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Representing pedestrian activity in travel demand models: Framework and application

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ABSTRACT

There have long been calls for better pedestrian planning tools within travel demand models, as they have been slow to incorporate the large body of research connecting the built environment and walking behaviors. Most regional travel demand forecasting performed in practice in the US uses four-step travel demand models, despite advances in the development and implementation of activity-based travel demand models. This paper introduces a framework that facilitates the abilities of four-step regional travel models to better represent walking activity, allowing metropolitan planning organizations (MPOs) to implement these advances with minimal changes to existing modeling systems. Specifically, the framework first changes the spatial unit from transportation analysis zones (TAZs) to a finer-grained geography better suited to modeling pedestrian trips. The MPO's existing trip generation models are applied at this spatial unit for all trips. Then, a walk mode choice model is used to identify the subset of all trips made by walking. Trips by other modes are aggregated to the TAZ level and proceed through the remaining steps in the MPO's four-step model. The walk trips are distributed to destinations using a choice modeling approach, thus identifying pedestrian trip origins and destinations. In this paper, a proof-of-concept application is included to demonstrate the framework in successful operation using data from the Portland, Oregon, region. Opportunities for future work include more research on the potential routes between origins and destinations for walk trips, application of the framework in another region, and developing ways the research could be implemented in activity-based modeling systems.

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1. Introduction

The personal and social benefits of increasing pedestrian travel are plentiful and include better public health, reduced demands on the transportation system, improved air quality, and reduced greenhouse gas emissions. Recognizing these benefits, many cities are striving to promote walking and are making strategic investments toward that end. In support of these public policies, research continues to strengthen our understanding of the links between urban form and walking (Saelens and Handy, 2008; Saelens et al., 2003); pedestrian data collection methods are becoming more widely available (AMEC, 2011; Ryus et al., 2014; Schneider et al., 2005), and land-use data are increasingly more detailed and disaggregate. In response to new policy demands, transportation planning tools are beginning to take advantage of these developments to represent walking behavior at a much finer spatial detail and with greater sensitivity to environmental and other influences (Kuzmyak et al., 2014).

Despite progress on the research, data, and scale fronts, regional travel demand forecasting models—key policy tools to evaluate project alternatives—lag in their representation of walking activity. Although about 10% of all U.S. trips are made by walking (Santos et al., 2011), many regional models in the U.S. do not forecast non-motorized travel (Singleton and Clifton, 2013). A travel modeling framework that represents walking behavior using pedestrian-scale spatial units and environmental influences could: improve model sensitivity to more walking-relevant variables (e.g., specific activity locations, fine-grained land-use mix, roadway and sidewalk conditions), yield results that are more responsive to socio-demographic changes and policy interventions (e.g., smart-growth strategies, pricing, pedestrian infrastructure investments), provide more accurate estimates of mode shifts and overall non-motorized and motorized trips, and generate more useful model outputs for pedestrian planning, safety analyses, health impact assessments, and greenhouse gas reduction evaluation. Accordingly, metropolitan planning organizations (MPOs), the primary stewards of regional travel demand models, would benefit from updating their methods of modeling pedestrian behavior.

The purpose of this paper is to introduce a comprehensive framework to represent pedestrian activity more effectively within four-step travel demand models, currently the dominant structure

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of transportation forecasting tools used by MPOs in the U.S. This framework:

- Incorporates the state of the knowledge in the use of non-motorized modes. There is now a substantial body of literature about pedestrian travel demand, and it is ready to be put into practice;
- Takes advantage of the widespread availability of disaggregate, spatially-explicit, behavioral data and fine-grained information about the built and natural environments;
- Operates at a scale relevant to pedestrians, so it is responsive to shorter trip distances and detailed environmental data previously masked by the zonal aggregation used in demand models; and
- Is scalable to fit within the traditional four-step travel demand forecasting framework, minimizing the degree of model reconfiguration required of MPOs.

The framework and methods are supported by a proof-of-concept application in the Portland, Oregon, region to demonstrate clearly their value and contributions to practice.

The following sections include a brief review of research on pedestrian behaviors and the practice of modeling pedestrians, an overview of the pedestrian modeling framework, and a proof-of-concept application of the framework. The paper concludes with a discussion of the benefits and limitations of the framework, the opportunities and challenges of applying it in other regions, and needs for future work.

2. Background

2.1. State of the research on environmental influences of pedestrian travel

Early efforts to model pedestrian travel were hampered by a lack of pedestrian data and commensurate information about the built environment at appropriate scales to assess walking behavior. However, the availability of data has vastly improved and thus pedestrian research has advanced over the last two decades, particularly in the literature linking travel behavior to the built environment (e.g., Ewing and Cervero, 2010; Saelens and Handy, 2008; Saelens et al., 2003). This research has identified many factors that influence how frequently people walk (rate of trip generation), whether people walk (mode choice), and activity locations where people walk (destination choice).

While the magnitudes of the effects vary across studies, research has identified a common set of built environment features that affect walking. Walk trip frequency and walk mode choice have been positively related to higher residential and employment densities, greater land-use mix or diversity, and more connected street networks or higher intersection densities (Ewing and Cervero, 2010; Saelens and Handy, 2008; Saelens et al., 2003). Some results also point to positive associations with accessibility to transit (Schneider et al., 2009) and street-level factors like sidewalks (Ewing and Cervero, 2010; Rodríguez and Joo, 2004). All of these built environmental influences appear to affect walking even when controlling for self-selection (Cao et al., 2009). Work now focuses on the appropriate spatial scale at which to operationalize these measures (Gehrke and Clifton, 2014). In general, smaller scale and individual-focused accessibility measures may be more strongly associated with walking behavior than regional accessibility measures (Greenwald and Boarnet, 2001; Saelens and Handy, 2008), emphasizing the need to use small geographic scales in pedestrian travel behavior research.

Very few studies have looked solely at environmental correlates of pedestrian destination choice (Clifton et al., 2016). Results of more general studies of walking suggest that distance to destinations is a motivating factor (Saelens and Handy, 2008). Borgers and Timmermans (1986) studied retail shopping trips made on foot in the city center of Maastricht, the Netherlands, and found that distance and retail floor area had significant impacts. Eash (1999) used a pedestrian environment factor (PEF) in destination choice models for non-motorized trips in Chicago, Illinois, but PEF was a relatively crude measure of conditions for pedestrians and had limited policy relevance.

2.2. State of the practice on modeling pedestrian travel demand

Transportation planning practice has not kept pace with progress on pedestrian research (Kuzmyak et al., 2014). Few regional travel-demand models estimate pedestrian travel demand (Liu et al., 2012; TRB, 2007), and those that do lack sophistication relative to the models for motorized modes. A recent review of the practice investigated the treatment of walking within MPO travel-demand models (Singleton and Clifton, 2013). Many models either excluded pedestrian travel or combined walking and bicycling together as a “non-motorized” mode. Only two-thirds of the largest MPOs modeled non-motorized travel, and less than half of those models distinguished walking from bicycling. Most MPO models with non-motorized modes included them as alternatives in a mode-choice model, while others created mode-split models before or after trip distribution or used a separate non-motorized trip generation process. Furthermore, the environmental influences on walking behavior represented in MPO models inadequately reflect the state of the knowledge. While most models included measures of residential and/or employment density, few used diversity or design variables or information on walking facilities to predict pedestrian demand. Finally, the majority of large MPO models operationalized basic environmental, demographic, and socioeconomic correlates of walking at a coarse spatial scale (Singleton and Clifton, 2013).

