categorization of these qualities including pedestrian accessibility, safety from crime (e.g., physical indicators of incivilities and crimes), traffic safety (e.g., protection from traffic and convenience of pedestrian facilities that separate pedestrians from vehicles), and pleasurability (e.g., aesthetics and level of interest).

These qualities are considered to be existing (or be absent) within the environment in which the choice to walk occurs and influence behavior through individuals' perception (Alfonzo, 2005, p. 819).

Pedestrian accessibility pertains to the ease of reaching destinations via walking. Many past studies used pedestrian accessibility measures (or some composite indices constructed with these measures) interchangeably with measures of 'walkability' (De Vos et al., 2022). Pedestrian accessibility of a place is shaped by ways in which land is used (i.e., proximity, which refers to the Euclidean distance between different land uses) and the street network is designed (i.e., connectivity, which pertains to the directness of travel between origin and destination) (Saelens et al., 2003, pp. 81). Pedestrian accessibility is commonly operationalized using macroscale measures such as residential density, land use mix, intersection density, and retail floor area ratio (Frank et al., 2005). The transportation literature also employs a similar set of built environment dimensions as influencing travel demand, namely Density, Diversity, and Design (3Ds), which were later appended by two more Ds, Destination accessibility and Distance to transit, resulting in the 5D framework (Ewing & Cervero, 2010). Some studies included Demand management and Demographics as additional Ds, although demographic is not part of the built environment (Ewing & Cervero, 2010). Some include the completeness of sidewalk networks as a component of accessibility (e.g., Alfonzo, 2005) as a part of pedestrian accessibility measures, while most empirical studies, particularly those from the field of transportation, have relied on macroscale measures.

The other qualities—safety from crime, traffic safety, and pleasurability—are arguably more closely associated with microscale streetscape features than with macroscale factors (Alfonzo, 2005; Bereitschaft, 2017, 2018; Bornioli et al., 2019; Ewing & Handy, 2009). The fear of being a victim of crimes have been identified as a potential barrier to walking or physical activity (Adkins et al., 2017; Bornioli et al., 2019; Foster, Knuiman, Hooper, Christian, & Giles-Corti, 2014; Foster & Giles-Corti, 2008; Hong & Chen, 2014; McDonald, 2008; Rees-Punia, Hathaway, & Gay, 2018). The routine activity theory suggests that one of the preconditions for criminal activity is the absence of effective authority or capable guardians that can invigilate and respond to crimes (Donovan & Prestemon, 2012). The broken window theory suggests that poorly maintained neighborhoods can attract criminals because the signs of neglect can indicate unmonitored spaces (Donovan & Prestemon, 2012; O'Brien, Farrell, & Welsh, 2019). The built environmental features relevant to the routine activity and broken window theories include the visibility of activities on sidewalks from nearby houses, the presence of streetlights which can increase visibility when criminal activities occur, and visual cues of disorder and neglect such as excessive graffiti and poorly maintained buildings and landscapes (Foster & Giles-Corti, 2008). Attractive streetscape features such as street trees can also contribute to a sense of safety from being a victim of crime by inviting more pedestrians and increasing natural surveillance (Donovan & Prestemon, 2012; Kondo, Han, Donovan, & MacDonald, 2017; Lee, 2021). However, the evidence on the association between safety from crime and walking or physical activity has been mixed, partly due to measurement limitations (Foster & Giles-Corti, 2008). The built environment characteristics that suggest incivilities in the neighborhood may heighten the fear of crime, but the fear of crime is only weakly correlated with actual crime statistics (Lewis and Maxfield, 1980, taken from Foster & Giles-Corti, 2008, p.249).

Traffic safety, either actual or perceived, can facilitate walking (Bornioli et al., 2019; Jacobsen, Racioppi, & Rutter, 2009). Traffic safety can be influenced by microscale streetscape features related to pedestrian infrastructure that provides protection from vehicles, such as walk signals, crosswalks, curb ramps, sidewalks, and sidewalk buffers. Some studies also found that more enclosed streetscapes (e.g., more tree canopy cover, higher building-to-street proportion, and greater continuity of buildings along the streets) can contribute to the sense of comfort by encouraging safer driving behaviors. Harvey and Aultman-Hall (2015) reported that crashes are less likely to be fatal if it happens on more enclosed, tree-lined streets, arguably because drivers are more cognizant of possibilities of unexpected hazards when the streetscape is more constrained and offer less design consistency. Similarly, Dumbaugh and Rae (2009) found that higher-density developments in which buildings are placed close to streets are associated with fewer crashes.

Pleasurability is the attractiveness of streets with respect to walking experience (Alfonzo, 2005, p. 829). Because attractiveness is a subjective perception for which the contributing factors and their effects can vary by individuals, the factors related to pleasurability are diverse (Day et al., 2006). Urban design literature describes attractiveness through such terms as imageability, enclosure, human scale, transparency, and complexity (Ewing & Handy, 2009). Various streetscape features can contribute to these qualities. Tall buildings and other large objects along a narrow street can create a sense of enclosure by blocking the lines of sight (Ewing & Handy, 2009). Enclosed streetscapes can offer pedestrians a feeling of being inside while in an outdoor space, making the street a more pleasant place to be in. Street trees are an example of large objects that can add enclosure. With their overhead canopy, trees can also subdivide the vast space between tall buildings into more human-sized spaces, adding human scale to the streetscape. Street trees can also provide complexity through the shape of their stems and branches that constantly move (Harvey et al., 2015). Building materials, glass windows on facades with retail uses, and other styling ornaments can add transparency and complexity to the street (Ewing & Handy, 2009).

Note that the objective measurements of the built environment and the individuals' perception of them do not perfectly overlap (Jun & Hur, 2015; Pot, van Wee, & Tillema, 2021), although they tend to align well (e.g., Arvidsson, Kawakami, Ohlsson, and Sundquist (2012) and Gebel, Bauman, and Owen (2009)). It is the individuals' perception that mediates between the built environment features and walking behavior (Alfonzo, 2005; Ewing & Handy, 2009; Ortiz-Ramirez, Vallejo-Borda, & Rodriguez-Valencia, 2021). Various measures of perceived walkability have been developed, including Neighborhood Environment Walkability Scale (NEWS), Physical Activity Neighborhood Environment Survey (PANES), and Leyden Walkability Instrument. Studies that used both objective and perceived walkability measures usually found stronger effects of perceived walkability, although both types showed significant effects in most cases (De Vos et al., 2022). An example of an exception is Brown and Jensen (2020), which found that objective measurements of walkability showed stronger effects on walking than perceived walkability.

