Impact of County-Level Built Environment and Regional Accessibility on Walking: A Washington, DC–Baltimore Case Study

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Abstract: Existing research on built environment's impact on nonmotorized travel behavior has focused on neighborhood-level factors. However, because people live and work at a regional scale—using transit and cars to access jobs and other destinations—it can be hypothesized that a region's built environment can also be influential in nonmotorized travel behavior. This study examines the role of county-level built environment and regional accessibility in walking by developing mixed-effects models applied to household data from the Washington, DC and Baltimore metropolitan areas. The results indicate that in addition to neighborhood-level built environment, county-level built environment and regional accessibility can affect walking travel behavior by residents. The findings suggest that land-use policies to promote walking will not be fully effective if only considered at the neighborhood level. More effective land-use policies are those that consider the overall physical form of urban areas, including the composition of population and employment, the extent of street network connectivity, and regional accessibility across an entire metropolitan area. **DOI: 10.1061/(ASCE)UP.1943-5444.0000452.** *© 2018 American Society of Civil Engineers.*

Introduction

Recognizing the documented health, economic, and environmental impacts of automobile use, it is worth examining the factors that influence a household's travel choices. Health problems including obesity have reached alarming levels in the United States. In 2011, approximately 65% of the population in the United States was either overweight or obese; 32% lived with hypertension; and 9% suffered from asthma (Milne and Melin 2014). Thus, the value of adopting a healthier lifestyle has been increasingly recognized by individuals, communities, and government agencies. Additionally, the US economy has been impacted by the ever-worsening traffic congestion conditions, pollution emission levels, and high energy consumptions, especially in growing urban areas. In 2011, traffic congestion caused Americans who lived in cities to spend an extra 5.5 billion hours traveling and purchase an additional 2.9 billion gallons of fuel (Milne and Melin 2014). Further, the transportation sector is responsible for environmental impacts, generating a high portion of greenhouse gas (GHG) emissions and other harmful pollutants (Nasri and Zhang 2014). According to the US Environmental Protection Agency (EPA), transportation activities accounted for approximately 35% of US carbon dioxide (CO_2) emissions from fossil fuel combustion, and 27% of total GHG emissions in 2015 (EPA 2017).

There has been a surge of research efforts and policies to find effective long-term solutions to mitigate these health, economic, and environmental problems. Reduction of the amount of automobile travel seems to be the most promising solution so far. As a result, nonmotorized modes of travel (walking and bicycling) have received increased scholarly attention as suitable alternatives to driving.

Walking and bicycling offer numerous health and social benefits, at both individual and community levels. These modes of travel are also inexpensive, enjoyable, and available to most people. Yet, the most recent National Household Travel Survey (NHTS 2009) showed that of all trips taken in the United States, the shares of walking and bicycling trips were only 10.4 and 1%, respectively. Moreover, approximately 70% of trips shorter than one mile were made by private automobile (Milne and Melin 2014). These statistics have motivated researchers to determine the factors that influence the decision to walk or cycle rather than drive. One influence is the built environment. Characteristics of an individual's place of residence have been proven to impact travel behavior of individuals (e.g., Cervero and Kockleman 1997; Kitamura et al. 1997; Handy and Clifton 2001; Cervero and Duncan 2003; Targa and Clifton 2005; Nasri and Zhang 2012).

Studies that examine the link between the built environment and travel behavior generally use two geographical scales for the built environment: microlevel, which considers the local or neighborhood level built environment, and macrolevel which examines the built environment of the regional urban area.

Research on the relationship between nonmotorized travel and the built environment has been concentrated on neighborhood-level built environment (i.e., residence or destination neighborhood). The underlying assumption has been that, compared with vehicle and transit trips, nonmotorized trips are shorter in length, and therefore, originate and conclude in the neighborhood (Cervero and Duncan 2003). Nonetheless, the complex interrelation between the land use, transportation network design, and travel choices gives rise to untested hypotheses about the potential role of the macrolevel built environment in nonmotorized travel behavior.

Theoretically, macrolevel built environment characteristics can be influential in nonmotorized travel behavior. One reason can be that as macrolevel built environment influence motorized travel

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Note. This manuscript was submitted on April 4, 2017; approved on December 7, 2017; published online on May 8, 2018. Discussion period open until October 8, 2018; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Urban Planning and Development***, © ASCE, ISSN 0733-9488.

behavior (i.e., driving), it can also affect nonmotorized travel behavior, consequently. For example, more driving trips by household members, may indicate less walking trips. Additionally, in trip chaining, people tend to continue using their private vehicle for the entire chain once they use the private vehicle for one part of the trip chain. In this sense, macrolevel built environment that reduces reliance on regional automobile travel and supports regional transit (e.g., commuter bus/train, city to city bus, and intercity train) trips may lead to generation of more transit-related walking trips. Previous empirical evidence has shown that macrolevel built environment characteristics influence households' vehicle miles traveled (VMT) (Nasri and Zhang 2012, 2014). Therefore, it can be hypothesized that macrolevel built environment can influence a household's nonmotorized travel behavior as well. Another reason is that walking and bicycling trips may occur more frequently in already-walkable and bikeable neighborhoods in counties with an overall built environment that supports nonmotorized trips, perhaps with regional bike trails or an extensive sidewalk network.

Further, the characteristics of regional accessibility (vehicular or transit) can also influence destination and travel mode choice. Increased regional accessibility (in terms of number of activities within a given travel time from home) has been found in previous research to reduce a household's vehicular travel (Ewing 1995). Thus, it can be hypothesized that regional accessibility characteristics have a potential to affect nonmotorized travel behavior through affecting vehicular travel. For instance, if some households may generate fewer automobile trips due to availability of more transit options and transit-accessible destinations within the region; a case which may lead to generation of a higher number of transit-related walking trips from those households. On the other hand, a pedestrian-friendly neighborhood in a region without much regional accessibility can encourage more walking trips within the neighborhood. This is because in a region with low regional highway or transit accessibility, residents may find it difficult to travel to farther destinations and so, they may choose destination options within their neighborhoods. If their neighborhood is walkable, residents may choose to make more walking trips to nearby destinations rather than making vehicular trips to farther, hard-to-reach destinations.

Considering the above examples, it is hypothesized that the macrolevel built environment can be influential in a household's travel outcomes including the nonmotorized travel behavior. Testing macrolevel (e.g., county level) built environment and regional accessibility factors for their potential roles in household nonmotorized travel behavior, therefore, could give a more complete picture of travel behavior.

However, the potential role of macrolevel built environment in nonmotorized travel behavior has been largely overlooked in the past. Very few studies included measures of macrolevel built environment in their analysis of nonmotorized travel behavior. Because of the limited empirical research on the link between walking and macrolevel built environment, this study considers the association between the two by including measures of macrolevel (defined as county-level in this study) built environment and regional accessibility in its analysis.

More specifically, the hypothesis of this study is that in addition to microlevel (i.e., neighborhood) built environment factors, macrolevel (i.e., county-level) built environment factors including population and employment densities, street network design, and the extent of mixed-use development and regional accessibility characteristics influence people's decisions to walk. The study employs mixed-effects models—also known as multilevel models—to investigate the correlations between walking travel behavior and microlevel (neighborhood-level) as well as macrolevel (county-level) built environment characteristics and regional accessibility factors. The mixed-effects model is a powerful statistical method which allows for capturing correlations between walking and built environment at both neighborhood and county levels, simultaneously.

To the best of the authors' knowledge, this study is one of the first to advance the body of knowledge on walking travel behavior by including several measures of macrolevel built environment (i.e., county-level built environment and regional accessibility) in addition to microlevel (i.e., neighborhood-level) built environment measures in the analysis of walking trips. The knowledge developed from this study can be integrated with past research that focused on the impact of microlevel (i.e., neighborhood-level) built environment on walking to provide a more comprehensive understanding of how the built environment influences walking travel behavior.

Literature Review

Existing literature suggests that the built environment influences travel through factors famously known as the *5 Ds*: density, diversity, design, destination accessibility, and distance to transit (Ewing and Cervero 2010). Investigation specifically into factors influencing nonmotorized travel behavior has intensified during recent years with the emergence of new concepts such as smart growth, transit-oriented development (TOD), complete streets, livable communities, and sustainable transportation. All these concepts shift the view from traditional land-use planning, network design, and travel behavior, which has focused on the private automobile as the main mode of travel, to planning and designing frameworks that support nonmotorized travel and sustainable travel behavior (Cervero and Kockleman 1997).