This notable gap between pedestrian travel demand research and practice exists for several reasons. First, accurate, detailed, and widespread information on walking behaviors across an urban area historically has been difficult to obtain. The rich data collected for the studies identified above tended to have smaller sample sizes and narrower geographic scopes; regional travel model applications require larger samples collected across entire metropolitan areas. Until the 1990s, many regional household travel surveys omitted walking trips altogether or only asked respondents to record walking trips of certain types or those over a minimum distance or duration threshold (Clifton and Muhs, 2012).

Second, relevant measures of the built environment were not always available. Metrics of density, diversity, and design have been challenging to calculate for the entire spatial extent of the modeled region because of the difficulties obtaining consistent land use and transportation system data, particularly information about the existence and completeness of sidewalk networks (Peiravian et al., 2014). Third, many model applications have relied (and continue to rely) on large-scale transportation analysis zones (TAZs) and high functional class street networks. This coarse scale fits nicely with census geographies and eases computational modeling burdens by dealing with smaller matrices (TRB, 2007), but it is a relic of an era when travel models were designed to forecast demand for automobile and transit modes, exclusively. Large zones can muddle the determinants of walking, as TAZ averages of spatial and environmental measures can obscure finer-grained variations that matter at the pedestrian scale. In addition, walking trips can be hidden as intra-zonal travel; walking activity often occurs within neighborhoods and along lower-volume roadways and off-street paths. As a result, TAZ-based models can yield poor estimates of pedestrian travel demand and walking distances-traveled. Given these considerations, many practicing transportation modelers perceive travel survey and built environment data limitations to be key barriers inhibiting a more realistic and policy-sensitive representation of walking in applied models (Singleton and Clifton, 2013).

2.3. Motivations for a new framework

Today, many of the barriers identified in the previous sections have been surmounted, and they are no longer valid excuses for inadequately representing pedestrian activity in travel demand models. First, improved travel survey questionnaires and GPS-based travel surveys allow for more accurate and sometimes passive reporting of walking trips (Clifton and Muhs, 2012). At the same time, pedestrian count data collection methods have evolved (AMEC, 2011; Ryus et al., 2014; Schneider et al., 2005), providing the ability to externally validate pedestrian model outputs. Second, fine-grained, archived spatial datasets (e.g., Metro, 2011a) are becoming more widely available, including point-, parcel-, or block-level measures of the built environment. Information on pedestrian-scale environmental influences like sidewalk extent and off-street networks are being collected and geocoded for use in transportation planning and modeling (APD, 2010). Third, the rapid pace of computational processing power means smaller TAZs and more complex street networks do not compromise model run times (Balmer et al., 2009; Miller and Shaw, 2015). Small scale spatial analysis units and full pedestrian networks can now be used to locate more precisely walking trips and estimate more accurately zone-to-zone walking distances for an entire region.

Indeed, some transportation agencies are taking advantage of these advances to create improved planning tools for estimating pedestrian demand (Kuzmyak et al., 2014; Singleton and Clifton, 2013). Enhancements to four-step travel demand models include increasing the models' sensitivities to built and natural environmental factors and reducing the size of TAZs. Post-processing tools can take travel model outputs and use GIS and other methods to predict walking activity more finely. Other tools involve estimating pedestrian demand directly from local environmental and street characteristics (Hankey et al., 2012; Schneider et al., 2009), separately from a travel demand model. A recent report recommended pedestrian demand estimation tools for use in planning projects, that operate at a small spatial scale with detailed representation of environmental influences, can be integrated with multimodal travel demand models, and have the opportunity to operate as stand-alone tools (Kuzmyak et al., 2014).

In summary, with research reaching consensus on the environmental correlates with walking, and improved travel behavior and built environmental data being collected at relevant scales, it is time to rethink how pedestrian activity is represented in travel demand models, particularly within the dominant four-step modeling approaches. In this paper, we address this need by presenting and applying a pedestrian modeling framework that is designed to narrow the gap between research and practice.

3. Method

This section describes the framework to represent pedestrian travel within a four-step travel demand modeling paradigm, along with examples from a proof-of-concept application of the framework in the Portland, Oregon, region.

3.1. Pedestrian modeling framework

The framework is illustrated in Fig. 1 and includes the following procedures to facilitate improving representation of the pedestrian environment and walking behaviors:

1. Change the spatial unit of analysis for trip generation from transportation analysis zones (TAZs) to smaller pedestrian analysis zones (PAZs). Apply trip generation models at this geographic scale;
2. Estimate and apply a walk mode split model to predict the portion of trips generated in each PAZ that are made by walking. This binary logistic regression model includes spatially disaggregate, detailed built environment and socioeconomic variables that quantify associations between walking and the physical environment;
3. Aggregate trips by vehicular modes (auto, transit, and bicycle) to the zonal structure of the regional travel model (TAZs) and proceed through the remaining stages (destination choice, mode choice, and assignment) for these modes; and
4. In a parallel procedure, estimate and apply a pedestrian destination choice model to distribute the number of walk trips generated in each PAZ (step 2 above) to destination PAZs.

3.2. Proof-of-concept application

We developed this pedestrian modeling framework over the course of several research projects in coordination with Metro, the metropolitan planning organization (MPO) for the Portland, Oregon, region (Clifton et al., 2013, 2015). Metro's existing four-step travel demand model included walking as an alternative in the mode choice model,

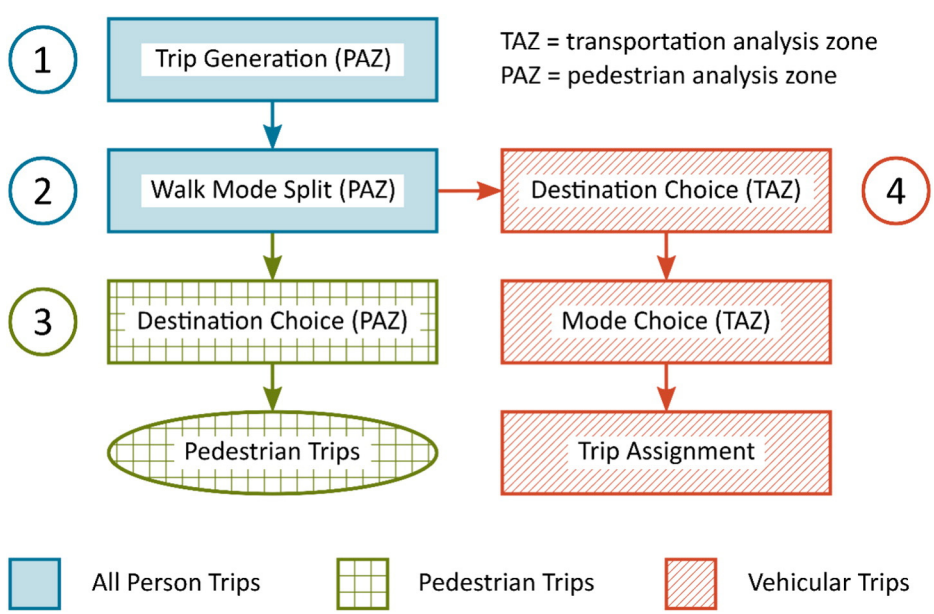

Fig. 1. Conceptual diagram of proposed pedestrian modeling framework.

as a function of distance and a local accessibility measure (Metro, 2008). The following subsections describe each step of the framework in more detail, including the data and methods used for estimation and application of the framework to the Metro example. Section 4 presents the results of this proof-of-concept application. Section 5 discusses the potential to generalize the pedestrian modeling framework to other communities.