2.2. Computer vision for streetscape measurements

As illustrated above, safety from crime, traffic safety, and pleasurability can be directly shaped by microscale streetscape features, and many audit tools have been developed to assess them. Despite their usefulness as measurement tools, conducting audits using these tools required extensive manual labor, increasing the cost of measurements (Lee & Talen, 2014). Researchers have turned to the combination of computer vision technology and the increasing availability of street view image services as an alternative measurement method. Computer vision-based streetscape measurements in the urban planning and public health literature can be grouped into proportion-based and presence-based approaches for convenience.

For the proportion-based approach, some of the most widely used computer vision models in the literature include Pyramid Scene Parsing Network (PSPNet) (H. Zhao, Shi, Qi, Wang, & Jia, 2017), Fully Convolutional Network (FCN) (Long, Shelhamer, & Darrell, 2015), and SegNet (Badrinarayanan, Kendall, & Cipolla, 2015), 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 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 and few buildings and trees are likely to represent main streets in auto-oriented suburbs. Streetscape measurements based on the proportion-based approach have demonstrated effectiveness as predictors of various outcomes, such as walking, physical activity, and mental health. Koo et al. (2021) used PSPNet and GSV to measure building-to-street ratio, greenness, and sidewalk-to-street proportion in Atlanta, GA. Using the 2017 National Household Travel Survey, the study showed that building-to-street ratio and greenness were significantly associated with walking mode choice after controlling for personal, trip-level, and accessibility covariates. Ki and Lee (2021) utilized FCN to extract green view index from GSV images in Seoul, South Korea. They reported that the image-based measure of green view index was more closely associated with walking time than the traditional greenery measures (i.e., park area and the number of street trees).

Another approach to utilizing computer vision technology focuses on detecting the presence (or absence) of streetscape features or objects of interest in a given image using image classification, object detection, or instance segmentation. Unlike semantic segmentation from which the number of pixels of different objects (or their proportions) is retrieved for each image, the presence-based approach focuses on categorical outputs denoting the presence or absence of certain characteristics or objects. The existing work in this line of research is largely focused on re-training pre-trained models and examining their accuracy rather than actually applying the trained models to applied research. This is because computer vision models are commonly trained using large image databases that offer high-quality annotation, such as ImageNet (J. Deng et al., 2009), ADE20K (Zhou, Zhao, Puig, Fidler, Barriuso, & Torralba, 2017), and Microsoft COCO (Lin et al., 2014). These databases often do not contain annotations of many streetscape objects pertaining to the built environment qualities that are important for pedestrians, except for a few generic ones such as sidewalks and traffic lights. Computer vision models that are pre-trained on these databases inherit this limitation. There have been efforts to re-train the pre-trained models to expand the list of objects detectable by computer vision models. For example, Koo, Guhathakurta, and Botchwey (2022) repurposed a pre-trained computer vision model named Mask R-CNN to automatically replicate the brief version of the Microscale Audit of Pedestrian Streetscapes (MAPS-mini) and validated the reliability by comparing the automated audit results with manual audit results completed by a trained human auditor. Nguyen et al. (2020) created a series of computer vision models each of which detected the presence of one of the following objects or characteristics: street greenness, crosswalks, single-lane roads, building type, and utility wires. Although the presence-based approach seemed to be less widely used in the literature on environmental influence on walking or physical activity, some studies have reported their effectiveness as predictors of health behaviors or health outcomes (Koo, 2021; Nguyen et al., 2019).

2.3. Ecological models and moderators

While the streetscape features pertaining to safety from crime, traffic safety, and pleasurability can contribute directly to walking and physical activity behavior (Sallis et al., 2015), the ecological models posit that they can also function as moderators of the relationship between accessibility and walking behavior (Sallis & Owen, 2015). Some of the core concepts of ecological models for walking behavior are that the behavior is influenced by factors in multiple levels and that the influence can interact across levels (Sallis & Owen, 2015). These levels include intrapersonal, interpersonal, organizational, community, physical environment, and policy levels. Studies at the intersection of urban planning and public health were primarily interested in the relationship between the walkable built environment and walking or physical activity, with some studies focusing on the moderators of the environment-walking relationship. Various moderators were examined, including psychosocial (e.g., self-efficacy), socioeconomic (e.g., household income), and demographic factors (e.g., sex). Studies showed various degrees of moderating effects depending on, for example, which moderators were used to which population groups or how walkable built environment was defined.

In many past studies, walkability and pedestrian accessibility were used interchangeably (De Vos et al., 2022), which were often measured using macroscale factors (Adkins et al., 2017; Sallis et al., 2015). De Vos et al. (2022) write "[m]ost studies measuring objective walkability focus on macro- and *meso*-scale elements of the built environment, such as population density and land use mix. Microscale elements such as zebra crossings, quality of sidewalks, benches, presence of green, etc. are often not taken into account" (p.13). Naturally, the findings and policy implications revolved around accessibility aspects of the built environment. Relatively fewer studies examined how streetscape features in microscale can influence walking or physical activity, although they generally reported significant contributions (e.g., M. Alfonzo et al., 2008; McCormack, Shiell, Doyle-Baker, Friedenreich, & Sandalack, 2014; Sallis et al., 2015). Few studies considered streetscape characteristics pertaining to pedestrian infrastructure and traffic safety as *moderators* of 'walkable built environment-walking (or physical activity)' relationship (Cerin et al., 2018). These studies on the moderating effects of streetscapes observed some synergistic effects (Bracy et al., 2014; Cerin et al., 2018; Cerin et al., 2013; Cerin et al., 2013). For example, Cerin et al. (2018) demonstrated that intersection density, land use mix, and retail/civic area ratio were positively related to moderate-to-vigorous physical activity (MVPA) only in neighborhoods with good perceived pedestrian infrastructure/safety and traffic safety. Distance to public transport stops was associated with MVPA only in neighborhoods with pleasing aesthetics and better safety from crime. Similarly, Bracy et al. (2014) reported a positive interaction between pedestrian safety (e.g., well-lit streets; crosswalks and walk signals that help cross busy streets; social interactions with other people on the streets) and an accessibility index constructed with residential density, retail floor area ratio, intersection density, and land use mix.

In summary, based on the ecological models, several features were examined for their moderating effects on the relationship between accessibility measures and walking or physical activity. However, only a limited number of studies incorporated streetscape characteristics that pertain to various needs of pedestrians –safety from crime, traffic safety, and pleasurability – as either main effect or as moderating factors. This study contributes to filling this gap. Additionally, an increasing number of studies are developing computer vision models to automate the measurement of microscale features, but only a few studies have demonstrated their effectiveness in applied research. Another contribution of this study is in filling this gap.