Evidence provided by many studies suggests that the 5 Ds of the built environment are correlated with the choice and amount of nonmotorized travel (Frank and Pivo 1994; Cervero and Radisch 1996; Cervero and Kockleman 1997; Kitamura et al. 1997; Handy and Clifton 2001; Cervero and Duncan 2003; Targa and Clifton 2005).

Among the studies that examined walking behavior, Frank and Pivo (1994) found that the proportion of household walking work trips was positively and significantly correlated with the first D, density, particularly population and employment densities at the neighborhood level. In other studies, higher densities at the neighborhood level were also found to be associated with more nonmotorized trips, particularly walking.

As for the second D, diversity, previous findings on the association between the level of a neighborhood's mixed land use (land-use diversity) and walking are inconsistent. Frank and Pivo (1994) reported that overall, local mixed land use had significant effects on walking work trips, but they did not find any significant association between mixed land use and walking trips for local shopping. Kerr et al. (2007) however, found that commercial land-use mix was significantly correlated with walking, whereas Rodríguez et al. (2009) found that entropy (a variable capturing extent of mixed-use developments) was not correlated with walking to destinations.

Many studies investigated the effects of factors representing the third D, design, in their analysis of nonmotorized travel. Among those studies, Hess et al. (1999) found that neighborhood design factors including block size influenced pedestrian volumes. Cervero and Duncan (2003) argued that pedestrian and bicycle-friendly designs, particularly, intersection configuration and block sizes did not affect the likelihood of walking. Zhang (2004) found that increased network connectivity at trip origins promoted nonmotorized travel.

Other Ds, destination accessibility and distance to transit stations showed negative correlations with nonmotorized travel behavior in past studies (Cervero and Kockleman 1997; Handy and Clifton 2001; Targa and Clifton 2005; Schneider 2015). For instance, Handy and Clifton (2001) found that in neighborhoods with a greater distance to stores, fewer residents indicated a tendency to walk to stores, and Schneider (2015) found that walking was associated with shorter trip distances (in terms of travel times) to local shopping opportunities. Accessibility emerges from the literature as an important factor that impacts travel behavior (Ewing 1995; Handy 2005). Highway accessibility can encourage automobile mode choice and lead to an increased level of household VMT and less nonmotorized trips. Moreover, both local and regional accessibility to transit can negatively affect a household's vehicle ownership and use, and thereby promote nonmotorized trips. Different studies measure accessibility in various ways (e.g., distance or travel time to transit or destinations, number of transit stations or stores in the area). Nevertheless, all these methods quantify either destination or transit accessibility. Hansen (1959) defined accessibility as the number of activities (e.g., employment, residential, and commercial) around a zone adjusted for some measure of impedance (e.g., time, distance, or cost) for traveling to those activities.

Beyond the 5 Ds, another stream of research into the relationship between the built environment and nonmotorized travel behavior addresses the issue of correlation or causality. This literature suggests that the existence of a correlation does not guarantee existence of causality; therefore, an observed correlation between nonmotorized travel behavior and the built environment does not necessarily indicate that changing the built environment would lead to changes in nonmotorized travel behavior. These studies investigate the issue of self-selection and its role in explaining nonmotorized travel behavior.

The self-selection argument takes into consideration individual preferences and attitudes when making residential location and travel choices. The underlying assumption is that individuals who prefer to walk or bike may self-select themselves into walkable and bikeable residential locations. In this case, individual preferences, and not the effect of the built environment's characteristics, can be considered as a possible explanation for nonmotorized travel behavior occurring at those locations (Handy and Clifton 2001; Schwanen and Mokhtarian 2005; Handy et al. 2005, 2006; Cao et al. 2006). For example, Handy and Clifton (2001) suggested that self-selection of residents with preferences toward walking was the most important cause of the correlation observed between walking and neighborhood characteristics. Other studies found that even after controlling for residential self-selection, neighborhood characteristics did significantly influence walking behavior (Handy et al. 2005).

All of the aforementioned studies examined the association between nonmotorized travel behavior and the built environment by focusing on microlevel (i.e., neighborhood-level) built environment factors only. Very few studies investigated the link between macrolevel built environment measures and nonmotorized travel behavior. For example, to examine the impact of macrolevel land use on walking behavior, Greenwald and Boarnet (2001) included regional level (defined as zip-code level in their study) population density and retail employment density in their analysis. Even though the study concluded that regional densities were not important determinants of walking, the authors suggested that the effects of regional (macrolevel) density attributes and other regional-level built environment measures (such as pedestrian environment) should be examined in future studies to allow inferences about the impact of the built environment beyond the local level.

Based on the review of this literature, the present study hypothesizes that macrolevel (i.e., county-level) built environment plays a role in walking travel behavior. For instance, households that are located in a county with better walking opportunities (e.g., smaller block sizes which indicate more connected street networks) may generate more walking trips than households in a county with less pedestrian-friendly built environment and fewer walking opportunities. This is not to imply that the microlevel (i.e., neighborhood-level) built environment is not important in generating walking trips, but to draw attention to the potential importance of the macrolevel built environment. Macrolevel land-use factors have not been comprehensively tested for their association with nonmotorized travel behavior in the past. By including county-level built environment and regional accessibility variables and neighborhood-level built environment measures in the same model; this study attempts to fill that gap in knowledge.

Data

This study used data from Baltimore, Maryland and Washington, DC, metropolitan areas in the United States. These two metropolitan areas were chosen for the analysis because their travel surveys and land-use data were conducted at the same time resulting in consistent datasets. The two metropolitan areas are located close to each other which facilitates mapping efforts and comparison. Even though the two metropolitan areas are similar in many ways such as their highway systems, they are different enough in terms of income levels, built environment, public transportation systems, and regional accessibility characteristics to allow a statistical model to capture the most significant effects of the built environment on travel behavior.

The final database for the statistical models for this study consisted of the following datasets: (1) metropolitan household travel survey data; (2) land-use data; (3) metropolitan highway and transit skimming matrices; (4) Walk Score data; and (5) spatial data in the form of geographic information system (GIS) shapefiles.

The first two datasets, metropolitan household travel survey and land-use data, were obtained from the Metropolitan Washington Council of Governments (MWCOG), and the Baltimore Metropolitan Council (BMC). Both organizations conducted travel surveys in 2007 with Washington, DC including 11,000 households and Baltimore including 4,650 households. These data provided information on each surveyed household's socioeconomic and demographic characteristics and trips made by individuals within each household during a particular day. The two organizations also collected land-use data in 2005, which included population and employment information and the number of establishments in each land-use class for each transportation analysis zone (TAZ).

The third dataset, highway and transit skimming matrices, provided information on highway and transit travel times between various origin-destination (O-D) pairs in the two metropolitan areas, and terminal times for transit trips. The O-D zones considered in the skimming matrices were TAZs.

The fourth dataset, Walk Score data, provided information on neighborhood destination accessibility. Walk Score (2017) is a publicly available dataset which provides information on walkability of locations. A Walk Score is an objectively-measured number that assesses the walkability of a location based on a destination accessibility-oriented approach. Distance to nearby desired walkable amenities (e.g., educational, retail, services, food, and recreational destinations) is used in an algorithm which calculates the Walk Score of a specific point. The Walk Score methodology also considers other factors in calculation of Walk Score. These factors include: population density and street network attributes (e.g., block length and intersection density). Research has validated Walk Score as a measure of neighborhood walkability at multiple spatial scales and for various geographic locations (Duncan et al. 2011). Additionally, Walk Score has been shown to outperform other walkability measures in predicting actual amounts of walking (Manaugh and El-Geneidy 2011). Consequently, Walk Score has become a widely-known measure of walkability in recent years and has been utilized by many researchers in the transportation, urban planning, real estate, and public health fields (Pivo and Fisher 2011; Li et al. 2014; Wasfi et al. 2016). Walk Score ranges from 0 for a car-dependent location to 100 for the most pedestrian-friendly location.

Finally, GIS shapefiles from the US Census Bureau's TIGER/Line dataset provided census block-level, and county-level data within the study area. Additional GIS data came from MWCOG and BMC TAZ-level shapefiles. Because the TAZs provided by MWCOG are smaller and can provide finer-level details, any TAZ in the overlapping area between the two metropolitan areas was considered a Washington, DC TAZ.