3.3. Spatial unit: pedestrian analysis zones

To remedy the problems of representing walking using the large zonal structures (TAZs) found in most regional travel demand models, this pedestrian modeling framework used a new spatial structure called pedestrian analysis zones (PAZs). The PAZs in this study were 264 ft.-by-264 ft. (80 m-by-80 m) raster grid cells; thus, the edges of a PAZ represent a one-minute walking distance at 3.0 mph (4.8 kph). This choice of geography was one of convenience, as the same grid cells were already being used by Metro for other planning tasks (see Section 3.4), and one PAZ is roughly the size of a Downtown Portland city block. Using a compatible spatial unit populated with archived data is crucial for the long-term success and usefulness of the pedestrian modeling framework. In contrast to blocks or parcels, grid cells have a uniform size, regardless of land-use density, that makes zonal calculations and comparisons easier. Over 1.5 million PAZs (compared to only 2147 TAZs) cover the four counties included in Metro's model of the Portland region: Multnomah, Clackamas, and Washington Counties in Oregon, and Clark County, Washington. Fig. 2 illustrates the difference between PAZs and TAZs.

3.4. Data sources

Basic inputs to travel demand models include zonal estimates of the number of households with different household characteristics, the number of jobs by employment type, and various measures of the built environment. In this application, the number of households in each PAZ was calculated from parcel-based estimates of households, weighted to match the 2010 U.S. Census block-group totals. Household characteristics were not available at the parcel level, so the joint distribution of household characteristics (by size, age of head, income, and numbers of workers, children, and autos) for all PAZs within a TAZ was assumed to match that TAZ's joint distribution of household characteristics. PAZ-level employment by type was computed from the point locations of establishments in the 2009 Quarterly Census of Employment and Wages database (BLS, 2009).

Measures of the built environment were obtained from two different data sources. Many built environment measures were constructed from the 2011 version of Metro's Regional Land Inventory System (Metro, 2011a), a GIS database of archived regional geospatial data. Others, especially those used to construct a composite pedestrian environment measure (see Section 3.6), came from Metro's Context Tool (Metro, 2011b), a spatial dataset quantifying the character of the urban environment through multiple objective measures of a place. The Context Tool measures were defined at the scale of the PAZs. Each measure was first calculated around PAZ centroids using a circular buffer (usually a 0.25-mile (0.40-km) radius) and then reclassified using natural breaks into five categories: 1 (low) to 5 (high) (Singleton et al., 2014). See Section 4.2 for the definition of each Context Tool measure.

Individual models within a travel demand forecasting model system are estimated using travel survey data. To estimate models for our pedestrian modeling framework, we employed travel behavior data from the 2011 Oregon Household Activity Survey, or OHAS (OMSC, 2011). One-day travel diaries were collected on weekdays from April to December 2011 for 6108 households living in the four-county Portland, Oregon, metropolitan area, yielding 55,878 full trips. Public transit access and egress trips were excluded for simplicity, resulting in models that underestimate total walking activity. Trips were grouped by purpose: home-based work, shopping, recreation, school, and other; and non-home-based work and other. Only about 90% of these trips

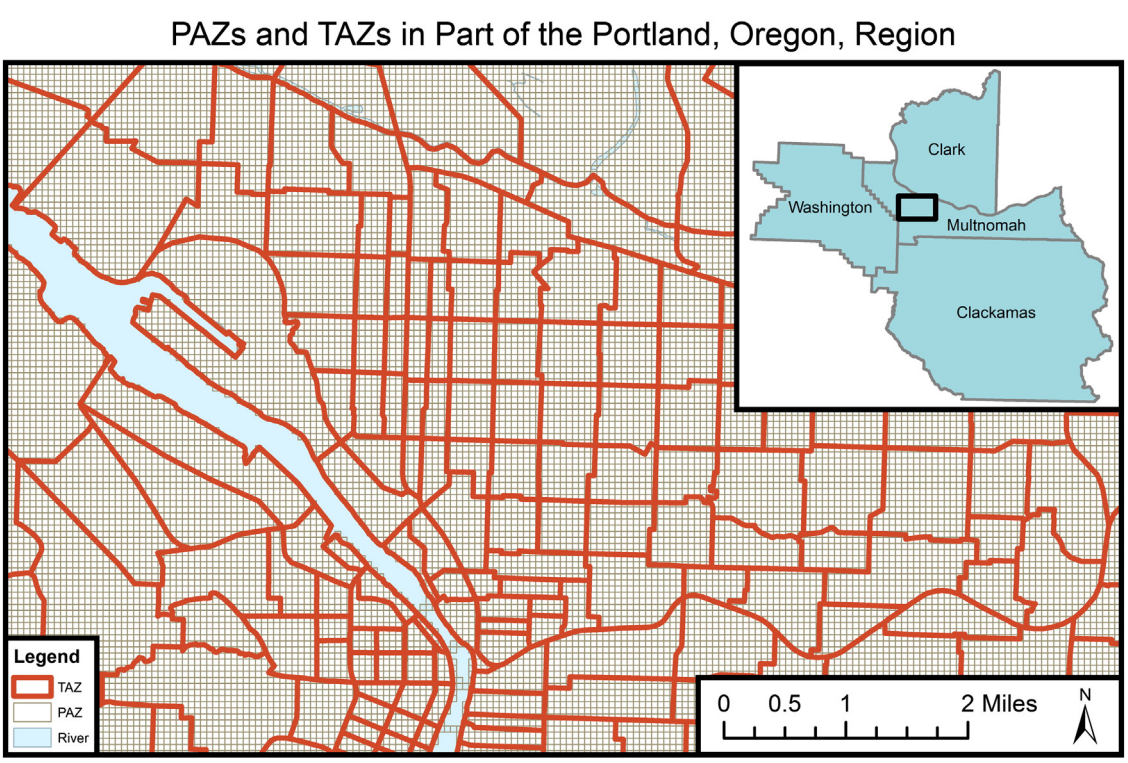

Fig. 2. Comparison of two zonal structures—PAZs and TAZs—in part of the Portland, Oregon, region.
Source: Created by the authors.

(N = 50,271) were used for model estimation. A 10% random sample, stratified by pedestrian/vehicular mode and trip purpose, was withheld for model validation (not presented here). The estimation sample contained 4094 walk trips (8%, unweighted). Of these walk trips, 44% were TAZ-intrazonal while only 9% were PAZ-intrazonal, highlighting an additional advantage of using smaller spatial units to represent walking. Trip origins and destinations were located using addresses and assigned to PAZs and TAZs.

3.5. Trip generation

The first stage of the four-step travel demand modeling process—trip generation—calculates the number of trips by all modes produced by and attracted to the model's spatial units based on demographic inputs. Our pedestrian modeling framework adopted Metro's (2008) existing cross-classification trip production models and trip rates, developed for use with TAZs. Assuming scalable models (see Section 4.1), we applied them at the PAZ level. Trip attractions were not used because Metro's model structure includes destination choice models to distribute trips. The cross-classification models predict the number of trips T_i produced in zone i as a function of trip rates t_h and the number of households HH_h in category h, according to the following equation:

$$T_i = \sum_{h \in H} (t_h \cdot HH_h) \tag{1}$$

Depending on the trip purpose, demographic categories are defined based on a subset of household characteristics: size, age of head, and numbers of workers and children (Metro, 2008).