3. Data and analytical methods

3.1. National household travel survey data

This study was conducted in the City of Atlanta, Georgia, USA. The 2017 National Household Travel Survey (NHTS) was used to derive the following variables: walking mode choice for each trip, socioeconomic and demographic status of the travelers and their households, vehicle availability, number of walking activities in the past 7 days, and trip-related variables such as trip distance and trip purpose. The NHTS is a national survey administered by the Federal Highway Administration that aims to gather information about daily travel covering civilian, non-institutionalized population of the U.S. The U.S. households selected through stratified random sampling were asked to provide information on household, person, vehicle, and trip-specific information. The sampling frame excluded group housing such as dormitories, and prisons. The 2017 NHTS first used address-based sampling to recruit survey respondents and then conducted a person-level retrieval survey through phone or web response. We acquired the NHTS Georgia add-on data from the Georgia Department of Transportation. Individual trips were used as the unit of analysis. Following Koo et al. (2021), this study only considered trips that have trip origin locations within the City of Atlanta and did not consider the built environment of the destination location to reduce computational resources. As will be shown in the result section, trip origin location provided the goodness of fit statistics that can be considered high without the consideration of destinations (McFadden, 1974). The 2017 NHTS Georgia add-on had 8,631 households with 59,876 trips across the state. After dropping trips that originated outside of the City of Atlanta, 2,189 trips were retained. We limited the study to non-work trips because they are likely to be more susceptible to local conditions compared to work trips (Manaugh & El-Geneidy, 2011), which retained 1,501 trips. We also excluded trips made by those who are<10 years old as their decision to walk can be determined by factors not considered in this study, such as the availability of caregivers. We excluded unrealistic data entries as determined by the Federal Highway Administration and those for which critical information (e.g., race) is not recorded, leaving 1,195 trips. We also narrowed the study to trips that traveled less than or equal to 1.66 miles, which is the maximum distance walked among the 1,195 trips, leaving 460 trips. This distance roughly aligns with the maximum distance walked for various trip purposes reported previously (Sugiyama, Kubota, Sugiyama, Cole, & Owen, 2019). Finally, six trips were deleted because GSV images were unavailable. The household income in NHTS is a categorical variable with income ranges (e.g., $10,000 to $14,999), and the present study converted this into a numeric variable using the midpoint of the range.

3.2. Macroscale factors

This study measured macroscale accessibility of the built environment using Walk Score. Walk Score is chosen among many accessibility measures because it has been widely used by both scholars and non-scholars and therefore is well-understood and that it can be easily accessed by scholars, practitioners, and the general public. Walk Score also is available for all of the U.S. and several international addresses (Duncan, 2013). Walk Score was collected using the API for each NHTS trip origin location. In addition to Walk Score, the appendix of this study provides the results using a more comprehensive measure of accessibility based on the 5D framework (see appendix for a more detailed description of the 5D measurement method and the outputs from regression models).

3.3. Microscale features

This study primarily uses Google Street View images and computer vision technology to measure the microscale features of walkable built environments. This study combines two automated audit methods developed in Koo et al. (2021) and Koo et al. (2022) to measure traffic safety at crossings, traffic safety along segments, safety from crime, and aesthetic pleasurability. Detailed explanations about the sampling of street view images for each street segment, training and application of computer vision models, and/or validation can be found in Koo et al. (2021) and Koo et al. (2022), and the present study provides brief overviews. Finally, traffic safety at crossings, traffic safety along segments, safety from crime, and aesthetic pleasurability are summed to calculate a composite microscale index. For the consistent use of terminology, specific measures of streetscape features used in this study will be referred to as microscale features. A total of 171,955 images were used to measure microscale features.

3.3.1. Presence-based measures

Most of the microscale features are measured using an automated audit method (see Koo et al. (2022) for details and the validation of this method). This method applies a custom-trained computer vision model named Mask R-CNN to Google Street View images that are collected at 5-meter intervals along the streets and at intersections. The computer vision model detects the presence of various objects included in the brief version of the Microscale Audit of Pedestrian Streetscapes (MAPS-mini). MAPS-mini is a validated 15-item walkability audit tool focusing on microscale features for walking and physical activity (Sallis et al., 2015). The 15 items in the MAPS-mini are walk signal, curb ramp, marked crosswalk, commercial land uses, public parks, public transit stops, seating, streetlights, building maintenance, graffiti, bike path, sidewalk, sidewalk buffer, trip hazards on the sidewalk (e.g., cracks, overgrowth), and overhead coverage for shade. Out of these 15 items, eight are selected for inclusion. Four items were excluded as they either conceptually overlap with Walk Score (e.g., commercial land uses in the MAPS-mini) or because their connection to pedestrians' safety from crime, traffic safety, or pleasurability is unclear (e.g., bike path). The other three items were excluded due to the low performance of the custom-trained computer vision model, including the presence of graffiti, trip hazards, and seating. Table 1 shows the validation metrics of the custom-trained Mask R-CNN on the validation set with the intersection-over-union threshold of 0.3. Note that in Table 1, streetlights are measured by looking both horizontally and vertically upward. Streetlights can appear indistinguishable from utility poles when they are close to cameras because only the base of streetlights (i.e., only the pole) can be seen. Such cases are common in most road configurations in residential land uses. The light fixture can be found only by looking up above the eye line. When the whole shape of streetlights is to be visible, streetlights are often located far from the camera. The limited visual information on streetlights, particularly the light fixtures, may have contributed to the low recall value of streetlights. The three streetlight-related measures—streetlights from a horizontal view, streetlights from a vertical view, and light poles—were added to create one streetlight measure.

Table 1
Class-wise validation metrics of the custom-trained Mask R-CNN at 0.3 intersection-over-union.