For this study, the household was selected as the unit of analysis rather than individuals. Due to very limited data on bicycling trips, only household walking trips were considered in the analysis. Specifically, a household's number of daily per capita walking trips and a household's daily walking mode share were considered for statistical modeling. A previous study argued that households (as opposed to individuals) are the appropriate unit of analysis in travel research (Ewing 1995). Households have been used as units of analysis in past travel behavior research (e.g., Nasri and Zhang 2012, 2014) including research on nonmotorized travel behavior (Friedman et al. 1994).

Each household's TAZ code was used to spatially link the built environment and regional accessibility characteristics of the household's location to the walking trips of the household members by utilizing GIS tools (ArcMap 10.2.2). This generated the final integrated database for the statistical models.

Model Variables

Dependent Variables

Two dependent variables were modeled in this study: (1) the household's number of daily per capita walking trips; and (2) the household's daily walking mode share. To construct the first variable, the total number of a household's daily walking trips was calculated by summing the number of walking trips recorded in the travel survey during the travel day for all members of a household. Then, the total number of household walking trips (computed from the first step) was divided by the total number of household members to obtain the household's daily per capita walking trips. The second variable was constructed by dividing the total number of walking trips made by all household members during the travel day by the total number of all trips made by all household members during the same day.

Figs. 1 and 2 map the average number of household per capita walking trips and the average walking mode share for each TAZ in the study area. The figures show that the average number of household per capita walking trips and average walking mode share are generally higher in TAZs closer to the central business district (CBD) of the two metropolitan areas. The two figures also show that the average number of household per capita walking trips and average walking mode share in some suburban communities in the study area are relatively high, especially, in the Baltimore area. This may be reflecting leisure walking trips by residents of those suburban communities. In addition, the figures reveal that compared with Baltimore households, Washington, DC households are within TAZs farther from its CBD.

Table 1 lists the counties within the study area for which walking data were available and provides descriptive statistics for walking dependent variables by county. The table shows that the average number of per capita walking trips and average walking mode share are highest in counties containing the CBD areas of Washington, DC (District of Columbia) and Baltimore (Baltimore City) with the Washington, DC CBD county (District of Columbia) having slightly higher values for the number of per capita walking trips and average walking mode share compared with the Baltimore CBD county (Baltimore City). The table also shows that among the remaining counties, the counties with the highest average number of per capita walking trips and average walking mode share are Howard, Montgomery, and Anne Arundel Counties in the Baltimore study area, and Arlington County, City of Alexandria, and Fairfax County/Fairfax City/Falls Church in the Washington, DC study area.

Independent Variables

The independent variables were categorized into four sets: (1) control variables which provided information on socioeconomic characteristics of each household; (2) the neighborhood-level built environment variables for each household location; (3) the county-level built environment variables for each household location; and (4) the regional accessibility variables.

Built environment and accessibility characteristics were measured at the neighborhood and county levels to capture the impact of the built environment at both microlevel and macrolevel geographical scales on walking. More detailed descriptions of the independent variables and methods used for their computations are provided below.

Household Control Variables

These variables capture a household's size, annual income, number of students, number of workers, number of vehicles owned, number of licensed drivers, and number of bicycles owned. The values of the variables are taken directly from the MWCOG or BMC travel survey data.

Neighborhood-Level Built Environment Variables

These variables are represented by the attributes of a household's TAZ. Previous nonmotorized travel behavior research has used TAZ-level factors to represent neighborhood built environment characteristics (Ewing et al. 2004; Mitra and Builing 2012). A recent report that assessed the factors influencing nonmotorized travel suggested that a spatial scale finer than TAZ be used in future studies (Kuzmyak et al. 2014). In the present study, however, the TAZ was selected to represent neighborhoods because geocoded data for household locations were unavailable (which limited the use of smaller geographical areas such as block group or buffer distances) and thus, TAZs were the smallest geographic area for which travel survey and land-use information were available.

The neighborhood-level variables include: population density, employment density, average block size, local transit accessibility, Walk Score, Transit Oriented Development (TOD) status, and an entropy variable. Some of these variables including population and employment density variables, average block size and the entropy variables were chosen based on previous related research (Nasri and Zhang 2012, 2014) because they showed statistically significant effects on vehicular travel behavior in those studies,

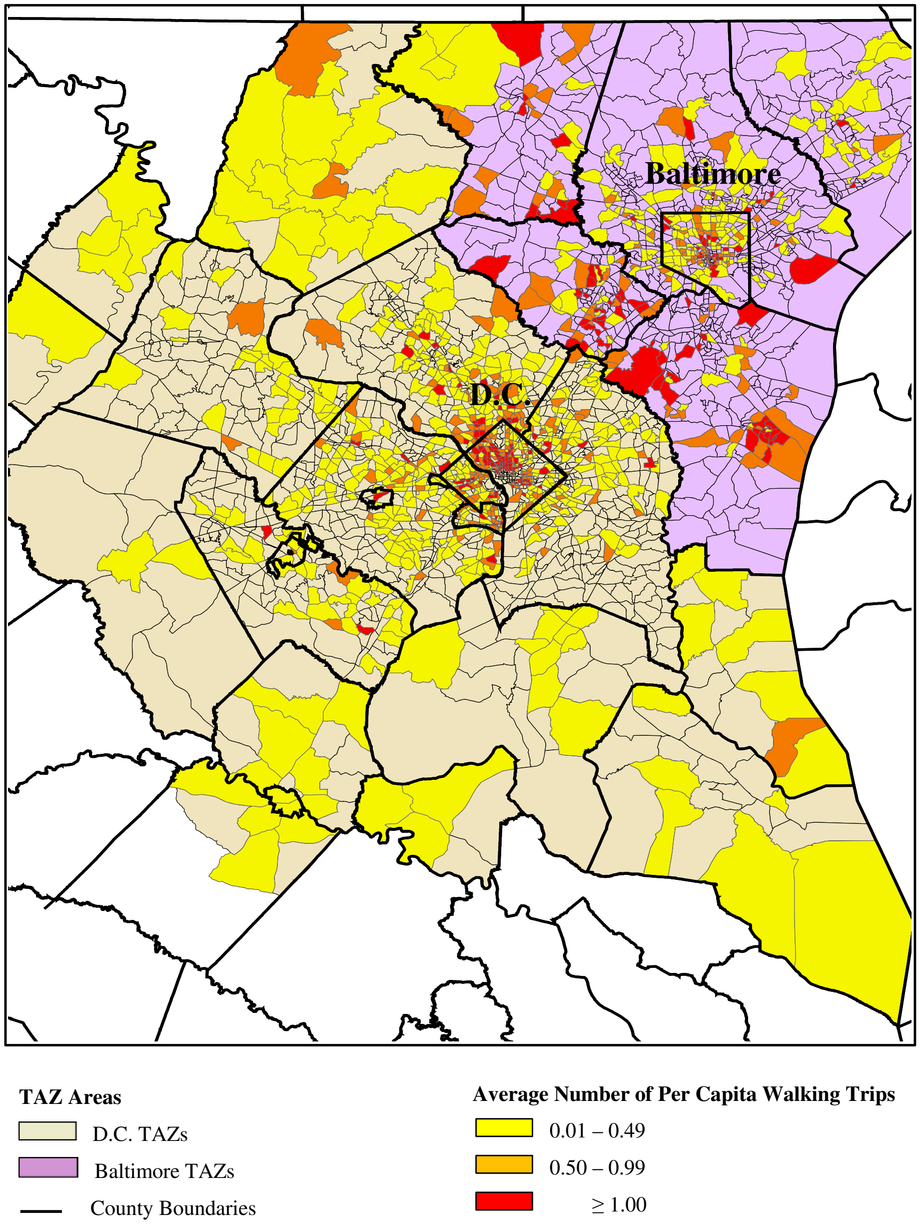

Fig. 1. Average number of per capita walking trips by TAZ.

and therefore, they could influence nonmotorized travel behavior (in this case, walking).

Population and employment density variables were calculated for each TAZ by dividing its total population or employment by its area. Block sizes have been postulated in previous studies to capture the extent to which streets are interconnected (Ewing et al. 2003). Thus, the average block size was selected in the present study to represent street network connectivity attributes. This variable was computed by averaging the areas of all blocks within the household's TAZ.