3.6. Pedestrian index of the environment (PIE)

To address multicollinearity issues related to modeling the effects of the built environment on travel behavior, we constructed a new index: the pedestrian index of the environment, or PIE (Singleton et al., 2014). The PIE was based on Metro's Context Tool (Metro, 2011b), the spatial dataset of multiple environmental measures available at the PAZ level (see Section 3.4). Six measures were chosen for theoretical association with walking: activity (population and employment) density, transit access, block size, sidewalk extent, comfortable facilities, and urban living infrastructure (ULI). The comfortable facilities measure, while based on proximity to bicycle facilities, is relevant to walking behavior because it identifies multi-use paths and low-traffic streets as most comfortable. ULI includes shopping and service destinations used in daily life (e.g., banks, pharmacies, dry cleaners, grocery stores, restaurants) (Johnson Gardner, 2007). Similar measures have been used in other indices of the pedestrian environment (Peiravian et al., 2014). An exploratory analysis showed that many of the Context Tool's built environment measures were highly correlated with one another. Each measure is described in Table 1 (see Section 4.2).

To calibrate the PIE, the six relevant Context Tool measures were weighted based on the magnitude of their association with walking. A series of binary logistic regression models were estimated, regressing the choice of walking for OHAS trips against each built environment measure BE_m, according to the following equations:

$$P_{walk} = \frac{e^{V_{walk}}}{1 + e^{V_{walk}}} \tag{2}$$

$$V_{walk} = \alpha + \beta_m \cdot BE_m. \tag{3}$$

Based on the estimated slope coefficients (β_m), weights were generated such that PIE varied from a minimum weighted value of 20 to a maximum weighted value of 100 (Singleton et al., 2014).

3.7. Walk mode split

A central component in our pedestrian modeling framework is the walk mode split model (Clifton et al., 2013), which separates trips produced during the trip generation stage into pedestrian and vehicular (auto, transit, and bicycle) trips. In most travel models, walk trip segments serving as access and/or egress to/from other modes (e.g., transit) are modeled using a separate process (usually nested within mode choice). In the framework presented here, only single-mode walk trips between two activity destinations were considered.

Using OHAS trips, we estimated binary logit walk mode split models (segmented by trip purpose) to predict the probability of walking for a given trip produced in a particular PAZ i. Binary logit is an appropriate practical and theoretical choice, as it is used by many agencies (Singleton and Clifton, 2013) and researchers (Cervero and Duncan, 2003; Krizek and Johnson, 2006) for non-motorized mode split/choice models. Explanatory variables included traveler characteristics TC_c, matching those in Metro's (2008) model; PIE, our composite measure of the built environment; and transportation system variables TS_t, as shown in the following equation:

$$V_{walk} = \sum_{c \in TC} (\beta_c \cdot TC_c) + \beta_{PIE} \cdot PIE_i + \sum_{t \in TS} (\beta_t \cdot TS_{t,i}) + \beta_0. \tag{4}$$

Measures of the generalized cost of travel are not available for use in the walk mode split model because destinations of trips have not yet been determined in the model. Linking trip ends via destination choice occurs in a later step. Instead, we used accessibility measures as proxies. Local accessibility was represented by PIE, while regional accessibility was represented by some of the transportation system variables.

3.8. Pedestrian destination choice

After estimating the number of walk trips produced in each zone, the pedestrian modeling framework predicts the destinations for those walk trips (Clifton et al., 2016). Instead of common growth factor or gravity model approaches to trip distribution (DHS, 1993; Ortúzar and Willumsen, 2011), we used destination choice models, which predict

Table 1
PIE data sources and calibration results.

Measure	Definition	Range	Weight[a]	Minimum	Maximum
Activity density	# people + # jobs within ¼ mile	1–5	4.615	4.615	23.075
Transit access	# transit stops within ¼ mile, weighted by frequency	1–5	3.529	3.529	17.645
ULI	# neighborhood businesses within ¼ mile	1–5	3.120	3.120	15.600
Block size	# blocks within ¼ mile	1–5	3.086	3.086	15.430
Sidewalk extent	Miles of continuous sidewalks within ¼ mile	1–5	2.842	2.842	14.210
Comfortable facilities	Miles of low-stress/traffic calmed streets				
Within 1 mile	1–5	2.808	2.808	14.040	
Total				20.000	100.000

[a] See other sources (Clifton et al., 2013; Singleton et al., 2014) for full details on PIE's calibration.

the probability of selecting a particular destination zone for a given trip. Using walk trips in the OHAS dataset, we estimated multinomial logit pedestrian destination choice models (segmented by trip purpose) to predict the probability P of a walk trip going from production zone i to attraction zone j, given a choice set of attraction zones K, according to the following equation:

$$P_{j,i} = \frac{e^{V_{j,i}}}{\sum_{k \in K}\left(e^{V_{k,i}}\right)}. \tag{5}$$

To make the choice set generation and model estimation/application processes more feasible, we split the pedestrian destination choice process into two sequential models, as shown in Fig. 3. First, we aggregated PAZs into superPAZs (a grid of $5 \times 5 = 25$ PAZs) and estimated destination choice models using superPAZs as described above. These destination choice sets were constructed by randomly sampling up to 10 zones (including the production zone and the chosen attraction zone) located within 3 miles (4.8 km) of the production zone; more than 99% of OHAS walk trips were 3 miles or less in length. Second, we developed destination choice models to allocate walk trips from an attraction end superPAZ to an attraction end PAZ. These destination choice sets were a full enumeration of the up to 25 PAZs contained within each superPAZ.

Consistent with destination choice modeling practice, utility equations were specified using impedance terms, a log-sum of size terms, and pedestrian trip supports and barriers, as shown in the following equation:

$$V_{j,i} = \beta_{Imp} Imp_{ij} + \beta_{size} \ln\left[\sum_{s \in S}\left(e^{\beta_s} Size_{s,j}\right)\right] + \sum_{p \in P}\left(\beta_p Support_{p,j}\right) + \sum_{b \in B}\left(\beta_b Barrier_{b,j}\right). \tag{6}$$

Impedance Imp_{ij} was represented by the shortest-path network distance (including off-street paths) between the centroids of zones i and j. Size terms $Size_s$ included zonal employment by type and the number of households. We also used destination measures of pedestrian supports $Support_{p,j}$, including the presence of parks and PIE scores, as well as pedestrian barriers $Barrier_{b,j}$, including the presence of freeways, the proportion of industrial-type jobs (a proxy for industrial land uses), and the average slope in the destination zone. The superPAZ-to-PAZ destination allocation models used the same model specification, excluding the impedance term (but they are not presented here).

4. Results

The pedestrian modeling framework as described in Section 3 was applied to the Portland Metro region. Abbreviated results from the calibration of PIE, the estimation of walk mode split and pedestrian destination choice models, and the application of the entire pedestrian modeling framework are presented in the following subsections. In most cases, only results for the "home-based other" trip purpose (excluding home-based work, shopping, recreation, and school purposes) are presented as an example. Full results are available elsewhere (Clifton et al., 2013, 2016).