	Precision	Recall	F1 Score	Ground truth instance
Walk signal	0.929	0.637	0.756	102
Crosswalk	0.860	0.804	0.831	168
Curb ramps	0.748	0.615	0.675	169
Sidewalk	0.765	0.543	0.635	433
Buffer	0.850	0.528	0.651	161
Boarded buildings	0.812	0.382	0.519	102
Streetlights (from horizontal view)				
Streetlights	0.917	0.458	0.611	144
Light pole	0.831	0.954	0.888	108
Streetlight (from vertical view)	0.879	0.903	0.891	113

Because the NHTS does not provide the actual route of trips, this paper used a 400-meter buffer around each trip origin to select street segments that can be relevant to the mode choice. Distance of 400-meter has been used frequently in the literature to measure walkability of the built environment (Cerin et al., 2013; Ewing, 2013; Moudon & Lee, 2003). Street segments are excluded if<20% of the street segment intersected with the buffer. For the selected street segments, an automated audit was conducted. Note that each item in the MAPS-mini can be rated as 1 or 2 if the item is found on a street and 0 if not. If the item measures an unfavorable feature for pedestrians (e.g., the existence of trip hazards), a street is given a value of 1 when the item is not found on the street. There can be multiple streets within the buffer of a trip origin. Item scores for each trip origin are calculated by averaging the item scores of street segments around the origin location. For example, if five street segments fall into the buffer of a given trip origin location and if three of the streets had sidewalks detected, the sidewalk score for the trip origin location would be three divided by five.

Note that when downloading street view images through the GSV API, it is not possible to specify which year's image the API would

Table 2
Measures of microscale streetscape design features related to pedestrian needs.

Quality	Contributing Factors	Method
Safety from crime	Lack of rundown buildings with boarded windows, streetlights	Koo et al. (2022)
Traffic safety at crossing	Walk signal, crosswalk, curb ramps	
Traffic safety on segment	Sidewalk, sidewalk buffer	
Pleasurability	public parks (GIS)	
	Building-to-street ratio (B2S), greenery	Koo et al. (2021)

return, and the API can return different images for the same location if Google has updated images for that location. Most of the images for presence-based measures were taken between 2016 and 2020.

3.3.2. Proportion-based measures

Building-to-street ratio and greenery are measured using the method in Koo et al. (2021). This method uses Pyramid Scene Parsing Network (PSPNet), a computer vision architecture developed by Zhao et al. (2017) to label each pixel in a given image with the most probable class name (e.g., building, road, tree). This study used PSPNet trained on ADE20K dataset (Zhou et al., 2017) with a mean of class-wise intersection over union of 41.68% and pixel-wise accuracy of 80.04% (H. Zhao et al., 2017). The Google Street View images are collected at intersections and at the midpoint of street segments. The same 400-meter buffer used for the presence-based measures was utilized to select GSV images relevant to walking mode choice. The images used for measuring proportion-based measures are mostly taken between 2016 and 2018. The GSV images are processed through PSPNet to calculate the proportion of eight objects relevant to the pedestrian experience: building, house, sidewalk, road, car, tree, grass, and plant. For each image, building-to-street ratio and greenery are calculated by the following formula:

$$\text{Building}-\text{to}-\text{street ratio} = \frac{\%\,Building + \%\,House}{\%\,Sidewalk + \%\,Road + \%\,Car}$$

$$\text{Greenery} = \%Tree + \%\,Grass + \%\,Plant$$

The individual item used to calculate traffic safety at crossings, traffic safety along segments, safety from crime, and pleasurability are summarized in Table 2.

3.4. Analytical methods

This study first examines bivariate correlations between Walk Score and the 10 microscale features in Table 2. The correlation is presented to provide an overview of the relationship between Walk Score and microscale features. Multivariate relationships between walking mode choice and various aspects of walkable built environment are examined using binary logistic regression. The dependent variable is the binary mode choice of each trip that was derived from the NHTS (i.e., walking = 1, non-walking = 0). All regression models adjusted for personal, household, and trip-related covariates that may affect the choice to walk over other modes. The moderation effects are examined by an interaction term between Walk Score and each of safety from crime, traffic safety at crossing, traffic safety at segment, aesthetic pleasurability, and the composite microscale index. This combination produced a total of five models. Adopting the approach used in Bracy et al. (2014), Walk Score and one of safety from crime, traffic safety at crossing, traffic safety at segment, pleasurability, and the composite microscale index were examined for their main and interaction effects in each model. Significant interaction terms at $\alpha = 0.05$ are interpreted by making predictions for when Walk Score is at −1 standard deviation (SD; i.e., low) and + 1 SD (i.e., high) from the mean, and when the microscale feature is at −1 SD and + 1 SD from the mean, while holding all other variables at their mean (i.e., continuous variables) or at mode (i.e., categorical variables).

Table 3
Demographic and trip characteristics (number of trips = 318).

Variable	Mean (S.D.) or Count (%)	Range
Dependent variable		
Walking mode choice	Walking: 242	(53.3%)
	Non-walking: 212	(46.7%)
Independent variables		
Age	44.454 (16.911)	11.00–86.00
Household income ($)	97825.451 (69342.808)	5000–249998
Vehicles per adult	0.935 (0.528)	0.000–4.500
Count walk trips in the past 7 days	9.370 (9.002)	0.000–40.00
Travel distance (miles)	0.649 (0.453)	0.009–1.662
Sex	Male: 260	(57.3%)
	Female: 194	(42.7%)
Race	White: 296	(65.2%)
	Black: 125	(27.5%)
	Other races: 33	(7.3%)
Educational attainment	Less than high school: 16	(3.5%)
	High school or higher: 438	(96.5%)
Driver status	Driver: 403	(88.8%)
	Non-driver: 51	(11.2%)
Macroscale factor		
Walk Score	74.172 (19.081)	7.000–98.00
Microscale features		
Traffic safety at crossing (max = 3)	1.879 (0.488)	0.200–2.903
Traffic safety on segment (max = 2)	1.243 (0.297)	0.350–1.791
Safety from crime (max = 2)	1.517 (0.184)	1.000–1.931
Pleasurability (max = 3)	0.866 (0.246)	0.276–1.775
Microscale index	5.505 (0.874)	2.501–7.382

Table 4
Correlation between microscale features and macroscale factors.

	Correlation with Walk Score
Traffic safety at crossing	0.717***
Walk signal	0.605***
Crosswalk	0.631***
Curb ramp	0.659***
Traffic safety on Segment	0.452***
Sidewalk	0.620***
Buffer	0.218***
Safety from crime	0.482***
No boarded building	0.015
Streetlight	0.477***
Pleasurability	0.147**
Public parks	0.053
Building to street ratio	0.659***
Greenery	−0.643***
Microscale Index	0.696***

**$p < 0.01$; ***$p < 0.001$.

4. Results

4.1. Descriptive statistics

The unfiltered NHTS data contained 2,189 trips that had origin locations in the City of Atlanta. After excluding trips that are unsuitable for walking using criteria in Section 3.1, 460 trips remained. We also removed 6 trips because there were no streets with GSV images within 400 m, leaving 454 trips in the final sample. The average age of the survey respondents was 44.5, about 57% were male, and over 65% were white. Over 88% of the survey respondents had driver's licenses, and more than 96% were at least high school graduates. Table 3 shows the

Table 5
Standardized regression coefficients and confidence intervals in odds ratio.