The number of rail transit stations and bus stops in each TAZ were summed to obtain the value of the local transit accessibility variable. In addition, a variable indicating the status of TOD has been included in the model because past literature suggests that TODs create a friendly environment for nonmotorized travel, particularly for walking trips (Roshan Zamir et al. 2014). The TOD variable is dichotomous in format, that is, it indicates whether or not a TAZ in the study area is identified as a TOD. The method for TOD designation was adopted from Roshan Zamir et al. (2014).

The Walk Score variable has been included in the model as a proxy for neighborhood destination accessibility. The Walk Score for the centroid of each household TAZ has been included in the model as the Walk Score variable.

The entropy variable captures the extent of mixed-use development in the TAZ. The values of this variable were computed using the following well-established formula used in previous research (Frank and Pivo 1994; Cervero and Kockelman 1997; Cervero and Duncan 2003):

$$\text{Entropy} = -\sum_{j} \frac{P_j * \ln(P_j)}{\ln(J)} \qquad (1)$$

J = number of land-use classes in the household TAZ; and P_j = proportion of land use in the jth class. Five land-use classes

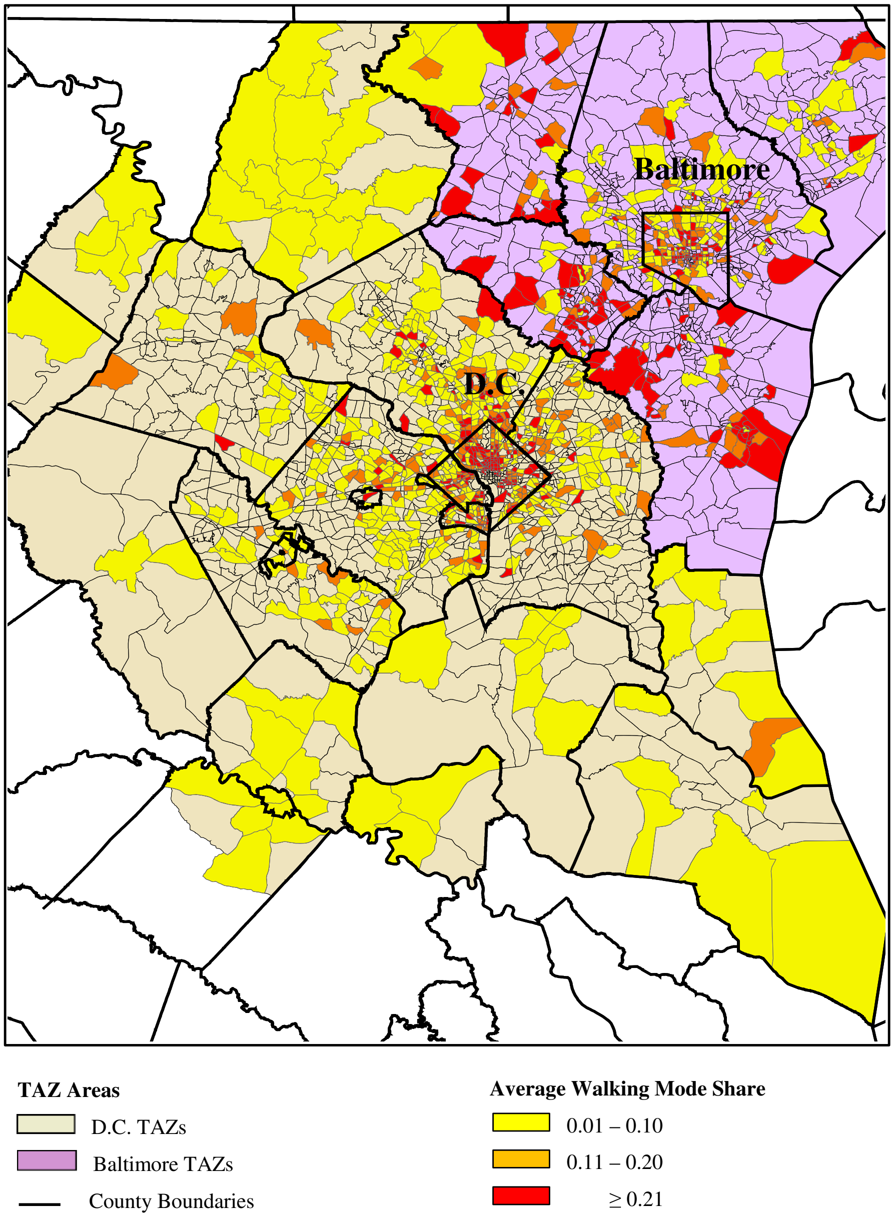

Fig. 2. Average walking mode share by TAZ.

are considered: residential, retail, office, industry, and other (i.e., $J = 5$). The value of the entropy variable ranges from 0 to 1 representing one-type-only (nondiverse) land use to well-mixed (most diverse) land use, respectively.

County-Level Built Environment Variables

These variables capture the connectivity and accessibility of the street network, extent of mixed-use development, and population and employment densities of the household's county. To obtain the county-level measures, the TAZ-level measures were aggregated for each household's county. This method of calculation of built environment measures for larger scales prevents measurement biases (Nasri and Zhang 2014).

The county-level built environment variables are: the average total population density of the household county, the average employment density of the household county, the average block size for each county, and the average entropy (mixed-use development) for each county.

Regional Accessibility Variables

As stated previously, literature suggests that the effects of regional-level accessibility on nonmotorized travel behavior should be examined (Handy 2005). Thus, measures of regional accessibility have been included in the models in this study to capture the effects of regional accessibility on a household's walking trips. These include a variable representing the distance from the household location to the center of the city and three variables representing interzonal accessibility: a highway accessibility index, a transit-drive accessibility index, and a transit-walk accessibility index.

The distance to the center of the city variable is computed as the measure of a straight line connecting the centroid of the household's TAZ to the CBD of the corresponding study area (i.e., MWCOG or BMC area).

The interzonal accessibility variables have been computed based on Hansen's formula [i.e., Eq. (2)] which provides a relatively simple method for calculating accessibility for regions (Hansen 1959):

Table 1. Descriptive statistics for walking dependent variables by county

County by metropolitan planning organization (MPO)	Observations (households)	Walking travel behavior: Household's number of per capita walking trips		Household's walking mode share	
		Mean	Standard deviation	Mean	Standard deviation
Baltimore MPO area (BMC)					
Anne Arundel County	208	0.59	0.79	0.18	0.22
Baltimore County	493	0.46	0.87	0.13	0.20
Baltimore City	1,047	1.79	1.19	0.23	0.27
Calvert County	71	0.35	0.43	0.08	0.08
Carroll County	80	0.55	0.77	0.16	0.18
Charles County	145	0.24	0.36	0.07	0.09
Frederick County	297	0.34	0.69	0.10	0.13
Harford County	203	0.40	0.91	0.13	0.19
Howard County	149	0.65	0.76	0.19	0.20
Montgomery County	1,285	0.61	1.07	0.16	0.21
Prince George's County	905	0.45	0.82	0.14	0.18
St. Mary's County	38	0.33	0.28	0.08	0.07
Washington, DC MPO area (MWCOG)					
Arlington County	691	0.83	1.14	0.19	0.23
City of Alexandria	318	0.77	1.04	0.18	0.22
City of Fredericksburg	41	0.45	0.71	0.09	0.13
Clarke County	36	0.24	0.53	0.08	0.16
District of Columbia	1,450	1.91	1.62	0.29	0.31
Fairfax County/Fairfax City/Falls Church	1,081	0.51	0.67	0.11	0.15
Fauquier County	29	0.19	0.19	0.07	0.05
Jefferson County	71	0.20	0.25	0.06	0.06
King George County	41	0.25	0.37	0.08	0.09
Loudoun County	278	0.37	0.47	0.09	0.13
Prince William County/Manassas/Manassas Park	327	0.39	0.56	0.10	0.12
Spotsylvania County	71	0.20	0.27	0.03	0.06
Stafford County	126	0.22	0.39	0.04	0.09
Total number of observations; counties			9,481; 25		

$$A_{ij} = \sum_j \frac{S_j}{T^e_{(ij)}} \tag{2}$$

Here, A_{ij} = relative accessibility measure at zone i to an activity located within zone j. S_j = size of the activity in zone j (i.e., the number of jobs in zone j for employment accessibility or the number of people in zone j for population accessibility). $T_{(ij)}$ indicates travel time or distance between zones i and j; and e is an exponent capturing the effects of travel time between zones i and j. This exponent differs depending on the trip purpose; the more important the trip purpose, the smaller the exponent e. A smaller e indicates the individuals' willingness to travel farther for more important activities (e.g., work trips). The total accessibility index for each zone i to some activity (i.e., employment, shopping, and population) in zone j is the summation of the accessibilities to each of the individual zones j neighboring zone i. The accessibility of zone i increases as this sum increases.