4.1. Trip generation

Fig. 4 is a map of home-based other trips produced. It demonstrates the level of spatial resolution obtainable from trip generation model outputs when using PAZs, which can better capture the variation in land development intensity, pedestrian supports, and other built environment features associated with walking than TAZs. As previously mentioned (see Section 3.4), base year (2010) PAZ-level trip production model inputs were constructed from point/parcel-level data when possible. To test for empirical scalability of the cross-classification trip generation models, we aggregated trips produced at the PAZ level to TAZs. Our results almost perfectly matched TAZ-level trip productions (Clifton et al., 2013), suggesting that it is feasible to use smaller spatial units, such as PAZs, as the basis for models of trip generation.

4.2. Pedestrian index of the environment (PIE)

Results from the calibration and weighting of the pedestrian index of the environment (PIE) are shown in Table 1. Based upon the coefficients from the univariate models described in Section 3.6, the activity density measure was weighted the most, while the measure of comfortable facilities was weighted the least. The variation of PIE values across the Portland region is shown in Fig. 5. The highest PIE scores of 100 were found only in the central city in Downtown Portland, while scores of 70–80 represented neighborhood commercial centers and suburban downtowns. Predominantly residential areas saw PIE scores ranging from 60 for inner-city neighborhoods to 40 for disconnected suburban subdivisions. The lowest PIE values of 20 were found in rural, undeveloped, and forested areas. (See Singleton et al., 2014, for a more detailed description of PIE.)

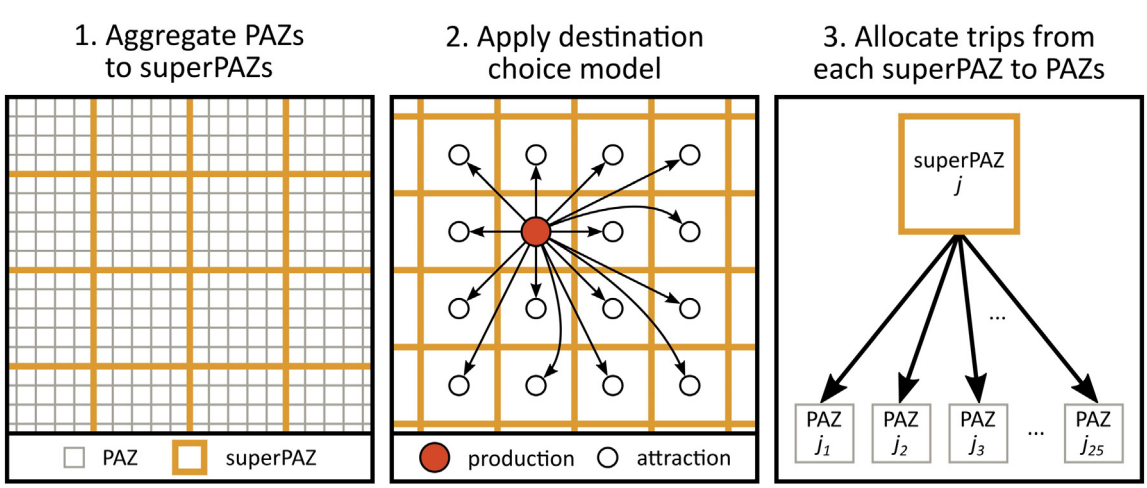

Fig. 3. Walk trip destination choice modeling framework.

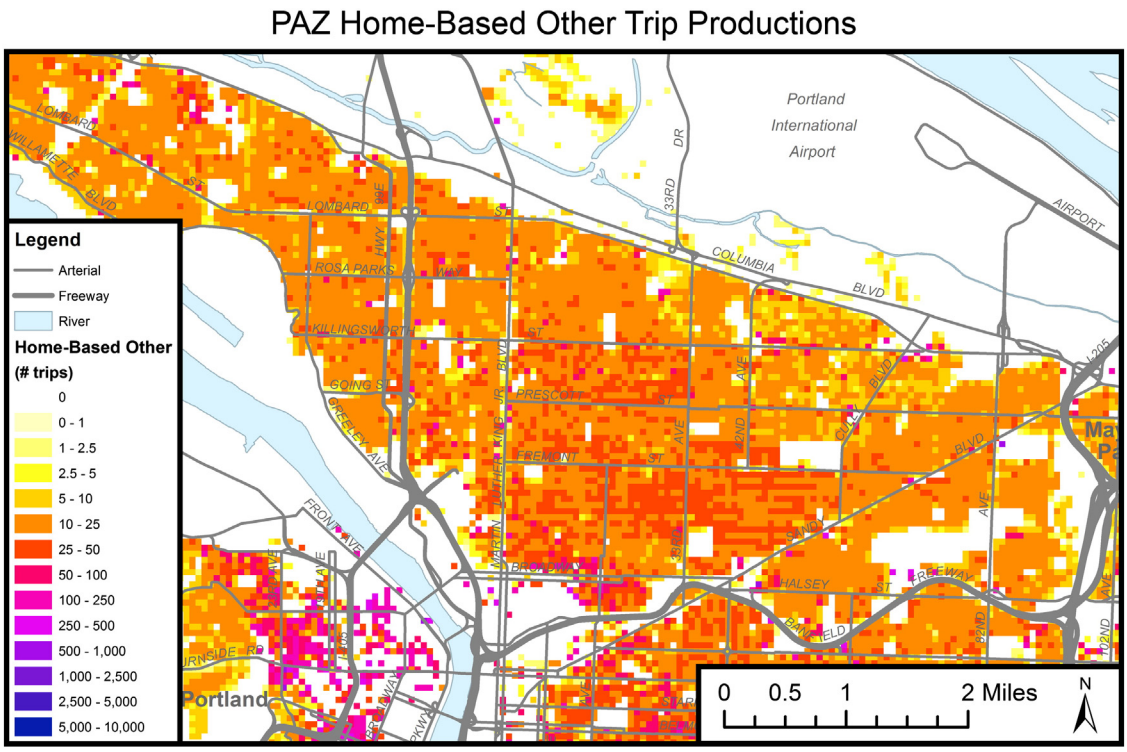

Fig. 4. Map of home-based other trip productions.
Source: Created by the authors.

4.3. Walk mode split

Walk mode split model estimation results for home-based non-work trips (including home-based shopping, recreation, school, and other purposes) are shown in Table 2. Full model estimation results are documented elsewhere (Clifton et al., 2013). Independent variables included six traveler characteristics (household size, income, age of household head, workers, children, auto ownership); the PIE index to represent the pedestrian environment; two transportation system variables (the local density of freeways and trails); and trip purpose