	Model 1: Microscale = Traffic safety at crossing	**Model 2:** Microscale = Traffic safety on segment	**Model 3:** Microscale = Safety from Crime	**Model 4:** Microscale = Pleasurability	**Model 5:** Microscale = Microscale Index
Constant	0.358 (0.092–1.395)	0.288 (0.076–1.097)	0.384 (0.095–1.562)	0.255* (0.067–0.972)	0.361 (0.092–1.422)
Age	0.705* (0.535–0.931)	0.687** (0.524–0.901)	0.729* (0.554–0.96)	0.677** (0.516–0.888)	0.722* (0.547–0.952)
Sex (base: female)	1.052 (0.640–1.728)	1.116 (0.680–1.83)	1.093 (0.662–1.804)	1.093 (0.665–1.798)	1.122 (0.680–1.85)
Race: Black (base: White)	0.615 (0.300–1.261)	0.874 (0.452–1.692)	0.637 (0.319–1.272)	1.069 (0.536–2.135)	0.600 (0.299–1.205)
Race: Other (base: White)	1.503 (0.56–4.033)	1.745 (0.668–4.558)	1.570 (0.579–4.254)	2.061 (0.803–5.292)	1.600 (0.607–4.214)
Household Income	0.990 (0.737–1.330)	1.086 (0.821–1.437)	0.961 (0.714–1.293)	1.062 (0.798–1.414)	0.938 (0.695–1.267)
Cars per adult	1.089 (0.811–1.462)	1.163 (0.874–1.547)	1.120 (0.835–1.503)	1.242 (0.915–1.686)	1.105 (0.815–1.497)
Education high school or higher (base: less than high school)	2.358 (0.654–8.505)	2.946 (0.830–10.461)	2.334 (0.620–8.782)	3.481 (0.982–12.342)	2.362 (0.642–8.689)
No driver license (base: have driver license)	5.505** (1.866–16.238)	6.227*** (2.152–18.019)	6.203** (2.042–18.844)	7.67*** (2.664–22.082)	6.149** (2.061–18.343)
Number of walking trips in past 7 days	2.04*** (1.535–2.711)	2.004*** (1.515–2.651)	2.125*** (1.588–2.845)	2.055*** (1.550–2.725)	2.058*** (1.547–2.739)
Trip distance	0.268*** (0.198–0.363)	0.256*** (0.190–0.344)	0.278*** (0.205–0.378)	0.236*** (0.172–0.324)	0.269*** (0.198–0.365)
Macroscale factor (i.e., Walk Score)	1.622* (1.067–2.466)	1.805*** (1.290–2.526)	1.494* (1.062–2.102)	1.465** (1.099–1.954)	1.390 (0.941–2.053)
Microscale feature	1.356 (0.914–2.012)	1.020 (0.744–1.399)	1.546** (1.118–2.138)	1.732*** (1.314–2.284)	1.853** (1.261–2.724)
Interaction: Macro × Micro	1.532*** (1.227–1.914)	1.250* (1.019–1.534)	1.617*** (1.252–2.087)	1.022 (0.792–1.318)	1.500*** (1.211–1.858)
Observation	454	454	454	454	454
LL	−200.175	−206.729	−198.145	−200.921	−197.938
McFadden Adj. R^2	0.317	0.296	0.324	0.315	0.324
AIC	428.350	441.458	424.291	429.841	423.876

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

mean, standard deviation, and range of the variables used in the analysis. The average Walk Score was 74, which is higher than the city's average Walk Score of 48 as reported on the Walk Score website, suggesting a more compact and accessible development pattern (accessed March 19, 2023).

4.2. Association between macroscale measures and microscale features

The majority of microscale features showed significant levels of correlation with Walk Score, most with positive coefficients except for greenery (see Table 4). The constituent variables of traffic safety at crossing (i.e., walk signal, crosswalk, and curb ramp) showed particularly strong and consistent correlations with Walk Score. After individual microscale features were combined to create traffic safety, safety from crime, and aesthetic pleasurability, pleasurability had the weakest correlations with Walk Score. Microscale index showed a positive and significant correlation with Walk Score as well.

Table 5 shows the coefficients in the odds ratio (OR) format and 95% confidence interval of the coefficients. All numeric predictors were standardized by converting them into z-scores before the fitting of the models. McFadden's adjusted R^2 ranged between 0.296 and 0.324, suggesting good model fits (Domencich & McFadden, 1975). The main effect of Walk Score was significantly associated with walking mode choice across all models except Model 5 (i.e., microscale feature = microscale index). When microscale features are at their mean, an increase in Walk Score by one standard deviation is associated with roughly 62%, 81%, 49%, and 47% increases in the odds of walking in Model 1 ~ 4, respectively.

Three microscale features showed statistically significant and positive main effects, including safety from crime, pleasurability, and microscale index. The odds ratio of the main effect of safety from crime was 1.546. When Walk Score is at its mean (i.e., zero, due to the centering), an increase by one standard deviation in safety from crime is associated with about 55% increase in the odds of choosing to walk (95% CI of OR: 1.118 ~ 2.138). Similarly, when Walk Score is at its mean, increases in pleasurability and microscale index by one standard deviation are associated with about 73% (OR: 1.732; 95% CI of OR: 1.314 ~ 2.284) and 85% (OR: 1.853; 95% CI of OR: 1.261 ~ 2.724) increase in the odds of walking, respectively.

Macro- and microscale factors showed positive and significant interaction effects in all but one model. Model 4 (i.e., microscale feature = pleasurability) was the exception in which the interaction term was positive but statistically insignificant. As shown in Fig. 1, the interaction terms indicated that the effect of Walk Score was larger when traffic safety at crossings was higher (i.e., +1 SD). For example, when traffic safety at crossing is at + 1 SD, increasing Walk Score by 1 SD from its mean increased the predicted probability of walking by 0.203. When traffic safety at crossing is at −1 SD, the same change in Walk Score accounted for 0.014 changes in the predicted probability of walking. Similarly, when traffic safety on segment is higher (i.e., +1 SD), an increase in Walk Score by 1 SD from its mean increased the predicted probability of walking by 0.194. When traffic safety on segment is lower (i.e., −1 SD), the same change in Walk Score increased the probability of walking by 0.091.