This study considers two types of activities in its interzonal accessibility computations—employment and population activities. When travel times between zones are expressed in terms of travel time plus terminal times (as the case in the present study), the exponent e for these activities was found in previous studies to be equal to 2.20 for employment and 2.35 for population (Hansen 1959).

In constructing accessibility indicators, Cervero and Kockelman (1997) used travel times between zones estimated for regional highway networks and the numbers of jobs to measure destination attraction. For the present study, zone-to-zone highway and transit skimming matrices from MWCOG and BMC were used to calculate travel and terminal times between TAZs. Further, employment and population accessibilities for each TAZ were added together to obtain one accessibility index for each TAZ. Through these calculations, three variables capturing interzonal accessibility measures were obtained: the highway accessibility index, the transit-drive accessibility index, and the transit-walk accessibility index. These accessibility indices measure accessibility (by mode) of each TAZ to all other TAZs in the region. Thus, they are referred to as regional accessibility (or interzonal accessibility) in this paper. It is noted that even though these indices are computed for each TAZ, they are not measuring TAZ-level accessibility because they go beyond a particular TAZ to measure its accessibility to other TAZs in the region. In this sense, Hansen's formula provides an aggregated measure of accessibility for each TAZ (to all other TAZs.)

Table 2 presents the descriptive statistics for models' dependent and independent variables for households in each of the study areas computed based on the household travel survey data, highway and transit skimming data, and the land-use data from MWCOG or BMC and the GIS spatial information and data.

The table indicates that the average number of household per capita walking trips and the average household walking mode share are higher in Baltimore. Also, some variation exists in the household socioeconomic characteristics between the two study areas. The household size is slightly larger in Washington, DC, whereas the average number of household students is larger in Baltimore. Also, Washington, DC households have a higher average number of workers and earn a higher average annual income compared with Baltimore households. Additionally, DC households have more licensed drivers and own more vehicles and bicycles compared with

Table 2. Descriptive statistics for model variables by case study area

Variable	Washington, DC (within MWCOG area) Mean	Washington, DC (within MWCOG area) Standard deviation	Baltimore, MD (within BMC area) Mean	Baltimore, MD (within BMC area) Standard deviation
Dependent variables				
Household's daily per capita walking trips	0.51	1.09	0.58	1.07
Household's daily walking mode share	0.11	0.22	0.15	0.25
Independent variables				
Household socioeconomics				
Number of members (size)	2.20	1.22	2.17	1.25
Number of students	0.53	0.91	0.57	0.94
Number of workers	1.25	0.81	1.13	0.86
Number of vehicles	1.68	0.99	1.51	1.01
Number of bicycles	1.12	1.48	0.96	1.47
Number of licensed drivers	1.65	0.73	1.49	0.77
Annual income (1,000s of dollars)	75–100	N/A	50–60	N/A
Microlevel (neighborhood) built environment (TAZ level)				
Population density (total population/acre)	22.35	36.42	23.14	36.44
Employment density (jobs/acre)	8.72	26.52	9.69	32.65
Average block size (acres)	17.84	26.11	12.77	22.07
Transit accessibility (number of transit stations + bus stops)	23.94	18.95	15.35	19.36
Walk Score[a]	40.94	31.05	49.52	28.35
Entropy[a]	0.43	0.22	0.49	0.22
Macrolevel built environment (county level)				
Mean residential population density (residential population/acre)	8.18	5.97	11.59	6.47
Mean employment density (jobs/acre)	14.94	18.87	18.25	13.92
Mean block size (acres)	27.33	23.86	20.05	19.71
Mean entropy[a]	0.44	0.07	0.53	0.02
Regional accessibility				
Distance to CBD (mi)	14.34	13.21	8.54	7.80
Highway accessibility index[a]	2,920	4,490	6,362	5,399
Transit-drive accessibility index[a]	2,828	2,686	3,772	2,017
Transit-walk accessibility index[a]	1,603	1,401	4,688	4,892
Total number of observations (households)	7,547		1,934	
Number of households with no walking trips	5,240		1,208	
Number of TAZs	867		413	
Number of counties	13		12	

[a]Dimensionless.

Baltimore households. These statistics are consistent with what a previous study reported (Roshan Zamir et al. 2014). The lower household average annual income in Baltimore metropolitan area likely explains many of the observed differences in the household socioeconomic factors between the two metropolitan areas.

Variations also exist between DC and Baltimore built environment characteristics of household locations. At the microlevel (i.e., neighborhood/TAZ level), Baltimore households have higher population and employment densities. Baltimore households are also located in neighborhoods with smaller average block sizes and a higher level of mixed-use development (i.e., entropy). The entropy and block size statistics variations are consistent with what previous studies of the two study areas reported (Nasri and Zhang 2012; Roshan Zamir et al. 2014). Also, the average Walk Score for household neighborhoods is higher in Baltimore, whereas Washington, DC households have access to a larger number of transit stations and bus stops within their neighborhoods.

In terms of macrolevel (i.e., county-level) built environment, average population and employment densities are higher in Baltimore counties. Additionally, Baltimore has a smaller average block size, and a higher entropy at the county level. These statistics indicate that Baltimore households are located within counties with better street network connectivity and higher extent of mixed land use.

The descriptive statistics for the interzonal accessibility variables also indicate differences between DC and Baltimore households. Baltimore households have higher accessibility to highways and transit (by both driving and walking means). These differences can be explained by the descriptive statistics on the *Distance to CBD* variable; because one may expect to see higher regional highway and transit accessibility in the Washington, DC area. Looking at the *Distance to CBD* variable, Table 2 and Figs. 1 and 2 show that compared with Baltimore households, Washington, DC households are a greater distance from CBD, where the core of activities locates. This also may be the reason for lower average statistics on the regional highway and transit accessibility indices and the average population and employment densities, Walk Score, and entropy variables for the Washington, DC study area.

Pearson correlation coefficients were calculated to examine correlation between the dependent variable and various original independent variables. The final independent variables were selected based on these correlation coefficients, and efforts were made to reduce the risk of multicollinearity in the models. For example, due to a high correlation between variables representing the number of household vehicles and licensed drivers ($r = 0.8$), the latter was excluded from the models. Further, because the variables representing population and employment densities at the county level were highly correlated ($r = 0.9$), these variables were replaced by an activity density variable that quantifies the density of total population plus employment opportunities within each county. Nonetheless, as Reilly and Landis (2003) argue, in reality, the effects of many built environment factors are correlated, and there is no easy way to separate these correlations. Thus, this study uses a correlation threshold of $|\mathrm{p}| > 0.7$ suggested by previous research to elimi nate highly-correlated independent variables (Kim and Susilo 2013).

To normalize any independent variable with an extremely skewed distribution, a few continuous variables were transformed into their naturally-logged form before inclusion in the models. Logarithmic transformation is a convenient way to transform a highly-skewed variable into one that is more approximately normal (Benoit 2011).

Mixed-Effects Model

As shown in Table 2 and Figs. 1 and 2, most households did not report any walking trips during the specified travel day. This introduces the potential that data may need zero-inflated treatment due to over-dispersion in walking data. However, as Kim and Susilo (2013) suggest, over-dispersed data should not be used as an ultimate criterion for rejecting models, and the appropriateness of different modeling techniques should be determined based on empirical analysis. Therefore, in this study, a linear mixed-effects model is developed to relate a household's daily number of household's per capita walking trips and walking mode share to household socioeconomic characteristics, neighborhood, and county built environment factors, and regional accessibility measures. The choice of the mixed-effects model was based on the fact that study data have a clustered nature and may be affected by spatial autocorrelation.