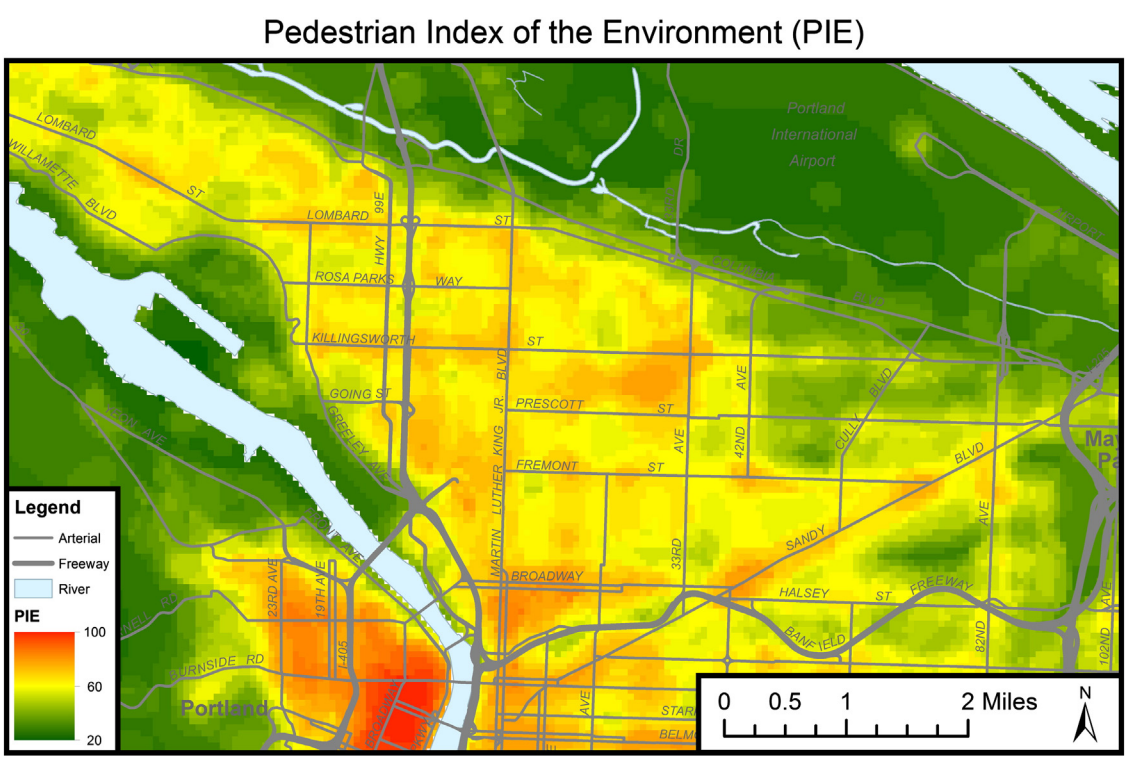

Fig. 5. Map of the pedestrian index of the environment (PIE).
Source: Created by the authors.

Table 2
Walk mode split model estimation results for home-based non-work trips.

Variable	Definition	β	SE	p	OR (e^{β})
Traveler characteristics[a]					
Household size	2 people	0.191	0.066	0.004	1.210
Age	56 < age ≤ 65	−0.242	0.067	0.000	0.785
Workers	1 worker	0.208	0.069	0.003	1.231
	2 workers	0.301	0.068	0.000	1.352
Children	1 child	0.295	0.074	0.000	1.343
	2 children	0.455	0.074	0.000	1.576
	3+ children	0.479	0.089	0.000	1.615
Auto ownership	0 autos	1.089	0.098	0.000	2.970
	2 autos	−0.463	0.056	0.000	0.629
	3+ autos	−0.690	0.071	0.000	0.502
Built environment					
PIE	Pedestrian index of the environment	0.043	0.002	0.000	1.044
PIE flag	Trip end located beyond PIE extents	0.530	0.295	0.072	1.699
Transportation system					
Freeways	Miles of freeways within ⅛ mile	−1.093	0.363	0.003	0.335
Washington	Trip end located in Washington state	0.792	0.286	0.006	2.208
Trip purposes[b]					
HB shopping	Home-based shopping purpose	−0.145	0.068	0.034	0.865
HB recreation	Home-based recreation purpose	0.288	0.058	0.000	1.333
HB school	Home-based school purpose	0.444	0.061	0.000	1.558
Constant	Constant	−4.377	0.123	0.000	0.013
Overall model statistics					
Trip ends	# and %: vehicular vs. walk	23,960	90.6%	2490	9.4%
Model fit	Log-likelihood: null vs. full	−8803	−7386		
Model fit	McFadden's adjusted R^2		0.160		

[a] Reference cases for traveler characteristics are people living in households with: 1 person, household head aged 26 to 54, 0 workers, 0 children, and 1 auto.
[b] The home-based other trip purpose is the reference case.

dummies. Traveler characteristics and transportation system variables with non-significant coefficients were removed from the model. Model goodness-of-fit was modest, with a McFadden's adjusted R^2 value of 0.16.

Results matched expectations. A one-point increase in PIE was associated with a 4.4% increase in the odds of walking for home-based non-work trips. All else equal, people in households with children were more likely to walk, and the odds of walking increased with the number of children. Furthermore, automobile ownership was negatively associated with walking: members of a zero-vehicle household had nearly three times the odds of walking than members of a one-vehicle household. An application of the walk mode split model for home-based other trips to part of the Portland region is illustrated in Fig. 6.

4.4. Pedestrian destination choice

The home-based other trip pedestrian destination choice model is presented as an example (Table 3). Full model estimation results for other purposes are documented elsewhere (Clifton et al., 2016). Independent variables included network distance as the impedance measure; retail, government, and all other employment and households as size measures; the average PIE score of PAZs within the superPAZ and the presence of parks as measures of a supportive pedestrian environment; and the presences of freeways, the proportion of industrial-type employment (a proxy for industrial land uses), and the average slope within the superPAZ as measures of barriers to walking. Interactions of traveler characteristics (income, presence of children, auto ownership) with distance were tested; there were no significant differences. The model fit was indicated by a McFadden's adjusted-R^2 value of 0.53.

Results suggested that longer distances reduced the odds of pedestrians choosing a particular destination. A one-mile increase in network distance yielded approximately an 86% decrease in odds. Destination zones with more employment were more attractive, particularly those with retail and government jobs; one additional retail or government job was worth about 46 additional jobs of other types. Measures of the built environment both supported (PIE) and deterred (slope) walking to a destination zone. A one-point increase in average PIE score was associated with a 2.5% increase in the odds of choosing that destination zone. An application of the pedestrian destination choice model for home-based other trips to part of the Portland region is illustrated by the map in Fig. 7.

5. Putting the framework into practice

This section discusses opportunities and limitations for generalizing the proposed pedestrian modeling framework and moving it more widely into practice. There are considerations for each step of the framework that will be unique to the structure of the parent travel model.

A variety of pedestrian-specific geographic analysis units are available from which to choose. PAZs could be blocks, street segments, nested sub-TAZs, uniform grid cells, parcels, or other units, depending on the planning needs and data availabilities/limitations of a particular region. Parcels and other zones based on built or natural environment features are often larger in low-density areas, reducing the ability of models to detect isolated hubs of pedestrian activity (e.g., near malls, near recreation facilities). On the other hand, small uniform grid cells may be unnecessary or introduce new challenges with larger land uses (e.g., parks, campuses). Smaller and less uniform PAZs may increase computational burdens. The development of PAZ geographies should also consider whether the necessary land use and built environment data are available and will be maintained and forecast at these spatial scales.