Fig. 1 shows that in Model 3 and 5, the effect of Walk Score can be negative if safety from crime and microscale index is low (i.e., −1 SD). When safety from crime is low, changing Walk Score from its mean to 1 SD above is associated with a slight reduction in the probability of walking by 0.019. When safety from crime is high (i.e., +1 SD), the probability of walking increases by 0.183 for the same change in Walk

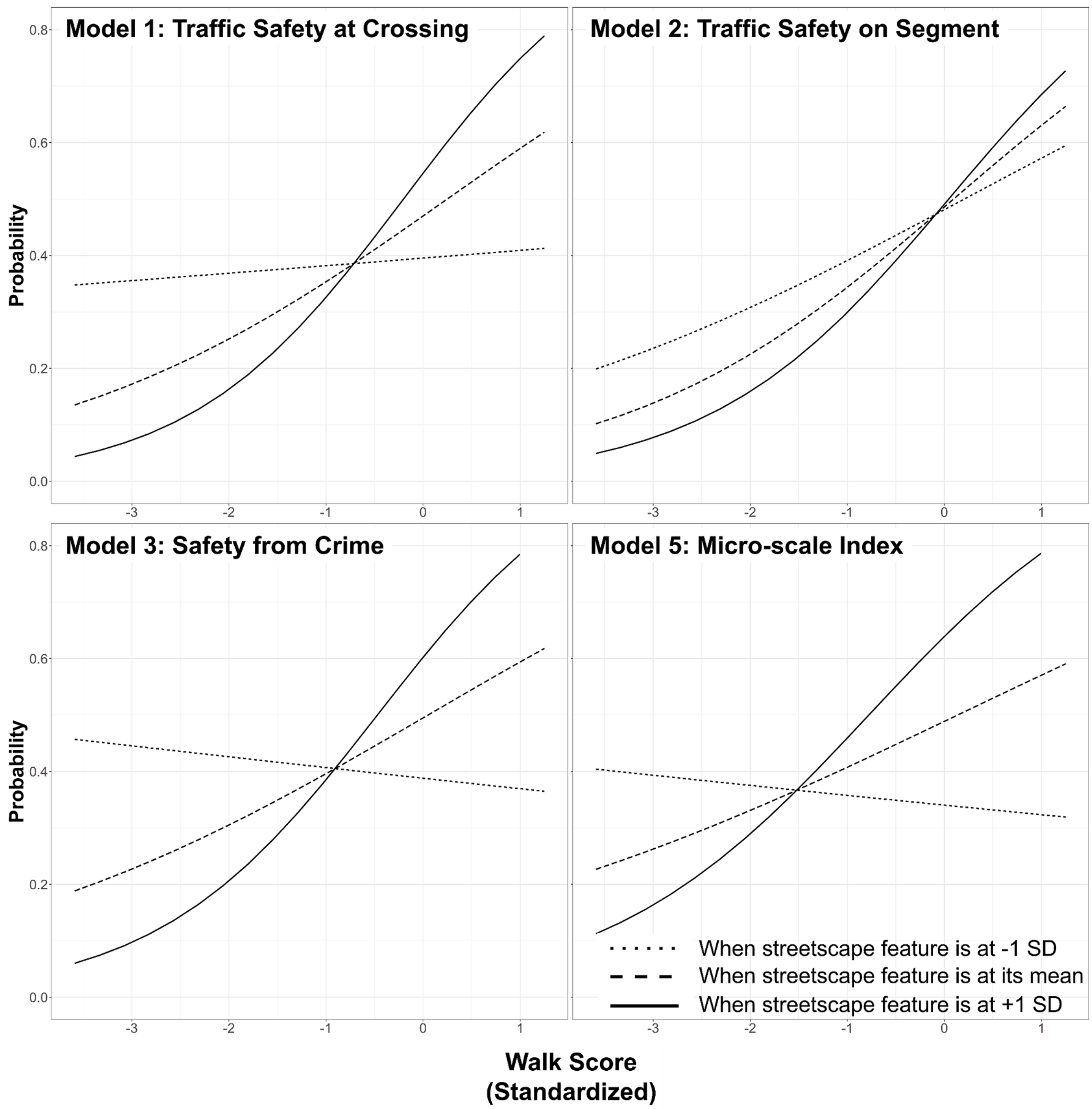

Fig. 1. Predicted probability of walking mode choice as a function of microscale features when Walk Score is at one standard deviation below its mean, at the mean, and one standard deviation above the mean.

Score. Likewise, when microscale index is low, increasing Walk Score by 1 SD from its mean reduces the probability of walking by 0.017. When microscale index is high, the probability of walking increases by 0.148.

5. Discussions

This study examined whether desirable streetscape design can enhance the benefits of accessible urban form. The findings indicate that the hypotheses regarding the main effects of microscale features posed above are accepted for the microscale features pertaining to safety from crime, pleasurability, and overall microscale index. The hypotheses regarding the interaction effects are accepted for all microscale features except pleasurability. Safety from crime and the overall microscale index had significant main and interaction effects. Regarding the main effects, trips that started from areas with fewer rundown buildings with boarded windows and more streetlights (i.e., better safety from crime) were associated with a greater probability of walking. Trips that originated in more aesthetically pleasurable areas with higher building-to-street ratios and urban greeneries (e.g., street trees and public parks) are more likely to be walking trips. In models that used safety from crime and microscale index (Model 3 and 5), the moderating effects of microscale features were large enough to render the effects of Walk Score negative when microscale features were unfavorable.

The findings of this study can offer potential lessons for urban planning and other related professions. Accessibility measures, as measured by Walk Score, consistently showed positive associations with walking mode choice in most cases, supporting the past findings. Similar results were found when accessibility was measured using 5D frameworks (see Appendix for details). Urban planners attempting to promote walking by built environmental intervention over the long term should pay attention to plans and policies aimed at promoting accessibility, such as smart growth and transit-oriented development. However, increasing accessibility requires modifications to macroscale urban form, which can require collective, long-term efforts by multiple stakeholders. This makes timely interventions in desired neighborhoods by urban planners and communities challenging. For more immediate impact, the results of this study suggest a focus on more readily modifiable microscale features such as installing walk signals, crosswalks, streetlights, planting street trees, and removing rundown buildings with boarded windows. Many of the interventions to microscale features can provide direct impacts on walking as well as indirect impacts by enhancing the effects of Walk Score. Some microscale features may not be as easily modifiable as others, such as building-to-street ratio. However, building-to-street ratio is determined by the combination of building heights and street widths. Even when building heights are held constant and the overall development density is fixed, the ratio can be increased by altering the relationship between buildings and streets (e.g., narrowing the street width) (Lehmann, 2016). For example, moving parking spaces away from the streets to behind the buildings and putting buildings close to the streets can increase the building-to-street ratio in areas where increasing the overall development density is not feasible. Finally, this study demonstrates that the data generated by the combination of custom-trained computer vision models and street view images is sensitive enough to generate results that align with expectations and past findings. The approach used in this study can be a cost-effective and scalable method for creating much-needed databases on microscale streetscape design features for urban design and planning at fine spatial (and maybe temporal as well) resolutions. Other recent studies also report similar results, which reinforces the benefits of using computer vision and street view images for measuring streetscape features in microscale (e.g., Adams et al., 2022).