The mixed-effects model can be viewed as a combination of analysis of variance, variance component, and regression models. This type of model treats clustered data, where due to correlation of error terms, the classical assumption of observations being independent and identically distributed (iid) may lead to inaccurate results. The mixed-effects model has a hierarchical (sometimes called multilevel) structure where observations in the same level are likely to be correlated because they share similar characteristics. The model's structure allows the analyst to simultaneously focus on both micro- and macrolevel associations and the interaction between the two levels (Healy 2001). Additionally, the mixed-effects model can account for spatial autocorrelation (Marshall et al. 2014).

According to Demidenko (2004), two sources of variation are assumed in the mixed-effects model: within clusters (intraclass variance) and between clusters (interclass variance). Two types of coefficients are estimated: population-averaged and cluster-specific. The former are called fixed effects and have the same meaning as in ordinary regression models; the latter are called random effects, and contain the effects of clustering of the observations under different levels. A small number of clusters with a large number of observations per cluster constitutes the treatment of the cluster-specific coefficients as fixed effects, whereas a large number of clusters with a small number of observations per cluster, necessitates the treatment of the cluster-specific coefficients as random effects (Demidenko 2004).

The linear mixed-effects model can be represented as

$$y = X\beta + Zb + \varepsilon \tag{3}$$

where $y = \mathrm{n} \times 1$ vector of observations with a mean of $X\beta$; $X = \mathrm{n} \times \mathrm{p}$ matrix of covariates for fixed effects; β = vector containing the overall mean and all the fixed effects; $Z = \mathrm{n} \times \mathrm{q}$ matrix of covariates for random effects; b = iid random effects; and ε = vector of random error term such that:

$$\begin{pmatrix} b \\ \varepsilon \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} D & 0 \\ 0 & \sum \end{pmatrix}\right)$$

D = variance-covariance matrix (variance components) of b and ε; and $\sum = \sigma_\varepsilon^2 I_n$ with n being the number of observations (Vebeke and Molenbeghs 1997; Demidenko 2004).

Data in this analysis are assumed to be clustered as groups of surveyed households located within the same neighborhoods (TAZs) and counties. As discussed previously, many past studies proved that neighborhood-level built environment characteristics influence the walking travel behavior of residents (e.g., Targa and Clifton 2005; Kerr et al. 2007; Rodríguez et al. 2009). Thus, this study first specifies random effects at the TAZ-level (neighborhood-level) in the mixed-effects model due to the importance of effects of neighborhood-level built environment. In other words, first TAZs (neighborhoods) are considered as clusters in this study, and their random effects are estimated in the model (Model 1). The study then specifies random effects at both TAZ and county-levels to capture and allow for comparison of the random effects of TAZ and county, concurrently (Model 2). The model design for Model 1 introduces two levels: the first level is the household and the second level is the TAZ, whereas the model design for Model 2 introduces three levels: the first level is the household, the second level is the TAZ, and the third level is the county.

The mixed-effects model is appropriate for application to these data because there may be correlations between households located within the same cluster (TAZ or county), whereas characteristics of individual households differ from each other. This introduces two sources of variation in the model to be estimated: the variation between different clusters (TAZs or counties) and the variation within each cluster (TAZ or county). Because TAZs represent neighborhoods in this study, the variances (random effects) estimated by Model 1 provide information on how random differences between neighborhoods affect walking travel behavior of residents. The variances (random effects) estimated by Model 2 provide information on how random differences between counties affect walking travel behavior of residents.

Results and Discussion

Tables 3 and 4 summarize the estimation results of the household's number of per capita walking trips mixed-effects model (Model 1) and the household's walking mode share model (Model 2). The results of the two models are consistent and show a strong association between household walking and built environment characteristics at both neighborhood and county levels. The results also indicate that regional accessibility measures have a statistically significant association with walking.

Household Control Variables Findings

Tables 3 and 4 depict, that as expected, household size has a significant and negative correlation with household walking; being a member of a larger household is correlated with less walking. The variable representing the number of household students shows a negative and significant correlation with walking, which is also expected; households with more students are more likely to choose driving (and not walking) as their mode of travel to and from school and other destinations. These statements are supported by previous research that analyzed trends in children's trips to school by

J. Urban Plann. Dev., 2018, 144(3): 04018020

Table 3. Results: Baltimore/DC mixed-effects Model 1—household's number of per capita walking trips

Variable	Coefficient	Standard error	p-value
Household socioeconomics			
Number of members (size)	−0.042406[a]	0.015275	0.006
Number of students	−0.032369[b]	0.018268	0.076
Number of workers	0.042216[a]	0.015859	0.008
Number of vehicles	−0.173206[a]	0.014139	0.000
Number of bicycles	0.035888[a]	0.008639	0.000
Annual income (1,000s of dollars)	0.008905[b]	0.004573	0.052
Microlevel (neighborhood) built environment (TAZ level)			
Population density (total population/acre)	0.003098[a]	0.001190	0.009
Employment density (jobs/acre)	0.002326[a]	0.000553	0.000
Average block size (acres)—logged	−0.060958[a]	0.024581	0.013
Transit accessibility (number of transit stations + bus stops)	0.000789[b]	0.000451	0.080
Transit oriented development	0.054637[b]	0.032939	0.097
Walk Score[c]	0.002266[a]	0.000801	0.005
Entropy[c]	0.233922[a]	0.070221	0.001
Macrolevel built environment (county level)			
Average activity density [(population + employment)/acre]	0.005705[a]	0.001168	0.000
Average block size (acres)—logged	−0.216641[a]	0.036458	0.000
Average entropy[c]	−0.032682	0.200349	0.870
Regional accessibility			
Distance to CBD (miles)—logged	−0.138385[a]	0.034738	0.000
Highway accessibility index[c]—standardized	−0.060069[a]	0.012139	0.000
Transit—drive accessibility index[c]—standardized	−0.047419[a]	0.011228	0.000
Transit—walk accessibility index[c]—standardized	0.044841[a]	0.013033	0.001
Variance estimates (random effects)			
TAZ	0.031561[a]	0.006311	0.000
Residuals	0.966883[a]	0.014791	0.000
Model goodness parameters			
Likelihood ratio test versus linear regression:	$\chi^2 = 43.54$[a]	N/A	0.000
R^2 marginal; R^2 conditional		0.146; 0.175	
Log likelihood		−13423.051	
Observations; clusters (TAZs)		9,481; 1,280	

[a]Coefficient significant at the 1% significance level.
[b]Coefficient significant at the 10% significance level.
[c]Dimensionless.

comparing national data from years 1969, 1995, 2001, and 2009. It concluded that walking to school decreased between 1969 and 2009 as more students were making automobile trips to school in 2009 compared with 1969 (McDonald 2005).

The number of household workers is positively and significantly correlated with household walking; living in a household with more employed members is associated with more walking trips. The correlation between household income and walking is positive and significant which probably reflects the recreational walking of individuals within wealthier households as Roshan Zamir et al. (2014) suggested.

The results also confirm previous findings that a household's number of vehicles owned is significantly and negatively associated with that household's walking (Cervero and Kockelman 1997; Kitamura et al. 1997; Cervero and Duncan 2003; Mitra and Buliung 2012). By contrast, the number of bicycles owned by a household is significantly and positively associated with a household's walking travel. This is also consistent with previous findings (Targa and Clifton 2005). In terms of magnitude, both models show that the effect of the number of household vehicles on walking is much more considerable than those of other household socioeconomic variables.

Neighborhood-Level Built Environment Variables Findings

A few neighborhood built environment variables are significantly correlated with household walking. In both Models 1 and 2, the population and employment density variables show significantly positive associations with household per capita walking trips and walking mode share. These results mean that increased levels of residents' walking are associated with increased neighborhood population and employment densities. This result confirms the findings of previous studies that reported densities at the local level significantly influence walking (Frank and Pivo 1994; Targa and Clifton 2005).

The average block size variable exhibits a significant and negative association with walking. This study considers this variable as a proxy for street network connectivity and pedestrian-friendliness, and finds the expected direction in the models; smaller block sizes indicate more connected and more walkable streets with shorter distances to neighborhood destinations, which thereby, can encourage more pedestrian trips.

Higher accessibility to local transit (both rail and bus) is significantly and positively linked to walking, which is consistent with previous findings (Kitamura et al. 1997; Targa and Clifton 2005; Ewing and Cervero 2010). The results also show that proximity to transit has a significant correlation with walking; residents who live in transit-oriented neighborhoods are estimated by the models to walk more—a finding suggested in previous research (Roshan Zamir et al. 2014).