Trip generation for all modes, segmented by trip purposes, is estimated at the PAZ level (see Section 4.1), requiring appropriate data and models. PAZ-level inputs need to be prepared and the MPO's trip generation equations must be scalable. Some TAZ-level inputs

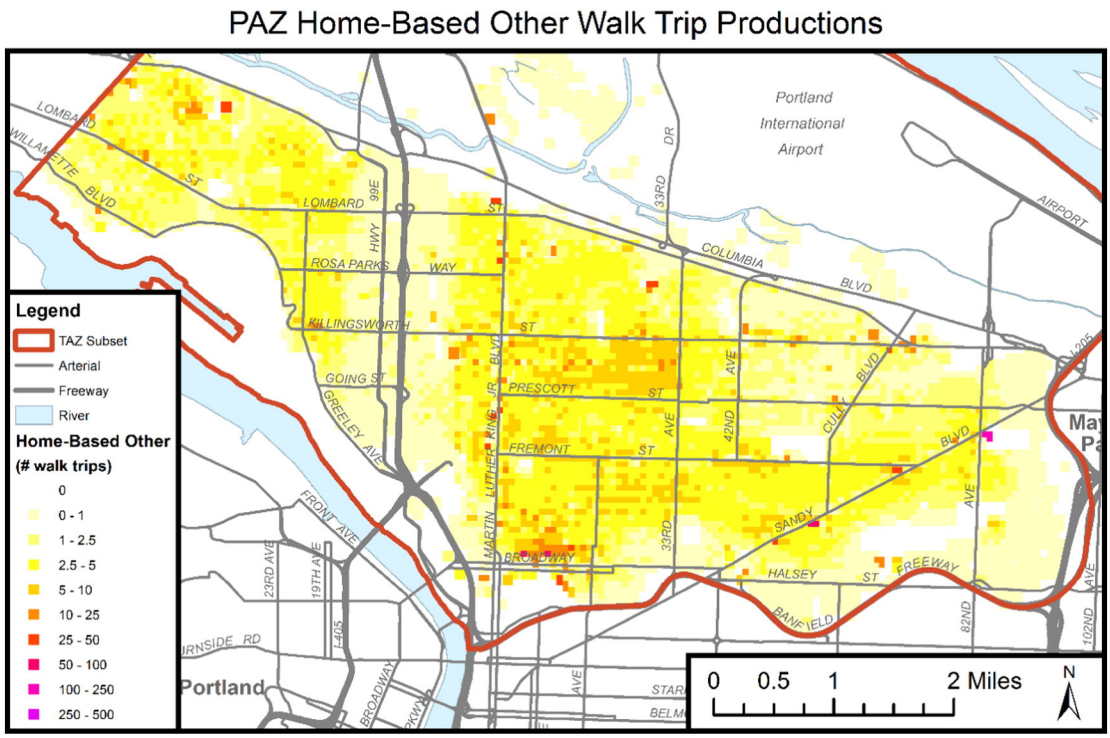

Fig. 6. Map of home-based other walk trip productions.
Source: Created by the authors.

(especially traveler characteristics) may need to be allocated to PAZs when data at the smaller scale are not available. This allocation process is not trivial and should be carefully considered when choosing PAZ geographies. Conceptually, most trip production and attraction models—including cross-classification and (linear or other) regression model structures—are independent of geographic scale. The operation of some trip generation models may have to be adjusted when assumptions of spatial scale have been built-in (e.g., zonal attractions = zonal productions).

The walk mode split model has many possible constructs. Various model structures may be and have been used for this purpose, including binary logistic regression, linear regression, and simple percentages. Given sufficient numbers of observations, the walk mode split model can be segmented to match the trip purposes (or aggregations thereof) from the travel model. In general, the choice of model structure should be guided by the availability of data and the nature of the relationship between walking and other variables.

The measure of the pedestrian environment (PIE) is specific to Portland in its variable structure and its scale. The PIE used specific Context Tool measures that may be unavailable elsewhere. Accordingly, it may be necessary to construct a region-specific PIE using locally-available data in order to apply the pedestrian modeling framework. For example, it may be desirable to construct a more localized "comfortable walking facilities" measure using traffic volumes, speeds, lanes, buffers, and crossing information, if such data are available. On the other hand, a more universal PIE measure could be estimated from widely-available built environment and national-level travel behavior data (EPA, 2013; FHWA, 2015). Such national-level built environment data could also be used for PIE if an agency does not have access to or the budget to collect more localized or smaller-scale data, although

Table 3
Destination choice model estimation results for home-based other walk trips.

Variable	Definition	β	SE	p	OR (e^{β})
Impedance	Network distance between zones (mi)	−1.94	0.062	0.00	0.14
Size	Total elemental destinations (logged)	0.40	0.034	0.00	N/A
Ret./gov. emp.	Retail & government employment (# jobs)	3.8	0.62	0.00	46.06
All other emp.	All other employment (# jobs)	0.0	N/A	N/A	1.00
Households	Households (#)	−2.0	0.87	0.02	0.14
Parks	Park in zone (yes)	0.12	0.094	0.22	1.12
Avg. PIE	Mean of PIE score of all PAZs in zone	0.025	0.007	0.00	1.03
Avg. slope	Mean of slope (°) within zone	−0.43	0.062	0.00	0.65
Freeways	Freeway in zone (yes)	0.10	0.191	0.60	1.11
Industrial	Proportion of industrial-type jobs	−0.40	0.224	0.08	0.67
Overall model statistics					
N	Number of observations		1108		
Model fit	Log-likelihood: null vs. full	−2511	−1181		
Model fit	McFadden's adjusted R^2		0.526		

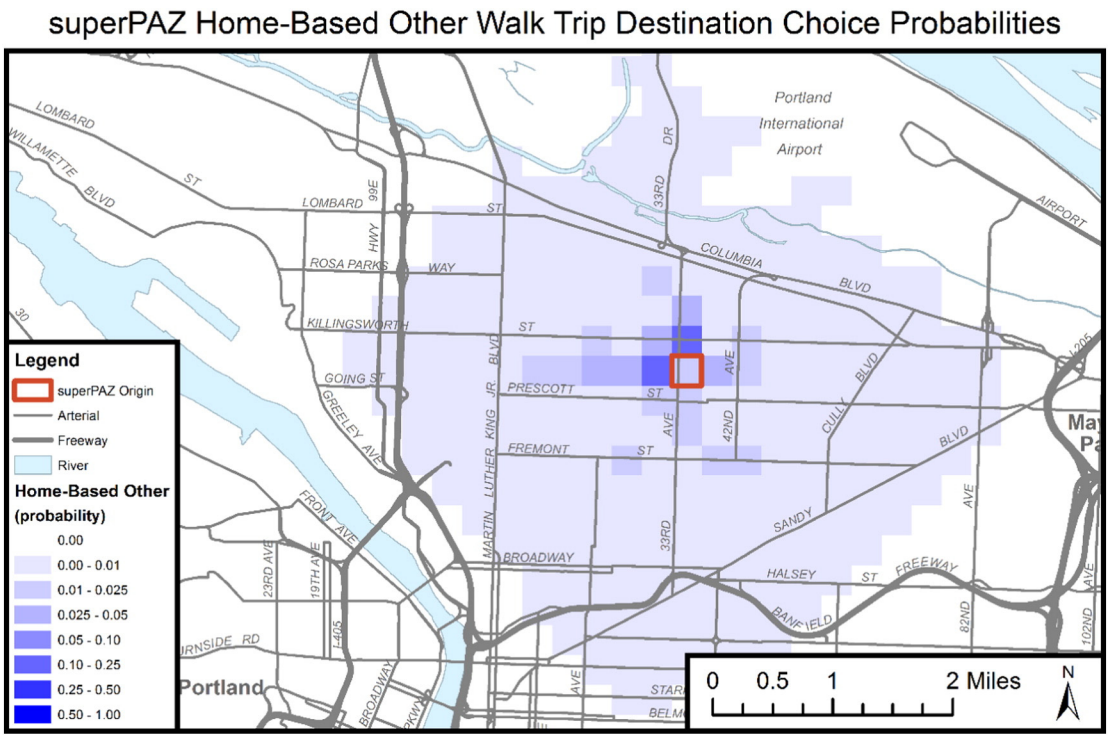

Fig. 7. Map of home-based other walk trip destination choice probabilities. (Source: Created by the authors.)

potentially at a loss of explanatory power. Because it was calibrated with observed walking data from the Portland area, a PIE measure for another region may have different weights.