One unexpected finding was that pleasurability, which is theorized to be the least prioritized need of pedestrians (Alfonzo, 2005), was one of the most significant predictors of walking. A potential explanation is that the building-to-street ratio and greenery can provide multiple benefits that are not limited to aesthetic pleasurability: street trees can offer complexity, human scale, and enclosure and make the street more enticing and attractive to pedestrians. More pedestrians on streets can increase 'eyes on the streets,' adding to the sense of safety (Jacobs, 1961). Street trees have been empirically associated with reduced crime rates (Donovan & Prestemon, 2012) and perceived safety (Harvey et al., 2015). More enclosed streetscapes (e.g., high building-to-street ratio) can be associated with less severe crashes (Harvery & Aultman-Hall, 2015), contributing to traffic safety. To better isolate the effects of traffic safety, safety from crime, and pleasurability, more refined measures are needed.

It is important to note that machine-driven automated audits using street view images have a few important caveats that future users will need to consider. Because street view images are taken by cameras mounted on vehicles running on the road, the view of objects that matters to pedestrians (e.g., sidewalks, buffers, walk signals, crosswalks, and building qualities) can be blocked by objects such as parked cars. When the road is wide, the camera can be farther away from sidewalks, and small objects and other details of the pedestrian environments (e.g., cracks on the sidewalk) can be obscured even without occlusion. Additionally, the availability and update patterns of street view images may vary systematically in different parts of a city depending on socioeconomic conditions (Fry, Mooney, Rodríguez, Caiaffa, & Lovasi, 2020), imposing potential biases in the audit results. These biases are less likely to occur for manual in-person audits. Another important caveat is that humans are biased in particular aspects, and computer vision models can inherit human biases embedded in the annotations of the training datasets. For example, contrary to the common assumption that annotation errors are random noises, datasets for training computer vision models can contain systematic biases and the trained computer vision models can inherit the biases, "produc[ing] biased outcomes against certain groups of people" (Chen & Joo, 2021, p. 14980). A study by Saha et al. (2019) showed that, for items that require subjective judgments, crowdsourced annotations for sidewalk-related issues yielded low recall or precision. Although whether the low recall or precision are random errors or contain systematic biases is not explored yet, automated audits using computer vision for creating a database of microscale streetscape features for policymaking should pay careful attention to potential sources of biases and their consequences, particularly when the annotators of the training dataset are not representative of the population being influenced by the data.

It is important to clarify the limitations of this study. First, this study only considered the origins of each trip. Although the models showed good model fits (i.e., adjusted McFadden's R^2 between 0.296 and 0.324), considerations of the destination (e.g., demand management through parking regulations) will likely offer better model fits as well as a richer understanding of the environment-walking behavior relations. Second, the design of the travel survey data introduced various limitations: (1) The limited sample size prevented us from subdividing the data by trip purpose, by home-based versus non-home-based trips, or by subgroups of population; (2) the sample size also may have resulted in the insignificance of some variables; and (3) because the study site is limited to Atlanta, the degree to which the result of this study applies to other cities is unknown. Third, there is a time difference between the year in which images used for detecting microscale features were taken and the year the NHTS 2017 was conducted. The NHTS 2017 data was collected between 2016 and 2017, and most of the images for microscale features were taken between 2016 and 2020. If there were meaningful changes in microscale features between 2017 and 2020, which is not implausible considering the modifiability of microscale features within a short time, the walking mode choice may have occurred in a different built environment than what is captured in our data. Fourth, the degree to which the microscale features measured in this study relate to perceived quality is not known, which can be a significant pathway linking the objective measures with health outcomes (Hipp, Gulwadi, Alves, & Sequeira, 2016). Although both perceived and objectively measured environment variables associate with physical activity, they are likely to be distinct measures that "may capture different sources of variability in behavior" (Orstad, McDonough, Stapleton, Altincekic, & Troped, 2016, p. 917). Lastly, this study fitted five different models using the same dataset, raising a potential risk of Type 1 error, an issue known as the multiple comparisons or simultaneous hypothesis testing (Benjamini & Yekutieli, 2001). Future research can consider research design that can minimize the risk of multiple comparisons issue.

6. Conclusion

This study provides evidence of direct and moderating effects of various microscale pedestrian streetscape features on walking mode choice, which add to the growing literature on the intricate relationship between the walkable built environment – macroscale accessibility and microscale streetscape features – and walking behavior.

Building upon the findings and limitations of this study, future research should incorporate built environment qualities of more diverse locations (e.g., origin, destination, and along the route) and use more refined measures of microscale features. As objectively measured and perceived qualities of the built environment may not align, the refined measures may benefit from reflecting perceptions of pedestrians. Consideration for different population subgroups and trip purposes may also be instructive. The use of computer vision and image datasets can be a promising method for addressing some of these issues. With rapid advances in computer vision and computing capacities, future research will be able to measure microscale features at more densely sampled locations over a larger geographic area than is currently feasible, which will enable researchers to incorporate other big behavior-related datasets into research frameworks (e.g., GPS trajectories of cell phone users and shared bikes and user-contributed platforms like Strava). Past studies also demonstrated that computer vision can also learn to predict people's perception of urban environments such as the sense of safety and aesthetics from street view images (e.g., by using Place Pulse dataset; see Harvey et al., 2015; Naik, Philipoom, Raskar, & Hidalgo, 2014; Salesses, 2012 for example applications).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

Table A1
Correlation between microscale factors and macroscale factors.