The Walk Score variable depicts a significant and positive correlation with household walking. This outcome confirms findings of previous studies that neighborhood destination accessibility is an influential factor in estimating walking trips (Handy and Clifton 2001).

Table 4. Results: Baltimore/DC mixed-effects Model 2—household's walking trips mode share

Variable	Coefficient	Standard error	p-value
Household socioeconomics			
Number of members (size)	−1.395536[a]	0.3129422	0.000
Number of students	−0.52236[b]	0.3149213	0.097
Number of workers	0.8053248[c]	0.3247709	0.013
Number of vehicles	−4.462447[a]	0.2905235	0.000
Number of bicycles	0.5019312[a]	0.1771788	0.005
Annual income (1,000s of dollars)	0.1732313[b]	0.0959332	0.071
Microlevel (neighborhood) built environment (TAZ level)			
Population density (total population/acre)	0.0447259[b]	0.0258661	0.084
Employment density (jobs/acre)	0.0535379[a]	0.0117695	0.000
Average block size (acres)—logged	−1.130769[c]	0.5480219	0.039
Transit accessibility (number of transit stations + bus stops)	0.0052946[b]	0.0029598	0.073
Transit oriented development	0.7803787[b]	0.4646384	0.093
Walk Score[d]	0.041203[c]	0.0176925	0.020
Entropy[d]	4.829856[a]	1.51974	0.001
Macrolevel built environment (county level)			
Average activity density [(population + employment)/acre]	0.0101533[b]	0.0059426	0.087
Average block size (acres)—logged	−2.61274[b]	1.567650	0.095
Average entropy[d]	−5.271672	10.9719	0.631
Regional accessibility			
Distance to CBD (miles)—logged	−4.191559[a]	0.849844	0.000
Highway accessibility index[d]—standardized	−1.132256[a]	0.2752759	0.000
Transit—drive accessibility index[d]—standardized	−0.7614542[a]	0.2523203	0.003
Transit—walk accessibility index[d]—standardized	0.7493803[a]	0.2863564	0.009
Variance estimates (random effects)			
County	16.4911[a]	6.318809	0.000
TAZ	18.18061[a]	2.771442	0.000
Residuals	401.71[a]	6.140169	0.000
Model goodness parameters			
Likelihood ratio test versus linear regression:	$\chi^2 = 100.28$[a]	N/A	0.000
Log likelihood		−42070.1	
Observations; counties; TAZs		9,481; 25; 1,280	

[a]Coefficient significant at the 1% significance level.
[b]Coefficient significant at the 10% significance level.
[c]Coefficient significant at the 5% significance level.
[d]Dimensionless.

The neighborhood-level entropy variable, a measure of extent of mixed land use, shows a positive and significant correlation with walking. This indicates that as expected, higher levels of neighborhood mixed land use are associated with more walking trips which parallels the findings of previous research (Cervero and Duncan 2003).

In terms of magnitudes of the neighborhood built environment effects, the entropy variable has the largest significant coefficient in both models. Therefore, it can be inferred that a better mix of residential, retail, office, and other uses within the neighborhood is the most important neighborhood-level built environment factor in determining household walking travel behavior.

Together, these outcomes confirm that neighborhood built environment is an influential element in estimating walking trips of residents.

County-Level Built Environment Variables Findings

At the county level, average activity density exhibits a positive and significant correlation with walking in both Models 1 and 2. This indicates that higher levels of walking trips by residents of a county are associated with higher population and employment densities within the county. These results confirm the hypothesis of this study that densities at the county level can be significantly associated with household's nonmotorized travel behavior.

The direction of the statistically significant average block size variable at the county level further supports the hypothesis that smaller block sizes (i.e., better street network connectivity) within the county are associated with more walking.

The effect of an average entropy variable at the county level is not significant in either of the models. Considering the magnitudes of effects, the average block size seems to be the most influential built environment factor at the county level in determining walking travel behavior. This result emphasizes the potential role of street network connectivity and pedestrian friendliness at various levels of geography in promoting walking trips.

Regional Accessibility Variables Findings

All regional (interzonal) accessibility variables show significant effects in both models, confirming the hypothesis that regional accessibility can be significantly associated with walking levels.

The Distance to CBD variable exhibits a significantly negative correlation with walking. This implies that living in suburban areas with greater distances from households to a city's business district is negatively associated with walking trips of the household members.

The highway and transit-drive accessibility indices are negatively linked to walking, confirming the hypothesis that increased regional accessibility by means of driving on the roads or driving to transit stations may discourage walking. However, the transit-walk accessibility index exhibits a positive association with walking trips; higher access to transit by means of walking throughout the region is associated with making additional walking trips. This result is expected because as walking access to transit increases, it is more likely that residents are encouraged to walk to and from transit stations.

Together, these findings provide evidence that accessibility at the regional level is significantly associated with walking travel behavior, just as it is at the local level.

Interpretation of Model Results

For brevity, only a few examples are provided here for interpretation of the model coefficients. The coefficient estimate of the TOD status of the neighborhood in Model 1 (0.054637) indicates that approximately 0.06 additional walking trips per household member are generated if the household is located within a TOD neighborhood rather than in a non-TOD neighborhood. The coefficient estimate of this variable in Model 2 (0.7803787) indicates that the household's walking mode share (a continuous number between 0 and 100 which represents the mode share as a percentage) increases by 0.78 percentage points if the household is located within a TOD neighborhood rather than in a non-TOD neighborhood.

Also, a few of the built environment variables in the models are log-transformed which should be considered in the interpretation of the coefficient estimates. For instance, the coefficient estimate of the county-level average block size variable in Model 1 (−0.216641) indicates that if the average block size in a county doubles (an increase of %100 in the value of the county-level block size variable), the number of walking trips generated by each household drops by nearly 0.22 trips per household member. The coefficient estimate of the same variable in Model 2 (−2.61274) indicates that if the average block size in a county doubles (an increase of %100 in the value of the county-level block size variable), the household walking mode share drops by 2.6 percentage points.

Similarly, the coefficient estimate of the *Distance to CBD* variable in Model 1 (−0.138385) indicates that if the distance (in miles) of a particular household to the CBD doubles (an increase of %100 in the value of *Distance to CBD* variable), the number of walking trips generated by each household drops by nearly 0.14 trips per household member. The coefficient estimate of the same variable in Model 2 (−4.191559) indicates that if the distance (in miles) of a particular household to the CBD doubles (an increase of %100 in the value of *Distance to CBD* variable), the household walking mode share drops by 4.2 percentage points.

These interpretations serve as examples for the impact of neighborhood and county built environment characteristics on walking trips of residents as estimated by the models.

As mentioned previously, the random effects of TAZs were considered in the models to assess how differences between neighborhoods affect walking. The between-TAZ component of variance in both Model 1 ($\sigma_u^2 = 0.031561$) and Model 2 ($\sigma_{uTAZ}^2 = 18.1806$) is much smaller than its corresponding within-TAZ component of variance ($\sigma_e^2 = 0.966883$ in Model 1 and $\sigma_e^2 = 401.71$ in Model 2). This is probably because the number of households in each TAZ (number of observations per cluster) is relatively small, whereas the number of TAZs (clusters) that are compared with each other is large (1,280 TAZs).

The total variance for Model 1 is $\sigma_u^2 + \sigma_e^2 = 0.031561 + 0.966883 = 0.998444$. Thus, the variance partition coefficient (VPC) is equal to $0.031561/0.998444 = 0.0316$. This indicates that 3.16% of the variance in the number of household per capita walking trips is attributed to unaccounted differences between TAZs (TAZ random effects).

As for Model 2, the total variance is $\sigma_{uCounty}^2 + \sigma_{uTAZ}^2 + \sigma_e^2 = 16.4911 + 18.18061 + 401.71 = 436.3817$. Thus, the variance partition coefficient (VPC) for TAZ is equal to $18.18061/436.3817 = 0.0417$. This indicates that 4.17% of the variance in household walking mode share is attributed to unaccounted differences between TAZs (TAZ random effects). Similarly, the VPC for the county is equal to $16.4911/436.3817 = 0.0378$. This indicates that 3.78% of the variance in household walking mode share is attributed to unaccounted differences between counties (county random effects).