Pedestrian trips from the trip generation and walk mode split models need to be distributed to destinations. There are many methods available to achieve this task. Legacy methods like growth factors and gravity model approaches are described in-depth in the literature (CS, 2012; Ortúzar and Willumsen, 2011). The state of practice is advancing toward destination choice models for individual travelers, which take the form of discrete choice models; however, guidance for model development is less abundant. The analyst should decide on a process to distribute trips based on data availability, the time available for estimating models, the trip distribution method used in the parent travel model, and the desired resolution and behavioral relevance of outputs.

If destination choice modeling is the chosen method, several issues should be considered, including: the appropriate spatial unit, choice set selection and size, and model specification. As with previous pedestrian modeling steps, geographic scale is fundamental: choice alternatives should remain at a scale relevant to pedestrian travel. However, it may be necessary or useful to aggregate PAZs to a slightly larger geographical unit in order to create a smaller destination choice set and to facilitate computations.

Another destination choice model consideration involves specifying the choice set. Unlike the mode choice problem, where there is a small and finite set of modal alternatives, the set of possible destination alternatives is very large and unknown. Researchers offer guidance on destination choice set generation methods (Ben-Akiva and Lerman, 1985; Lemp and Kockelman, 2012; Ortúzar and Willumsen, 2011; Pagliara and Timmermans, 2009). Previous work also offers guidance on the specification of destination choice models (Ben-Akiva and Lerman, 1985), including issues of agglomeration and competition (Bernardin et al., 2009; Borgers and Timmermans, 1988; Kitamura, 1984; Pozsgay and Bhat, 2001).

Additionally, because this stage of destination choice modeling is specific to pedestrians, it is appropriate to include measures of local accessibility, the built environment, and socio-economic characteristics in model specifications. Currently, there is little guidance available in the literature to inform model structures that are oriented around the destination choices of pedestrians. Our work on pedestrian destination choice (Clifton et al., 2016) adds to this literature and may be useful for agencies looking to adopt the pedestrian modeling framework.

Finally, a random sample of trips from the household travel survey data set could be retained for model validation. Otherwise, outside data sources like the National Household Travel Survey, American Community Survey (for home-based work trips), Safe Routes to Schools classroom counts (for home-based school trips), or specialized regional studies (e.g., trip generation studies, establishment-based intercept surveys) might be used. Given that most areas lack adequate validation data, there is an opportunity to implement region-wide intersection counts for an order-of-magnitude validity check on model estimates. While motor vehicle demand forecasts are often validated using traffic counts, most regional pedestrian counting programs are still in their early stages of development (Ryus et al., 2014).

6. Discussion and conclusions

The pedestrian modeling framework presented here has a wide range of benefits to travel demand modeling and pedestrian planning. Foremost, the framework improves and expands upon the available methods by which pedestrian activity is represented in travel demand models (Clifton et al., 2013). Using our framework, pedestrian demand can be forecast for an entire metropolitan region with spatial acuity and sensitivity to small-scale variations in the built environment. The framework improves travel model sensitivity to pedestrian-relevant factors, yielding results that are more responsive to socio-economic changes and policy interventions (e.g., smart-growth strategies, pedestrian infrastructure investments).

Not only do these methods provide a more accurate accounting for walking trips within a regional travel model (and potentially alongside, as a standalone tool), but they also have broader planning and policy applications. Area-wide estimates of pedestrian activity can be used for many planning activities. Health impact analyses may utilize physical activity estimates (derived from walking durations) for sub-area comparisons or equity assessments.

Predicted numbers of walk trips are useful for crash risk assessment activities, such as identifying areas with high potential for walking but suppressed pedestrian activity due to major roadway barriers. The walk mode split and pedestrian destination choice models' sensitivities to a variety of policy interventions means that the framework can evaluate the relative merits of a suite of pedestrian infrastructure investments and help to prioritize projects like sidewalk infill in particular corridors.

Despite the broad potential for planning applications, our pedestrian modeling framework is not without limitations. For practical reasons, the framework is linked to the traditional four-step travel demand modeling approach and its shortcomings. The development of activity-based models (ABMs) attempts to mitigate some of the limitations of four-step models, including aggregation bias and unrealistic representations of the behavior of travelers, including interrelated choices, household interdependencies, and tours (Castiglione et al., 2015). However, like ABMs, our pedestrian modeling framework is built around discrete choice models, and we see opportunities for ABMs to adopt smaller spatial units and more measures of the pedestrian environment, as our framework recommends. Another strong advantage of the framework—its fine-grained spatial scale—also yields challenges for forecasting. The framework requires inputs like sociodemographic characteristics and measures of the built environment to be constructed for future scenarios at micro-scale level of pedestrian analysis zones, a difficult task. Furthermore, it is often challenging for planners to predict the specific changes to the built environment (e.g., sidewalks, transit access) that might result from transportation projects and other future investments. Fortunately, the use of environmental constructs such as the PIE might allow planners to develop scenarios (e.g., a 20% increase in PIE scores) without having to prepare specific infrastructure improvements. Future work should attempt to develop improved methods of forecasting socio-demographic and built environment inputs at small spatial scales while examining various levels of intervention specificity. There may be potential to borrow techniques used in disaggregate land use forecasting models (Waddell, 2002).

Nevertheless, this pedestrian modeling framework advances pedestrian planning tools. There will undoubtedly be many improvements to this framework over time as the availability of disaggregate travel behavior, built environment, and household data increase. In order to further promote the inclusion of pedestrians in demand forecasting, there are several issues that must be taken up by the research community. For one, this framework did not address the issue of pedestrian route choice (Guo and Loo, 2013). The state of the research is too immature and route choice information was not available to permit inclusion. Additionally, as opposed to the traditional 4-step modeling process in which mode choice follows trip distribution, our pedestrian modeling framework splits trips by mode prior to destination choice. Although this was a practical choice to avoid dealing with massive matrices for destination choice, it also has theoretical and empirical implications (e.g., the inability to use a generalized cost for mode choice). Future work could use pedestrian route choice logsums in the destination choice model, and destination choice logsums in the walk mode split model to tie all the models together (Clifton et al., 2016). Additional research should also investigate the extent to which people may choose a destination first, choose to walk first, or consider destination and mode choices simultaneously. Finally, more research into the decision processes of pedestrians is needed, such as their considerations when choosing a destination, willingness to walk certain distances (Millward et al., 2013), and sensitivity to environmental factors for different socioeconomic groups. As demand models turn toward activity-based approaches, these issues will only become more pronounced. In the meantime, MPOs can take advantage of the opportunity offered by our pedestrian modeling framework to improve their existing tools and narrow the gap between research and practice.

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