	Correlation with Walk Score		Correlation with Accessibility Index	
Traffic safety at crossing	0.717	***	0.750	***
Walk signal	0.605	***	0.739	***
Crosswalk	0.631	***	0.566	***
Curb ramp	0.659	***	0.633	***
Traffic safety: Segment	0.452	***	0.237	***
Sidewalk	0.62	***	0.499	***
Buffer	0.218	***	−0.038	
Safety from crime	0.482	***	0.566	***
No boarded building	0.015		−0.011	
Streetlight	0.477	***	0.571	***
Pleasurability	0.147	**	0.179	***
Public parks	0.053		0.044	
Building to street ratio	0.659	***	0.820	***
Greenery	−0.643	***	−0.782	***

**p < 0.01; ***p < 0.001.

the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix

This appendix provides an additional analysis results by replacing Walk Score with the 5D framework as a measure of macro-scale accessibility to offer an additional insights (Ewing & Cervero, 2010). The 5D framework measures Density, Diversity, Design, Destination accessibility, and Distance to transit to quantify the degree to which the built environment is attractive, transit-friendly, and have convenient destinations close by, which make it walkable (Ewing & Cervero, 2010). Note that while a more comprehensive 7D framework exists, which adds Demographic and Demand management to 5D framework, this study opted to use 5Ds because (1) Demographic is not about environmental factors and (2) Demand management pertains to the destination characteristics while this study focuses on the characteristics of trip origins. In what follows, we describe how the 5D variables are

Table A2
Standardized regression coefficients and confidence intervals in odds ratio.

	Model 1: Microscale = Traffic safety at crossing	**Model 2:** Microscale = Traffic safety on segment	**Model 3:** Microscale = Safety from Crime	**Model 4:** Microscale = Pleasurability	**Model 5:** Microscale = Microscale Index
Constant	0.401	0.396	0.442	0.341	0.436
	(0.102–1.569)	(0.102–1.547)	(0.110–1.778)	(0.087–1.331)	(0.109–1.740)
Age	0.720*	0.725*	0.740*	0.710*	0.741*
	(0.545–0.951)	(0.551–0.955)	(0.563–0.974)	(0.539–0.934)	(0.561–0.977)
Sex (base: female)	1.003	1.004	1.029	1.011	1.047
	(0.607–1.656)	(0.609–1.655)	(0.623–1.700)	(0.609–1.677)	(0.633–1.734)
Race: Black (base: White)	0.566	0.737	0.635	0.908	0.577
	(0.277–1.157)	(0.377–1.441)	(0.321–1.260)	(0.451–1.827)	(0.288–1.158)
Race: Other (base: White)	1.135	1.246	1.198	1.338	1.295
	(0.401–3.206)	(0.457 – 3.401)	(0.428 – 3.351)	(0.502 – 3.566)	(0.467 – 3.593)
Household Income	0.981	1.019	0.943	0.981	0.922
	(0.727 – 1.323)	(0.763 – 1.360)	(0.699 – 1.272)	(0.730 – 1.320)	(0.680 – 1.249)
Cars per adult	1.133	1.232	1.204	1.285	1.169
	(0.848–1.515)	(0.921–1.648)	(0.901 – 1.609)	(0.942 – 1.754)	(0.869 – 1.574)
Education high school or higher (base: less than high school)	2.143	2.436	2.068	2.861	2.028
	(0.592 – 7.749)	(0.672 – 8.827)	(0.556–7.684)	(0.799–10.242)	(0.548–7.510)
No driver license	6.635***	7.870***	7.267***	8.587***	7.636***
(base: have driver license)	(2.239–19.661)	(2.643–23.430)	(2.416–21.852)	(2.946–25.031)	(2.535–23.001)
Number of walking trips in	2.136***	2.052***	2.096***	2.085***	2.051***
past 7 days	(1.609–2.836)	(1.556–2.707)	(1.585–2.773)	(1.576–2.758)	(1.552–2.710)
Trip distance	0.275***	0.267***	0.282***	0.248***	0.28***
	(0.203–0.374)	(0.198–0.360)	(0.208–0.382)	(0.180–0.341)	(0.206–0.381)
Macroscale factor	1.853**	2.077***	1.668**	1.923***	1.644**
(i.e., Accessibility Index)	(1.213–2.832)	(1.501–2.876)	(1.175–2.366)	(1.401–2.640)	(1.135–2.382)
Microscale feature	1.143	1.052	1.351	1.761***	1.611*
	(0.753–1.736)	(0.762–1.453)	(0.972–1.879)	(1.318–2.352)	(1.101–2.359)
Interaction: Macro × Micro	1.569***	1.218	1.455**	1.082	1.527**
	(1.219–2.020)	(0.923–1.608)	(1.111–1.907)	(0.802–1.459)	(1.185–1.968)
Observation	454	454	454	454	454
LL	−196.844	−202.415	−198.018	−195.390	−196.287
McFadden Adj. R^2	0.328	0.310	0.324	0.333	0.330
AIC	421.687	432.831	424.037	418.780	420.573

Note: *p < 0.05; **p < 0.01; ***p < 0.001.

calculated. *Density*: This study used the sum of residential and employment density within a 400-meter buffer around each NHTS trip origin. Residential density was calculated based on the 2018 American Community Survey by estimating the number of housing units within the 400 m buffer of NHTS origins and dividing it by the area of the buffer. For each Census Block Group that intersects with the buffer, the number of housing units within the buffer was calculated by (1) calculating the proportion of land area that each Census Block Group intersects with the buffer, which range between zero and one, and (2) multiplying the proportion by the total number of housing units of the Census Block Group. For the employment density, the 2015 Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) at Census Block was used. The employment density of a given origin location is calculated as the number of jobs of Census Blocks whose centroids fall into the buffer, divided by the area of the buffer. Because Census Blocks are usually small, the number of jobs were used without the adjustment based on the proportion of land area of the Census Block intersecting with the buffer. Residential density and employment density were then summed. *Diversity*: Land use diversity is measured using parcel-level data and the following formula:

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

where *n* is the area of each land use category *i* in the 400-meter buffer of NHTS origins (*i* = residential, commercial, institutional, and office uses); and N is the area of residential, commercial, institutional, and office uses combined within the buffer. *Design*: The design component in 5D refers to the design of street network. Intersection density was calculated by dividing the number of intersections in the 400-meter buffer by the area of the buffer. *Destination accessibility*: Walk Score was used to represent destination accessibility. Walk Score was collected using the API for each NHTS trip origin location. *Distance to transit*: The network distance from each NHTS trip origin to the nearest rail transit station was calculated in miles. Non-train transit stations were not considered for this variable. Variables with skewed distributions were log-transformed if the transformation improved the model fit measure. Finally, an accessibility index was created by converting the individual 5D variables into z-scores and summing them. See (Table A1 and Table A2).

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