These results suggest that differences between the built environments of neighborhoods (i.e., TAZ random effects) and differences between the built environments of counties (i.e., county random effects) play small, but statistically significant roles in the walking travel behavior of residents.

The Likelihood Ratio test is statistically significant in both models as evidenced by the values of chi-squared (χ^2) and the corresponding p-values, which indicates that the mixed-effects model is an improvement over an ordinary regression model. This justifies considering the effects of individual TAZs and counties on walking and using the mixed-effects modeling technique. The marginal R-squared value in Model 1 provides information on variance explained by fixed effects, whereas the conditional R-squared indicates variance explained by both fixed and random effects.

Multicollinearity Check

To further check if multicollinearity is an issue in the models developed, variance inflation factors (VIFs) were estimated for the models. Table 5 lists the VIFs for all the independent variables included in the models. All the estimated VIFs are less than 10, which

Table 5. Variance inflation factors (VIFs) for independent variables

Independent variables	VIF	1/VIF
Household socioeconomics		
Number of members (size)	3.37	0.2969
Number of students	2.67	0.3752
Number of workers	1.63	0.6132
Number of vehicles	1.90	0.5271
Number of bicycles	1.56	0.6402
Annual income (1,000s of dollars)	1.53	0.6540
Microlevel (neighborhood) built environment (TAZ level)		
Population density (total population/acre)	2.29	0.4358
Employment density (jobs/acre)	1.51	0.6635
Average block size (acres)—logged	3.69	0.2708
Transit accessibility (number of transit stations + bus stops)	1.19	0.8407
Transit oriented development	1.59	0.6288
Walk score	3.93	0.2547
Entropy	1.69	0.5918
Macrolevel built environment (county level)		
Average activity density [(population + employment)/acre]	5.56	0.1799
Mean block size (acres)—logged	7.77	0.1287
Mean entropy	1.64	0.6096
Regional accessibility		
Distance to CBD (miles)—logged	8.05	0.1242
Highway accessibility index	3.37	0.2970
Transit-drive accessibility index	3.59	0.2789
Transit-walk accessibility index	5.45	0.1834
Mean	3.20	0.4297

is the threshold for significant and potentially harmful multicollinearity (Franke 2010). Thus, it is concluded that multicollinearity is not a problem in the models.

Summary and Conclusions

Research continues to reveal health, social, and economic benefits of nonmotorized travel behavior at both individual and community levels. As a result, promoting nonmotorized travel behavior has become the focus of many transportation and planning professionals and agencies in recent years. Identification and better understanding of the factors that influence the extent of household nonmotorized trips is one of many key elements in planning sustainable and livable communities. In the past, researchers have argued that walking trips stay in the neighborhood due to the shorter trip lengths compared with trips made by other travel modes. Consequently, aside from very few studies, the existing research on walking travel behavior and its link with built environment has heavily concentrated on the microlevel (i.e., residence or destination neighborhood) built environment factors thus far.

The main hypothesis of this study was that, like motorized travel behavior, nonmotorized travel behavior (e.g., walking) has become more dependent on built environment factors of larger-scale spatial areas, such as those of the county of residence. Therefore, this analysis considered macrolevel (county-level) built environment and regional accessibility in addition to micro-level (neighborhood-level) built environment to more comprehensively capture the true effects of the built environment on walking.

The study employed mixed-effects modeling techniques to allow a concurrent examination of how walking trips are correlated with household socioeconomic characteristics, micro- (i.e., neighborhood) and macrolevel (i.e., county) built environments and regional accessibility measures.

The results indicated that both micro- and macrolevel built environment play a significant role in walking travel behavior. More specifically, even after adjusting for household socioeconomic characteristics, neighborhood level (microlevel) built environment attributes including higher population and employment densities, better street network connectivity, and improved transit and destination accessibilities are associated with increased levels of walking trips.

Further, the results supported the hypothesis that a household's walking behavior is significantly associated with county-level (macrolevel) built environment characteristics. Particularly, densely-populated county structures with more employment opportunities and better street connectivity throughout the county are correlated with increased levels of walking trips.

In addition, the results indicate that improved regional accessibility to transit by means of walking may encourage walking trips, whereas facilitated regional accessibility to highways and increased accessibility to transit by means of driving may discourage walking. Furthermore, residing in suburban locations farther from the CBD is associated with lower levels of walking trips.

This work contributes to the body of knowledge in nonmotorized travel behavior research and has policy implications, despite some data limitations.

Contributions

This study adds to the body of knowledge on walking travel behavior and its link with built environment by moving beyond the microlevel (i.e., neighborhood-level) built environment measures to include several measures of macrolevel (i.e., county-level) built environment and regional accessibility in the same model to analyze walking trips.

Macrolevel built environment characteristics have not been previously tested for their link with walking travel behavior. Thus, the contribution of this paper is a view of the bigger picture of the relationship between built environment and walking in terms of the position of a neighborhood with respect to the county it is located in when analyzing walking trips. By consideration of the role of the macrolevel built environment in walking in addition to that of the microlevel built environment, this study provides a more comprehensive framework of how built environment influences walking, specifically in large metropolitan areas.

Although it may be best to apply some caution with respect to the potential transferability of the results to other cities, the study results can be used to gain a better understanding of walking travel behavior in those US metropolitan areas that share similar built environment characteristics with metropolitan areas studied in this analysis (i.e., Washington, DC and Baltimore). Considering the study-utilized data sets that are either available from most MPOs (i.e., household travel surveys, land use and skimming O-D matrices data) or publicly available (i.e., Walk Score, US Census Bureau's TIGER/Line data), similar models can also be easily developed for other metropolitan areas using the approach proposed in this study.

In practice, more effective operational models can be developed by incorporating the proposed approach (i.e., consideration of both micro- and macrolevel built environment) to capture walking travel patterns and demand in US cities, and to develop planning and design processes accordingly.

Policy Implications

The findings of the study imply that some changes in the built environment throughout the county are correlated with increased walking levels and may promote walking trips. These changes include: (1) increasing densities in areas with existing low residential and employment densities; (2) improving street network connectivity and pedestrian-friendliness; (3) increasing transit accessibility, especially by improving walkability to transit stations; and (4) building residential locations closer to the CBD.

The policy implications of these findings can be helpful to decision-makers aiming to enhance the sustainability and livability of their communities, and to seek to improve the equity and affordability of transportation opportunities in their communities.

Study Limitations

The current study has a few limitations. First, cross-sectional data were used, which can capture correlations, but do not allow for a full examination of causal relationships. Future research can benefit from longitudinal data, allowing for a more thorough investigation of causal associations. Furthermore, this study did not address the role of self-selection in walking. Thus, whereas the models in this study confirm existence of statistically significant correlations between walking and measures of the built environment and regional accessibility, no inferences can be drawn from the results regarding causality and self-selection. Collecting and using data on preferences toward walking and considering the role of self-selection can enhance future research.

Also, the analysis was conducted at the household level. A more detailed analysis at the individual-level may provide more insights into the neighborhood and county level built environment factors that influence travel choices of individuals. Additionally, due to data limitations, the neighborhood-level built environment variables were considered at the TAZ level. Neighborhood-level data can be coded at smaller spatial scales (e.g., census block groups) in future studies.

To make use of readily available and consistent household travel survey and land-use data, only two metropolitan areas (Washington, DC and Baltimore) were analyzed. Whereas these metro areas are different in many ways (as evidenced by variations observed among the independent variables in Table 2), they are located close to each other with many overlapping commutes between them. Data from additional metropolitan areas can be analyzed in the future to further examine the relationship between walking and macrolevel built environment and regional accessibility.

Moreover, several other neighborhood and metropolitan-level factors that potentially influence walking can be considered in future studies. Congestion levels, tolls, climate, crime rates, parking policies, and number of parking lots (which can affect walking trips in CBD areas) all may influence the decision to walk. Measures of the destination neighborhood built environment can also be included in the analysis to help to further isolate the effects of macrolevel built environment and eliminate any possibility of the macrolevel built environment factors serving as proxies for destination built environment. Finally, similar research can be conducted on households' bicycle trips.

Acknowledgments

The authors are thankful to the Metropolitan Washington Council of Governments, the Baltimore Metropolitan Council and the Maryland State Highway Administration, which provided some of the data used in this study. The authors are solely responsible for all statements in this paper. The authors also thank the anonymous reviewers who helped improve the quality of this work by providing valuable comments on an earlier version of this manuscript.

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